



**UNIVERSIDADE FEDERAL DO RIO GRANDE DO NORTE
CENTRO DE CIÊNCIAS SOCIAIS APLICADAS
PROGRAMA DE PÓS-GRADUAÇÃO EM ADMINISTRAÇÃO**

ANDRE DIAS COSTA

**FOR A GREENER BRAZIL: A RISK ASSESSMENT MODEL PROPOSAL FOR
ILLEGAL MINING IN THE BRAZILIAN CAATINGA**

**NATAL
2023**

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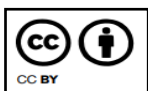
Doctoral Thesis proposal presented to the Postgraduate Program in Administration of UFRN (concentration area: organizational management) as part of the requirements for obtaining the title of Doctor in Administration.

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NATAL

2023



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Universidade Federal do Rio Grande do Norte - UFRN
Sistema de Bibliotecas - SISBI
Catalogação de Publicação na Fonte. UFRN - Biblioteca Setorial do Centro Ciências Sociais Aplicadas - CCSA

Costa, André Dias.

Por um Brasil mais verde: proposta de um modelo de avaliação de risco para a mineração ilegal na caatinga brasileira / André Dias Costa. - 2023.

453f.: il.

Tese (Doutorado em Administração) - Universidade Federal do Rio Grande do Norte, Centro de Ciências Sociais Aplicadas, Programa de Pós-Graduação em Administração. Natal, RN, 2023.

Orientação: Prof. Dr. Israel José dos Santos Felipe.

Coorientação: Prof. Dr. Gohar Petrossian.

1. Criminologia ambiental - Tese. 2. Mineração ilegal - Tese. 3. Modelagem econométrica - Tese. 4. Bioma - Caatinga - Tese. 5. Avaliação de risco - Tese. I. Felipe, Israel José dos Santos. II. Petrossian, Gohar. III. Título.

RN/UF/CCSA

CDU 005:343.9

To my children, João and Malu,
my greatest sources of inspiration
and motivation; to my wife, for
her unwavering love and support;
and to my mom, for always being
there for me

Acknowledgments

First and foremost, I owe immense gratitude to my family for enduring the many hours I spent studying and writing in front of the computer. To my wife, Alessandra, who shouldered a heavier burden both professionally and personally during these years; to my children, João and Malu, who often missed opportunities to play with their dad; to my mom, whose advice and help accompanied me through such difficult times.

I would also like to extend my heartfelt thanks to Anatalia Saraiva for providing me with the opportunity to be part of UFRN's Doctoral Program in Administration. My gratitude goes to David Carpenter, whose academic brilliance and human kindness have been an extraordinary example to follow. I am deeply grateful to Gohar Petrossian for her invaluable time, support, and guidance. Special thanks to Israel Felipe for his assertiveness, humbleness, and trust, particularly in the critical final stages of this journey. I express my sincere appreciation to Louise-Anne McNutt for her altruistic and affectionate hospitality. Finally, I am thankful to Najm Madani for bringing joy and ease to our world.

I cannot thank my colleagues at work enough, especially Alexandre Ferreira, who adeptly handled numerous challenges and missions in my absence. My gratitude extends to my boss, Polyana Pimenta, for her belief that my personal growth would contribute to the improvement of our agency. I am also profoundly grateful to Fulbright for awarding me the opportunity that enabled me to learn from so many fantastic individuals. Finally, I would like to express my gratitude to the Brazilian Federal Police for providing the data and the necessary leave that allowed me to complete this research.

During the preparation of this work, I have used Chat GPT in order to refine Python coding and enhance the quality of translations to English. After using this tool, I

reviewed and edited the content as needed and take full responsibility for the content of the publication.

This work was supported by the Fulbright Commission (Doctoral Dissertation Research Award) and by the Brazilian Federal Government (Leave for Participation in Stricto Sensu Postgraduate Programs).

ABSTRACT

This dissertation endeavors to construct an econometric model to evaluate the risk of mining-related criminal activities within the Brazilian Caatinga biome. Integrating concepts from rational choice and routine activity theories, the study categorizes mining tenements based on three critical dimensions: the offender through the efficacy of governance mechanisms overseeing miners (fines and police investigations), the target through the attributes of mined substances (VALUED approach for mineral desirability), and the geospatial characteristics of mining areas (legal mining areas and mining-related infrastructure). This research uses generalized linear regression models to analyze a grid composed of 10km² cells encompassing data aggregated over an eleven-year period (2010-2020) from such sources as ANM, CPRM, Federal Police, IBAMA, IBGE, Mapbiomas, Open Street Maps. The central findings of the research indicate a notable disconnect between the existing governance frameworks and their ability to deter illegal mining operations. Contrary to theoretical expectations, the study reveals that prevailing governance strategies, including law enforcement and regulatory fines, are largely ineffective in curbing illegal mining activities. Instead, the results highlight that the existence of legal mining operations considerably propel the likelihood of illegal mining activities. This suggests that areas with active legal mining inadvertently catalyze illicit endeavors. The dissertation contributes substantially to the fields of environmental criminology and mineral economics by providing empirical evidence against the effectiveness of traditional governance mechanisms in environmental crime prevention. It emphasizes the need for a paradigm shift from conventional enforcement models to more inclusive, participatory, and interlinked governance approaches. Furthermore, the study underscores the importance of considering the economic allure of minerals and the spatial dynamics of legal mining activities in formulating holistic policy interventions aimed at evidence-based prevention of mining-related crimes.

Keywords: Environmental Criminology; Illegal Mining; Econometric Modeling; Brazilian Caatinga Biome; Risk Assessment.

RESUMO

Esta dissertação objetiva a construção de um modelo econométrico para avaliar o risco de atividades criminais relacionadas à mineração no bioma da Caatinga brasileira. Integrando conceitos das teorias da escolha racional e da atividade de rotina, o estudo investiga a mineração ilegal com base em três dimensões críticas: o infrator, por meio da eficácia dos mecanismos de governança que supervisionam os mineradores (multas e investigações policiais); o alvo, por meio dos atributos das substâncias extraídas (abordagem VALUED para a desejabilidade mineral); e as características geoespaciais das áreas de mineração (áreas de mineração legais e infraestrutura relacionada). A pesquisa utiliza modelos de regressão linear generalizados para analisar uma grade composta de células de 10 km², abrangendo dados agregados durante um período de onze anos (2010-2020) de fontes como ANM, CPRM, Polícia Federal, IBAMA, IBGE, Mapbiomas e Open Street Maps. As principais descobertas indicam uma desconexão entre as estratégias de governança existentes e sua capacidade de dissuadir operações de mineração ilegais. Contrariamente às expectativas teóricas, o estudo revela que as estratégias de governança predominantes, incluindo policiamento e multas regulatórias, são em grande parte ineficazes na repressão às atividades de mineração ilegal. Os resultados destacam que a existência de operações de mineração legais impulsiona consideravelmente a probabilidade de atividades de mineração ilegal, sugerindo que áreas com mineração legal ativa inadvertidamente catalisam empreendimentos ilícitos. A dissertação contribui substancialmente para os campos da criminologia ambiental e da economia mineral, fornecendo evidências empíricas contra a eficácia dos mecanismos tradicionais de governança na prevenção de crimes ambientais. Enfatiza a necessidade de uma mudança de paradigma dos modelos de aplicação convencionais para abordagens de governança mais inclusivas, participativas e interligadas. Além disso, o estudo sublinha a importância de considerar o apelo econômico dos minerais e a dinâmica espacial das atividades de mineração legais na formulação de intervenções políticas holísticas voltadas para a prevenção baseada em evidências de crimes relacionados à mineração.

Palavras-chave: Criminologia Ambiental; Mineração Ilegal; Modelagem Econométrica; Bioma Caatinga; Avaliação de Risco.

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List of Acronyms

AIC - Akaike Information Criterion

ANM - National Mining Agency (Agência Nacional de Mineração)

ASM - Artisanal and Small-scale Mining

CFEM - Financial Compensation for Mineral Exploration (Compensação Financeira pela Exploração de Recursos Minerais)

CPRM - Geological Survey of Brazil (Companhia de Pesquisa de Recursos Minerais)

CSR - Corporate Social Responsibility

DEMs - Digital Elevation Models

DTVM - Securities and Exchange Brokerage Firms (Distribuidoras de Títulos e Valores Mobiliários)

ESDA - Exploratory Spatial Data Analysis

FOB - Free On Board

GDP - Gross Domestic Product

GEDI - Global Ecosystem Dynamics Investigation

GHG - Greenhouse Gases

GIS - Geographic Information System

GLM - Generalized Linear Models

GLR - Generalized Linear Regression

IBAMA - Brazilian Institute of Environment and Renewable Natural Resources (Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis)

IBGE - Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística)

ICMM - International Council on Mining and Metals

MRI - Mining-Related Illegal Income

OECD - Organization for Economic Co-operation and Development

OLS - Ordinary Least Squares

PIA - Annual Survey of Industry (Pesquisa Industrial Anual)

PRODLIST - Products and Services Classification List

RDAI - Relative Distance to the Average Income

SPSS - Statistical Package for the Social Sciences

STF - Supreme Federal Court (Supremo Tribunal Federal)

TRACIT - Transnational Alliance to Combat Illicit Trade

UNCAC - United Nations Convention against Corruption

UNEP - United Nations Environment Programme

UNODC - United Nations Office on Drugs and Crime

WFS - Web Feature Service

Introduction

With about 75% of Earth's surface already considerably changed because of human interventions and one million species in risk of extinction (IPBES, 2019), there is a most imperative necessity of coordinated action to prevent catastrophic events (IPCC, 2022). In this arena, the industry segment, which includes the mineral extraction sector, is the lead contributor to Greenhouse Gases (GHG) and is responsible for 34% of global emissions contributing to climate change (IPCC, 2022, p. 77).

Environmental damage and, consequently, GHG emissions, are inherent to mineral exploration and, even in developed countries, governance systems are lacking efficiency to reach the climate neutrality planned for 2050. In the European Union, for instance, UK, Italy, Germany, and Poland are the primary polluters, responsible for more than 65% of all gas and air hazardous emissions of the mining and quarrying sector and mining exploration continues to produce considerable volumes of GHG, dust and several other environmentally harmful events (Brodny & Tutak, 2020, pp. 22–23).

Although paramount, sustainability is, at the very least, a challenging goal for the mining industry. Because of that, some authors advocate, regardless of humanity's historical dependence on mineral exploration¹, that mining should not prevail over other more ecofriendly land uses (Malerba et al., 2012, p. 46). Nevertheless, despite generating

¹ Mining was always important for human societies. Since old Rome, Egypt and pre-Columbian America, precious metals and minerals have been enchanting and compelling societies to explore (Zabyelina & van Uhm, 2020, pp. 3–5).

significant negative impacts² even when performed in compliance with regulatory frameworks, the mining industry seems vital for building a more environmentally sustainable future.

Such duality appears to be a quasi-paradoxical dilemma (Wan & Wen, 2017), but mining extraction will continue to expand along with population and economic growth, and, consequently, increasing income and consumption (Ayuk et al., 2020, p. 4; Rademaker, 2019). Furthermore, the need to extract “critical materials” is indispensable for the energy matrix transition to renewable sources (Offerman, 2019, p. 1,17). This conversion to clean energy relies on the capacity of the mining industry, inherently destructive, to provide sufficient “critical minerals such as copper, lithium, nickel, cobalt and rare earth elements” (IEA, 2022, p. 4). Finally, mining endeavors have also been driven by steady price increases of some minerals such as gold (Interpol, 2022, p. 15) and critical materials (Ayuk et al., 2020, Chapter 4), consequence of rising scarcity/demand.

The rise of mineral extraction industry has been accompanied by the allegation that, if properly operated, mining entrepreneurship have the potential to promote important socioeconomic development, and generate positive impacts on UN Sustainable Development Goals (SDGs) (Ayuk et al., 2020; Monteiro et al., 2019). In this regard, both academia and industry are indeed developing strategies to mitigate mining exploration pitfalls and foster more sustainable practices (Brodny & Tutak, 2020; Cole & Broadhurst, 2021; Tost et al., 2018; Voncken & Buxton, 2019). Necessarily, Offerman (2019, Chapter 12) adapted the concept of sustainability to fit the mining industry characteristics: mining-related

² e.g. deforestation (Siqueira-Gay & Sánchez, 2021, p. 1), land degradation, biodiversity and ecosystem functioning loss (Lawer et al., 2019), and pollution (Zhou et al., 2020)

environmental sustainability is related to reducing the inevitable environmental externalities during the exploration and striving to rehabilitate the ecological balance after mine closure.

No illegal mining can be considered sustainable, though, since it aggravates environmental destruction and prevents economic development through tax evasion (Ranjan, 2018, p. 123). Hence, to obtain the necessary legal permits and environmental licenses before start exploring the subsoil - as well as complying with environmental and mining regulations as the exploration is performed - can be seen as the most fundamental measure of sustainability. Not reaching such minimal level of “sustainability” in mining endeavors is considered a crime in several countries, including Brazil.

The wealth associated with precious metals and minerals has been luring Organized Crime Groups (OCGs) and unethical corporations into environmental destruction, corruption and social harm (Zabyelina & van Uhm, 2020, p. 5) all over the world. In Brazil, despite being a federal crime with a maximum sentence of six years in prison, environmental crimes, such as illegal mining, have become a major source of income for multiple forms of organized crime, which have been using illegal mining profits to fund other criminal endeavors whilst spreading environmental, social, and economic damage (Igarapé Institute & Interpol, 2021).

Reliable data on illegal mining is hard to obtain, though, which constrains the development of effective strategies to prevent environmental crimes in Brazil. Along with underreporting (unreported and undetected crimes included), which is a common issue regarding the environmental crime data (e.g. Chawla et al., 2020; Muchtar & Yunus, 2019; Opsal et al., 2021; Paudel et al., 2022), the absence of public data on environmental crimes is a plain impediment for scientific research. The lack of transparency from governments, especially law enforcement, for which democratic policing (which includes public accountability, decision-making transparency, popular participation, and internal democracy

in the organization) is still an ideal (Hinton, 2005; Wazed & Akhtar, 2015), also prevents the necessary social control, frustrating society's right to collaborate with the development of environmental protection in Brazil.

The levels of unreported, undetected or undisclosed environmental crimes often compel researchers to use journalistic works (Paudel et al., 2022) (e.g. Igarapé Institute & Interpol, 2021) and proxies such as land use information to assess environmental crimes (Coelho-Junior et al., 2022). Studies like the one written by Coelho-Junior et al. (2022) use MapBiomas (2023a) to investigate crimes against nature in Brazil, particularly through the MapBiomas Alert platform. This system validates and refines deforestation alerts using daily high-resolution images, which include information on land use and soil transitions. By monitoring changes in land use patterns, such as deforestation or alterations in soil cover, the platform provides crucial data for detecting and understanding the extent of environmental crimes in the Brazilian Amazon.

Forest suppression is, in general, necessary to reach the soil to mine. Because of that, mining generates major deforestation, especially in developing countries (Ranjan, 2018), allowing for such change in land cover to be used as a proxy measure for mining (Caballero Espejo et al., 2018; Sonter et al., 2017; Swenson et al., 2011). Supplementarily, the increase of more than 600% in the Brazilian mining area since 1985 (MapBiomas, 2022), combined with the fact that, in 2022, the Amazon forest had one of the largest deforestation rates ever recorded (Imazon, 2022), reinforces the urgent need for intensification on illegal mining deterrence studies.

Hereof, Doussoulin and Mougenot (2022) evaluated the influence of mining-related conflicts on academic research using a bibliometric analysis of studies registered on the Scopus database from 1991 to 2020. The highest number of published papers was between

2013 and 2020, revealing that mining-related issues are capturing an increasing attention from academia.

Despite that, based on a scoping review that focused on 77 papers published in journals classified into the first quartile of SCImago Journal & Country Rank using SCOPUS and Web of Science databases, mining-related crimes annual scientific production has increased by 5.92 % in the last 5 years. Analyses have been concentrating on the negative effects of mining in a context of environmental and social violence involving large-scale mining (LSM), artisanal and small-scale mining (ASM), communities, government, and markets. Studies on the subject tend to focus on mining externalities, especially on conflicts and violence, not on the risk of illegal mining.

There is strong evidence to suggest that mining has a positive influence on violence and conflicts (Allen, 2017; Avcı, 2017; Bisht & Gerber, 2017; Cho & Kao, 2022; Hovardas, 2020; Perdue, 2018; Roberts & Mai, 2021; Zhuravskaia & Ryzhova, 2019), with the price of the substance directly affecting the size of the impact (Berman et al., 2017; Stoop et al., 2019). Conflicts associated with mining seem to be more an intrinsic result of the industry than an eventual phenomenon associated with specific contexts (Bezzola et al., 2022, p. 3). From this perspective, crime is often perceived as a mining-related externality, with direct violence being the most straightforward form.

This resonates on the academic production, which has been giving attention to regulations regarding due diligence on supply chains. However, research on corporate social responsibility (CSR) associated with conflict minerals (Dalla Via & Perego, 2018; Hanai, 2021; Hofmann et al., 2018; Partiti & van der Velde, 2017; Schleper et al., 2022; Swift et al., 2019) has often found that this indirect approach seems insufficient to prevent conflicts (and illegal mining) (Cusato, 2021, pp. 286, 289).

The perspective of crime as a mining-related externality is dominant, and scientific studies have lacked approaching illegal mining as an outcome variable. Because of difficulties with data access, some researchers have made the decision to exclude illegality from their quantitative models (Berman et al., 2017; Stoop et al., 2019), or hypothetically assume that every mine has passed through governmental analysis (Ranjan, 2018), while others (Bansah et al., 2022; Hilson, 2017; Le Tourneau, 2021) chose to approach the matter using qualitative methods with similar focuses, as presented below.

Bansah et al. (2022) examines the ineffectiveness of Ghana's military intervention in eradicating informal artisanal mining, highlighting the need for addressing underlying factors like unemployment, improving governance, and engaging stakeholders for sustainable solutions. Hilson (2017) scrutinizes the Ghanaian Government's forceful employment of military and police measures to eradicate unlicensed artisanal and small-scale mining – colloquially known as 'galamsey'. This aggressive approach was not anticipated, considering the sector's substantial role in contributing over 30% to the nation's gold output and providing direct employment to nearly a million individuals, alongside spawning numerous additional jobs in related upstream and downstream industries. Finally, Le Tourneau (2021) analyzes the resilience of illegal gold miners in French Guiana, focusing on the *garimpo* as an economic and social system that adapts to repression and risks. It provides insights into the *garimpeiro* identity and how it enables cohesion in the mining community.

Nevertheless, in the years to come, for the reasons stated above, an increasing pressure upon the already over-exploited mining industry will expand its influence and impacts. Consequently, negative externalities will continue to rise, making the prevention of mining-related crimes gain importance and magnitude. To address the previously described gap, this research proposes to build an econometric model capable of assessing the

occurrence of the risk of mining-related crimes in the Brazilian Caatinga, a unique Brazilian semi-arid biome.

In this thesis, both Rational Choice Theory (Becker, 1968; Ehrlich, 1973) and the three elements of Routine Activity Theory (Cohen & Felson, 1979) were utilized for investigating the influences on the risk of illegal mining in Brazil. The approach to handling offenders was encapsulated as a function of environmental governance by law enforcement and regulatory agencies. The management of place encompassed the geospatial attributes of mining tenements, while guardianship over the target was reinterpreted as a measure of market attractiveness, determined through a CRAVED-based methodology specific to the ten most sought-after mineral substances in Brazil. The study employed generalized linear regression models to analyze data from an eleven-year span (2010-2020) across a 10km² grid to assess the occurrence of illegal mining.

The findings of this research are intended to augment the scientific community's comprehension of the causes and consequences of illegal mining. Additionally, the insights could serve as valuable inputs for public agencies, such as the Federal Police, ANM, and IBAMA, aiding in the transition from their predominantly reactive strategies to more proactive ones, particularly in resource and staff allocation. This information could also be pivotal in identifying high-risk areas for illegal mining, thereby enabling authorities to focus their efforts more effectively. Such prioritization could further assist in developing algorithms for detecting mining activities in the Caatinga biome, where distinguishing mining areas from natural landscapes is challenging.

Most notably, the public disclosure of areas highly susceptible to illegal mining might exert a deterrent effect on environmental crimes. According to the Rational Choice Theory, the perception of being under surveillance could lead potential criminals to reassess the costs and benefits of mining activities, and consider the risk of legal sanctions or reputational

damage. Additionally, the dissemination of a list highlighting municipalities at higher risk of unauthorized mining, akin to the deforestation blacklist utilized in the Amazon in 2008 (Assunção & Rocha, 2019), could potentially replicate the success seen in curbing environmental offenses.

Hypotheses

Inferring the risk of a crime to happen is intrinsically associated with the prediction methods. Those, in turn, are heavily based on past events data on when, where, what and who committed/was a victim of a crime (Maxim, 2013, p. 17), and on the elements that are related to the occurrence of crime, such as demographic characteristics, inequality, institutional development, government effectiveness, incarceration rates, and the size of police forces (R. R. Soares & Naritomi, 2007, pp. 2–3).

On the other hand, communities have been playing a central role in ecological preservation, particularly in tropical regions. This has led economics researchers to include the concept of effectiveness in their interventions in the area and to pay a careful attention to institutions and their rules, which shape and are shaped by conservation instruments (Sills & Jones, 2018, p. 396).

Causality, nevertheless, is hard to prove even with precise crime data (L. Wilson & Boratto, 2020, p. 2), and shallow analysis of crime can yield false conclusions. Correlation between elements present on crime hotspots does not mean that they are causing crime. A violent but well-policed area can misidentify police as a causal effect of crime, for instance (Maxim, 2013, p. 17). Complementary, research results can be biased by underreporting, which is common in environmental crime data (e.g. Chawla et al., 2020; Muchtar & Yunus, 2019; Opsal et al., 2021; Paudel et al., 2022).

There is no certainty involving the magnitude of underreported environmental crimes, though, which can only be speculated (Catalano, 2006, p. 1). The inclusion of social and

spatiotemporal risk factors that prevent or contribute to criminal practices can mitigate the dependence on prior crime data and increase the accuracy and confidence on inferences for the future. Within this framework, careful use of scientific methods can aid the discovery of intricate connections, including causal interactions that were not visible at first (Lum & Kennedy, 2012, p. 5).

Maxim (2013, p. 18) presents six common analytic categories utilized in crime prediction (hot spot analysis, regression methods, data mining techniques, near-repeat methods, spatiotemporal analysis, and risk terrain analysis), dividing them into four classes:

- simple methods: heuristic hotspot and near-repeat analysis, linear regression, heat maps, and risk terrain modeling;
- classical statistical techniques: grid mapping, covering ellipses, kernel density, linear and leading indicators regression, spatiotemporal analysis using heat maps and seasonality;
- complex applications: geospatial predictive analysis, near-repeat analysis using ProMap and self-exciting point process, splines and stepwise regression, data mining using clustering and classification;
- tailored methods: which adapt existing methods to particular police necessities.

This research employs a blend of these methodologies to empirically test hypotheses concerning the likelihood of mining-related crimes occurring within Brazil's Caatinga region. Given the multi-faceted nature of the research subject, which encompasses economic, environmental, and governance dimensions, this study is underpinned by a set of hypotheses. These hypotheses aim to explore and understand the triad of forces that create opportunities for mining-related crimes: the absence of a capable guardian, and the presence of a suitable

target, and a favorable location. Each hypothesis is supported by a range of variables, with each serving a distinct role in the analytical framework.

Hypothesis 1 - Governance mechanisms for deterring miners

The absence of a capable guardian is related to the first hypothesis (H_1), which posits that effective governance mechanisms, such as environmental governance and law enforcement activities, act as significant deterrents to illegal mining. This hypothesis aims to explore the role of governance structures and their effectiveness in curbing illegal mining activities. Data pertaining to governance mechanisms, primarily acquired from federal police investigations, environmental, and regulatory fines provide the empirical foundation for testing this hypothesis. These variables offer critical insights into the capacity of existing governance structures to deter illegal mining activities, thereby serving as a measure of their effectiveness. An alternative hypothesis related to governance is that ($H_{1.1}$) long processing times required to obtain a mining permit have a positive influence in illegal mining.

Hypothesis 2 - Desirability and Attributes of Minerals

The suitability of the target pertains to the second hypothesis (H_2), which contends that the desirability and attributes of minerals, particularly those that are highly "VALUED" are positively related to illegal mining activities. This aspect is encapsulated in the Mining-Related Illegal Income (MRI) variable, an aggregate measure that captures the average economic value, abundance, and easiness of the minerals being accessed, used, explored and disposed in a particular cell. The variable serves as a proxy for opportunities for illegal mining, and this hypothesis seeks to examine the extent to which the economic benefits of mining-specific minerals influence the rate of illegal activities. By doing so, it offers a nuanced and multidimensional perspective on what makes certain minerals more attractive for illegal mining operations compared to others.

Hypothesis 3 - Geographic determinants of the mining tenements

Data on place (mining tenement) management effectiveness is limited. Despite the existence of geolocation files about police stations, tax, and environmental agencies that would eventually pull over mining trucks for inspection, there is no publicly available and reliable information about their effectiveness, efficiency, or efficacy³. Due to this shortfall, because mining-related crimes inherit the concentration of mineral deposits from Earth geoformation, producing clear "offender convergence settings" even in isolated places, the suitability of mining tenements for exploration will be considered a criminogenic factor⁴.

Hence, the third hypothesis (H₃) asserts a positive correlation between the geographic and infrastructural attributes of mining tenements and the frequency of illegal mining activities within these tenements. Building upon the Becker-Ehrlich model, which primarily employs deterrence and income to conceptualize criminal behavior, this hypothesis extends

³ The only exception is the Federal Highway Patrol (Polícia Rodoviária Federal), which, despite having made available to the general public data on traffic fines, did not add coordinates to the dataset, making it impossible to infer probabilities related to mining tenements.

⁴In alignment with crime pattern theory (Brantingham & Brantingham, 2008), which extrapolates from the geometric spatiality of criminal activities to elucidate the relationships between crimes and the loci—residential, occupational, and recreational—frequented by criminals, this framework acknowledges the pivotal role of accessibility. Such accessibility is designated as a criminogenic factor, as it influences the likelihood of criminal engagement in proximity to these focal points or along connecting pathways. Analogously, in the context of mining, spatial convenience becomes equally criminogenic, simplifying the complexities of exploration and thereby raising the propensity for illicit activities.

the model's scope by integrating spatial variables—road lengths, number of gas stations, CPRM mining occurrences, and urban areas. These variables not only enrich the foundational economic model but also offer a multi-dimensional framework for comprehending the intricacies of mining-related crimes. By doing so, H₃ posits that mining tenements with higher accessibility, as indicated by these spatial metrics, are more susceptible to illegal activities, thereby fostering a nuanced understanding in the domain of environmental crimes.

Finally, in the complex landscape of variables that influence mining tenements, the existence of legally authorized mining within a given spatial unit emerges as a pivotal consideration. Consequently, Hypothesis 3.1 posits also that the incidence of legal mining functions as a criminogenic catalyst for unauthorized mining operations. This supposition gains credence from the premise that lawful mining activities invariably necessitate the establishment of infrastructure, the allocation of specialized human capital, and the procurement of sophisticated equipment. Collectively, these components not only facilitate but also potentiate the likelihood of illegal mining, given their auxiliary roles in providing immediate access to a network of potential buyers and the rapid mobilization of unlawfully extracted minerals.

Literature Review

Mining-Related Crimes

Defining mining-related crimes is not a straightforward task. Mining involves a myriad of substances (almost 900 in Brazil) that range from water and petroleum to diamonds and gold. Usually, mining is a complex process, involving many actors, which goes from prospection, research, and exploration to transportation, processing, and commercialization. There are also nuances of magnitude, ranging from large-scale industrial mining to artisanal and small-scale mining (ASM).

Mining-related crimes are also not restricted to unauthorized extraction of mineral resources. Illegal mining has become a widespread and profitable criminal venture in many places throughout the globe, damaging not only the environment but also weakening peace and stability, hindering socio-economic development, and violating human rights in vulnerable communities (Interpol, 2022, p. 7). Hence, the classification should account for other environmentally important human actions that impact flora, fauna, water, the landscape, and public health (Nellemann et al., 2016, p. 17).

Complementing this internal assessment, an external crime convergence perspective on illegal mining points towards a structured activity led by organized criminal gangs, directed by illicit mining syndicates, with an intersection with other serious crimes, such as money laundering, illicit trading of explosives, firearms, hazardous waste and chemicals trafficking, modern slavery and human trafficking, drug trafficking, child and women abuse/exploitation and pervasive (sexual) violence, financing of terrorism and armed conflicts, corruption, forgery, tax fraud, threat, and other environmental crimes (Arikan et al., 2017, p. 469; Interpol, 2022, p. 7; Nellemann et al., 2016, pp. 17, 30, 65; UNODC, 2022, p. 1; Zabyelina & van Uhm, 2020, p. 6).

Despite this entanglement of aspects related to illegal mining, Ayuk et al. (2020, p. 86) postulate that the premise of classifying a mining endeavor as illegal is the existence of a legislation regulating or prohibiting mineral exploration. In this regard, Zabyelina & van Uhm (2020, pp. 11–13) use a legal pluralism argument to distinguish between illegal and informal mining. They argue that the fact that most ASM is performed in a legal grey area, with some measure of legality (usually due to excessive bureaucracy which prevent miners to finish the formalization process), should be sufficient to consider it an informal endeavor, not an illegal activity.

Becker's Rational Choice Theory (1968) can be used to better understand this frame of reference. If legal bureaucratic costs are higher than the costs of operating illegally (the chance of getting caught and its consequences), one would consider the crime a viable alternative. Hence, the propensity to commit environmental crimes would be positively impacted by the lack of financial resources available to finance sustainable practices, including environmental studies and legal permits. Extensive waiting times, for instance, could raise legal mining costs to a point that it encourages entrepreneurs to start exploring illegally. On the other hand, a capable law enforcement could raise the risk of getting caught and punished to a level that the cost-benefit of mining without a permit is not deemed it worthy.

For this reason, it would seem that governmental agencies institutional capabilities have an important reverberation on environmental crimes. As such, it has been advocated that, if the formalization process is not sufficiently accessible for the miners to legalize their work, referring to ASM as an illegal activity would not be correct. In such cases, “extralegal” would be more appropriate (Ayuk et al., 2020, p. 86).

Along with academic efforts to understand the different illegality levels in which mining is operated, illegal mining is defined by UNODC (2022, p. 2) as (1) prospecting and

extracting minerals without appropriate land rights, exploration and mining licenses or mineral transportation and other permits, (2) invading mining sites and (3) mining in protected areas. Similarly, Interpol (2022, p. 5) uses illegal mining as an umbrella term to refer to the illegal extraction and commercialization of minerals, including the use of harmful chemicals employed in mining.

Hence, for the purposes of this research, illegal mining will be defined as any activity related to mineral exploration that has commercial purposes and is performed without legal permission or environmental license, or in disagreement with the obtained authorization. Known causes of crime, such as a lack of institutional development and government effectiveness (R. R. Soares & Naritomi, 2007, p. 2), permit to associate Illegal mining with the lack of State, both qualitatively, as a matter of efficiency related to how governments support and regulate society and mining activity, and quantitatively, concerning efficacy or the presence of the State itself.

In central countries, where governments have a stronger presence and more rigid and effective governance systems are in place, less-polluting mining transformations are made and more valuable items are manufactured. Contrastingly, mining operations that are most harmful to the environment and produce outputs of lower added value are concentrated in peripheral countries (Malerba et al., 2012, pp. 13–14).

Mining is essential to many of these lower income countries, in spite of playing only a relatively minor role in supplying minerals to the global economy (Ayuk et al., 2020, p. 68). Of the 50 most mining dependent⁵ countries, 18 are lower-middle-income economies (LMIE)

⁵ A country is classified as mining dependent when metals and minerals account for more than 20 per cent of exports by value; or mineral rents are more than 10 per cent of GDP (ICMM, 2020, p. 1).

and 12 low-income economies (LIE), with a prevalence in Africa, Latin America and Asia (Ayuk et al., 2020, pp. 68–69; ICMM, 2020, p. 4). In terms of mining production monetary value though, wealthier (upper-middle or higher-income) countries dominate the scene, with China, Australia, USA, Indonesia, Russian Federation, Brazil, Chile, South Africa, Canada, and Peru as top ten explorers (ICMM, 2020, p. 5).

Although one could argue that crimes are not more concentrated than other related phenomena (Eck et al., 2017), mining-related crime occurrence derives from the geospatial distribution of mineral deposits, which are a product of Earth's geotectonic setting (Mao et al., 2021). Mineral resources are not evenly or arbitrarily available across its crust. Some minerals are widely dispersed while others are encountered in only a few places, which increases the risk of supply restrictions (Graedel & Reck, 2019, p. 108) and brings geopolitical problems to the surface (The Economist, 2021).

While the rich North focuses on improving due diligence on supply chains, the less developed South struggles to repress mining-related crimes. Notwithstanding dependency, production and governance levels, mining-related crimes remain a problem to be solved by every nation, either because of its economic importance or widespread socioenvironmental impacts. Specific literature on mining-related crime prevention is sparse, though. Most of the research on illegal mining has been addressing crime inside a larger framework of the mineral industry externalities.

Mining Externalities

As explained by Nordhaus (2021, p. 67), externalities characterize a market failure: a spillover is produced (in this case, any of the negative effects associated with illegal mining) without the perpetrator paying for the damage caused (to nature or public property). When the damage is as critical as in the mining industry, the government must intervene to repair the defect using fiscal (e.g. Financial Compensation for Mineral Exploration-CFEM) or

regulatory (which are enforced through criminal prosecution, fines, seizures, etc.)

instruments.

The negative effects of the mining industry are frequently associated with the “natural resource curse” (Brunnschweiler, 2008; Brunnschweiler & Bulte, 2008; Parker & Vadheim, 2017; Van Der Ploeg, 2011). The hypothesis is that countries with abundant natural resources tend to grow more slowly and, antithetically, cycles with elevated price rises in commodities can generate decrease in growth because of several unintended effects in important areas. In this regard, Table 1 presents an overview of economic, social, and environmental externalities related to mining explorations.

Table 1

Negative effects associated with mining

Economic	Social	Environmental
Agriculture loss due to pollution	Child work	Air (particles), sound (machinery), water (superficial and underground) and soil pollution
Food insecurity	Community conflicts and local tensions	Deforestation
Inequality increase	Compulsory displacements and expropriations	Hydrogeological connectivity reduction
Land monopolization	Crime escalation	Increase in waste generation (solid and liquid)
Loss of revenue to governments	Cultural and historical heritage loss	Landscape degradation
Market disequilibrium	Deaths and injuries	Loss of biodiversity
Municipal tax base reduction	Demographic change	Radiation hazards
Resource depletion	Environmental injustice	
	Food insecurity	
	Human rights violations	
	Increase in drug addiction, alcoholism, and other social problems	
	Indigenous rights violations	
	Lower school attainment	
	Modern slavery	
	Rise in human health issues	
	Violence against women	

Economic	Social	Environmental
	Violent repression of anti-mining activism/ criminalization of protest	

Note. Adapted from Aguilar-González et al., 2018, with additional contributions (Bezzola et al., 2022; Nellesmann et al., 2016; Partiti & van der Velde, 2017; Roza, 2020; Schleper et al., 2022; Sveinsdóttir et al., 2021; Yang & Ho, 2018).

Among contributing factors associated with such undesirable consequences, weak governance systems and mechanistic solutions (failing to properly understand the socioenvironmental effects associated with resource extraction) stand out (Rochlin, 2018, p. 330; Vélez-Torres & Méndez, 2022, p. 2,10).

Crime as a Mining Industry Externality. Although many studies on mining-related crimes are focused on Africa (Berman et al., 2017; Enaruvbe et al., 2019; Hilson, 2017; Hilson & Maconachie, 2020; Stoop et al., 2019) and Latin America (Aguilar-González et al., 2018; Arbeláez-Ruiz, 2022; Duff & Downs, 2019; Reeder et al., 2022; Rochlin, 2018; Toledo Orozco, 2022), mineral resources exploration has fueled armed and social conflicts all over the world (Allen, 2017; Avci, 2017; Bisht & Gerber, 2017; Cho & Kao, 2022; Hovardas, 2020; Perdue, 2018; Roberts & Mai, 2021; Zhuravskaia & Ryzhova, 2019).

Such prevalence makes mining-related conflicts seem to be more an intrinsic result of the industry than an eventual phenomenon associated with specific contexts (Bezzola et al., 2022, p. 3). In this sense, crime is often perceived as a mining-related externality with direct violence being the most straightforward form.

The apparent inevitability and complexity of mining-related crimes are compatible with public security⁶ risks, a wicked problem (Reinecke & Ansari, 2016; Rittel & Webber, 1973) that cannot be fully mitigated, only managed (Kessler & Daase, 2008). Hence, to effectively prevent an intricate problem, such as mining-related criminality, a systemic approach it is necessary, which drove researchers to have extensively documented positive impacts of mining on crime (Berman et al., 2017; Kotsadam et al., 2017; Mkodzongi, 2020; Sesele & Marais, 2022; Stoop et al., 2019).

Based on this, extensive and interdisciplinary analyses of how different kinds of mining-related violence (e.g. direct, structural and slow) affect communities (Vélez-Torres & Méndez, 2022), with special care to their livelihoods (Udelsmann Rodrigues et al., 2021) have been performed in the last five years (Allen, 2017; Ortiz-Riomalo & Rettberg, 2018; Roberts & Mai, 2021; Salas Carreño & Diez Hurtado, 2018; Salem et al., 2021).

The prevalent dynamic, though, is that mining increases conflicts locally and then criminal groups use the profits from mineral extractions to spread violence across territory and time, with less corrupted and religious nations being more resistant (Berman et al., 2017, p. 1565). In addition, almost every mining conflict happens outside urban areas and the majority are related to metals, followed by energy and construction-related materials (Aydin et al., 2017, p. 4).

Although discordances do exist (Axbard et al., 2021), mining-related crimes get stronger during extended periods of price rises (commodities super-cycles) (Berman et al.,

⁶ Here, embodying the United Nations concept of "human security", synthesized as freedom from fear and want: We recognize that all individuals, in particular vulnerable people, are entitled to freedom from fear and freedom from want, with an equal opportunity to enjoy all their rights and fully develop their human potential (United Nations, 2005).

2017) and are not restricted to the mineral exploration stage. Both mine decline and closure increase crime levels, particularly against women, due to social disruption, economic instability, and inadequate support systems, leading to heightened vulnerability and participation in crime for survival (Sesele & Marais, 2022, p. 12; Steele et al., 2019). Sesele and Marais (2022) document the rise in crime linked to the decline of mining in Matjhabeng, South Africa, particularly impacting women who, facing economic hardships and social instability, become both victims and perpetrators of crime. Steele et al. (2019) reveal a high incidence of sexual violence against women in a mining area in Rustenburg, South Africa, exacerbated by economic dependency and barriers to reporting and seeking care, underscoring the need for improved awareness and services.

Through violence, organized criminal groups are gaining power over mineral supply chains using illegal taxation and securitization, money laundering, and even acting as miners directly (Vélez-Torres & Méndez, 2022) to finance their illegal mining production of what became known as conflict minerals. Conflict minerals are substances originated from places where conflicts that affects mining exploration and trading are occurring (Islam & van Staden, 2018, p. 1).

In these regions, the profits of mineral exploration are used to finance conflicts, and mining conditions are inhuman and life threatening (Islam & van Staden, 2018, p. 1), with serious violations of human rights and international humanitarian and criminal law (Hofmann et al., 2018, p. 3). The term also addresses specifically the mining under the same circumstances of “coltan (the metal ore from which tantalum is extracted), cassiterite (tin), wolframite (tungsten) and gold, also known together as the 3TG minerals”, (Dalla Via & Perego, 2018, p. 773).

Illegal Mining as an Externality

As a case of misuse of a common-property resource similar to overfishing (Nordhaus, 2021, p. 70), illegal mining can be seen as an externality because the value of exploring a public resource and the reparation costs of socioenvironmental damage are not being paid by the miner. In addition, according to Soares (2007, pp. 4–5), crime has other important and less evident consequences. There are relevant social costs associated with crime deterrence, criminal justice, and prison systems. But, in consonance with the natural resource curse, it is the less known impact on welfare that comes to attention, since crime can affect productivity and limit entrepreneurship prospects to a point of becoming a barrier to development (R. R. Soares & Naritomi, 2007, pp. 4–5).

The usual remedy for misuse of common property resources is regulation and taxes (Nordhaus, 2021, p. 70). Hence, in order to prevent mining trade from boosting crime (Partiti & van der Velde, 2017, p. 5), central countries are regulating their mineral supply-chains through law enactments that address human-rights and transparency issues in order to improve due diligence over conflict minerals (Dalla Via & Perego, 2018; Hanai, 2021; Hofmann et al., 2018; Partiti & van der Velde, 2017; Schleper et al., 2022; Swift et al., 2019).

In this regard, two initiatives have been attracting more attention from researchers. The Dodd-Frank Act was a 2010 North American initiative that compelled every open-capital corporation in the USA to make a yearly disclosure if conflict minerals originating in Congo or neighboring countries were used in any of their inputs. If positive, these companies should prove that due diligence over the supply chain was made and certified by an independent private firm (Arikan et al., 2017, p. 473). In the same way, the European Union Regulation 2017/821 imposed supply chain due diligence obligations for importers of tin, tantalum and tungsten, their ores, as well as gold originating from conflict-affected and high-risk areas (Cusato, 2021; Macchi, 2022; Partzsch, 2018).

Research points out that due diligence over mineral resources supply chains is an important step toward Corporate Social Responsibility (CSR) in the mining industry. Since most of the companies involved with conflict minerals are renowned global corporations based in Australia, Brazil, Canada, South Africa, Switzerland and the U.K. (Aydin et al., 2017, p. 7), enforcing public transparency works to reduce crime because violations regarding human rights have a great impact on corporate reputation (Hofmann et al., 2018, p. 3).

On the other side of the supply chain, less developed nations are also striving to enhance their governance systems to contain environmental destruction and mining-related crimes (Aguilar-González et al., 2018; Bansah et al., 2022; Christel & Möhle, 2022; Hook, 2019; Leiva, 2022; Mohle, 2021; Toledo Orozco, 2022). Strategies in the southern hemisphere focus on formalizing artisanal miners and repressing both illegal mining and anti-mining through law enforcement and military interventions (Igarapé Institute & Interpol, 2021; Kempers, 2020, p. 275; Sveinsdóttir et al., 2021).

Despite their efforts, environmental crimes are still on the rise, with high levels of conflicts, lack of inter-agency collaboration, insufficient/inadequate resource allocation, detachment from community interests, weak state, and strong organized crime among the causes of consistent failure (Espin & Perz, 2021, p. 331; Rochlin, 2018, p. 330).

As a measure of failure, in 2016, a joint report from UNEP and Interpol (Nellemann et al., 2016) estimated that the value of environmental crimes could amount to USD 259 billion yearly, with illegal mining being responsible for as much as USD 46 billion. Despite the magnitude, the authors indicate that this is a gross underestimation, since over 90% of gold mining in some South American countries (e.g., Venezuela) is illegally explored (Nellemann et al., 2016, p. 20,69).

With Brazil, Chile, Mexico, and Peru being responsible for 85% of Latin America's mineral and metal exports (Doussoulin & Mougenot, 2022, p. 9), and several critical materials supply chains, including 61% of the world's lithium reserves (Nellemann et al., 2016, p. 69), depending heavily on the region, further efforts have to be made to improve governance and mitigate environmental crimes. The combination of such market potential and a low-risk high-profit finance source for criminal groups in a scenario of intrinsic conflicts helps to explain the resilience and prevalence of mining-related crimes in Latin America, where the association between armed groups and drug cartels has been producing devastating impacts on the environment and human security (Nellemann et al., 2016, p. 69).

Federal Crimes Against Nature in Brazil

Brazil has always been a central figure in the climate change arena. A place of unequal biodiversity and freshwater, with a continental size covered in precious natural resources that play a major role in world environmental balance, the country has been accumulating conservation setbacks under the current government. Behind these problems, there is a context of science denialism that has corroded the working capacity of many environment-related agencies, weakened laws and diplomatic agreements, starved research and transparency programs, and disavowed evidence presented by public health, climate and conservation scientists (Athayde et al., 2022; Oliveira & Siqueira, 2022; M. O. Soares et al., 2022; Thomaz et al., 2020).

Denial, however, does not change the fact that the climate crisis and other impacts of ecological degradation on human life are among the most serious problems governments will have to solve in the following years. The importance of effectively reaching sustainability in anthropic activities will only rise as their consequences (such as the COVID-19 pandemic) continue to change the world.

It is common to find scientific research addressing how to innovate and improve processes to become more sustainable, but less attention is given to the role of law enforcement in preventing environmental deterioration, particularly because of the lack of official data. Since legal compliance can be seen as the premise of every ecological commitment, this thesis also intends to present an overview of environmental crimes investigated by the federal police in Brazil between 2010 and 2020, providing, hopefully, sufficient statistical data to allow future studies to be made.

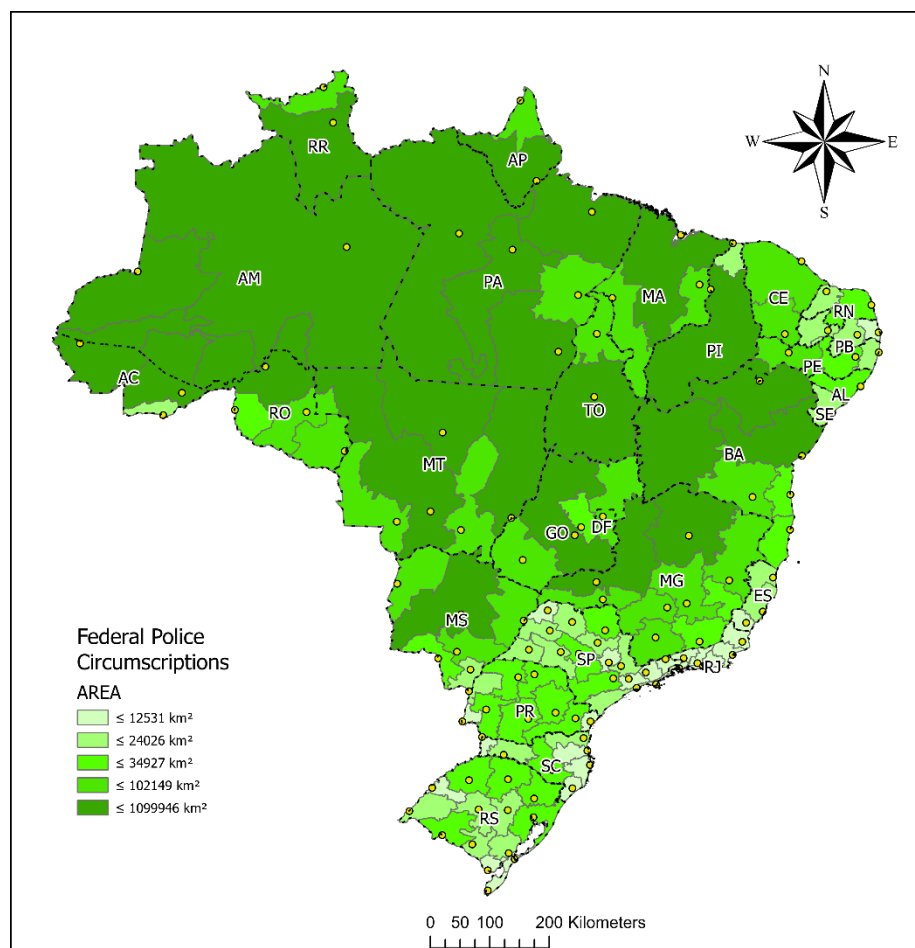
Brazilian law enforcement is divided according to a territorial jurisdiction. The bulk of public security in Brazil falls under the State responsibility. Brazilian States have their own civil police force that is responsible for conducting investigations of common crimes, and military police that responds to emergency calls and performs ostensive patrolling. Investigations conducted by the State Police are judged by State Penal Courts. On a municipal level, the town's police force is responsible for protecting the city patrimony.

However, every time a crime affects something the Union has an interest on, the competence for criminal judgment rises to the Federal Justice, and the Federal Police is the only police agency in Brazil that investigates federal crimes. It so happens that the interest of the Union is vast, and, because of that, there are a lot of federal crimes in Brazil, ranging from drugs and firearms trafficking, cybercrimes (bank fraud and pedophilia included), money laundering, corruption, bank robbery, and environmental crimes. Also, constitutionally, the Federal Police is responsible for policing the sea, ports, airports, and the country's borders. Hence, the Brazilian Federal Police have a considerable number of responsibilities that are distributed between general and specialized units, all inside the same agency.

Federal Police precincts in Brazil are classified as superintendence or police station (Federal Police, 2022c). The first are larger units located in all 27 Brazilian state capitals.

They are composed by several smaller specialized units, including a Crime Against Nature and Historic Heritage Unit, specialized in investigating environmental crimes (Federal Police, 2022b). On the other hand, the remaining 96 Federal Police Stations are smaller generalist police units distributed among the vast Brazilian countryside. Brazil, in 2022, had 123 Federal Police units to investigate every federal crime in their circumscriptions (PORTARIA DG/PF N° 16.145, 2022). With an average area of 69,083 km², Federal Police circumscriptions can reach 1,099,946 km², almost three times the size of California.

Figure 1. *Federal Police Units and Circumscriptions*



Note. The figure illustrates the circumscriptions of the Brazilian Federal Police, distinguished by color based on their respective areas. The map was made by the author based on data available in <https://www.gov.br/pf/pt-br/acesso-a-informacao/institucional/quem-e-quem/superintendencias-e-delegacias>.

The number of federal policemen stationed in each unit is not publicly available, but the total number of active personal as in June 2022 was 11,816 (Federal Police, 2022a), only

12% bigger than the staff in 2007 (see Appendix AAppendix A). In addition, despite the small growth in the number of policeman (1300 since 2007), the total size of the staff did not change because the number of the support personnel had decreased 32% in the same period.

Brazil has a territorial area of 8.510.345,540 km² and an estimated population of 203,062,512 people⁷. Hence, although police staffing is a complex subject - being multidimensional, systemic, and local (J. M. Wilson, 2012)- it is safe to say that, even if every federal policeman were to work exclusively on environmental crimes, Brazil would still have a serious shortage of Federal Police.

On the other hand, the Brazilian Federal Government has an important role in environmental conservancy. The Constitution of 1988 dedicated a whole chapter to the environment, asserting the collective right to an ecologically balanced environment but also determining that the people and the government are responsible for preserving nature for future generations (Constituição Da República Federativa Do Brasil, 1988, Chapter VI). Environmental protection, therefore, is a common constitutional attribution of the Union, the states, and the municipalities, who must act harmoniously, respecting their limits and helping each other as a system.

As a general rule, crimes against nature are judged and investigated by the State. Since the interest in protecting the environment is concurrent, the Federal Police, theoretically, could act in any environmental crime and send the investigation to the State Public Prosecutor. But the Federal Justice only judges environmental crimes that directly achieve some interest of the Union, its autarchies, foundations, or public companies. As already said above, given the chronic lack of staff and the fact that the Federal Police is the

⁷ <https://cidades.ibge.gov.br/brasil/panorama>

only responsible for carrying out federal investigations, federal policemen only deal with federal environmental crimes.

The Law n° 9605/1998 was created to regulate the constitutional determination to protect the environment. Known as Environmental Crimes Law, it consolidated many crimes that were present in other laws, but the responsibility of judging environmental crimes was not defined by the Law n° 9605/1998, being determined by the concrete fact. This law divided environmental crimes into five sections: Crimes against Fauna, Crimes against Flora, Pollution and other Environmental Crimes, Crimes against Urban Planning and Cultural Heritage, Crimes against Environmental Administration. Nevertheless, this thesis adopts another environmental classification to encompass all crimes against nature investigated by the Brazilian Federal Police, including the laws outlined in Table 2.

Table 2

Brazilian laws containing environmental crimes

Law number	Year	Law Name
2848	1940	Penal Code
4771	1965	Old Forest Code
4947	1966	Agrarian Law
5197	1967	Fauna Protection Law
6001	1973	Indigenous Statute
6766	1979	Urban Soil Management
7643	1987	Whaling Prohibition
7802	1989	Pesticides Law
7805	1989	Mineral Exploration Law
8176	1991	Crimes Against the Economic Order Law
9605	1998	Environmental Crime Law

Note. This table has been compiled based on the author's research and includes a comprehensive list of Brazilian laws that address environmental crimes on Federal level. It categorizes each law by its number, year of enactment, and official title.

Hence, since environmental Federal Police units also deal with crimes against historical and cultural heritage, the first level of classification adopted by this research divided the cases into three groups: Environmental, Historical/Cultural Heritage and other

types of crimes connected to environmental investigations, environmental crimes were categorized in twelve groups:

1. Cultural Heritage;
2. Environmental Administration;
3. Fauna;
4. Fishing;
5. Flora;
6. Generic;
7. Health;
8. Historical Heritage;
9. Land;
10. Mining;
11. Pollution; and
12. Related⁸.

Mining-related crimes in Brazil. In Brazil, all mineral resources, including those of the subsoil, belong to the Union, which has to concede and supervise every single mineral exploration (Constituição Da República Federativa Do Brasil, 1988, arts. 20, 76). Hence, mining without permission or in disagreement with what was allowed by the State is a federal crime.

Mining-related crimes are described in art. 55 of Law nº 9,605/1998 (illegal mining), "performing research, mining or extraction of mineral resources without the competent authorization, permission, concession or license, or in disagreement with what was obtained",

⁸ Crimes connected to environmental investigations but are not against nature (e.g. money laundering) are going to be referred to as "related".

and in art. 2 of Law nº 8,166/1991 (usurpation), "producing goods or exploiting raw materials that belong to the Union without legal authorization or in disagreement with the authorizing title". An illegal miner in Brazil is indicted with both crimes in a criminal charge stacking, with one and the other summing up for the sentence, which can reach six years in prison (one for illegal mining and five for usurpation).

This means that illegal mining is not considered a complex crime, where only the penalty for the most serious crime is imposed. If the environmental license is expired, for instance, one would be indicted on both crimes. The same would happen if the miner, despite having a valid environmental license to mine, did not have a mining permit.

Following the literature covered so far, the mining-related crime occurrence growth rate is influenced by the movement of the market, with crimes associated with the activity increasing during commodities surges. This effect is expected to be amplified in countries with high levels of mineral trade or mining dependence. This is the case of Brazil, the world's sixth largest mining producer in value of metallic minerals and coal (ICMM, 2020).

In 2021, 866.9 thousand mining applications were being processed by the National Mining Agency (ANM), with Iron (66.36%), Gold (11.12%), Copper (6.6%), Bauxite (2.15%), Granite (1.52%), Dolomitic Limestone (2%), Sand (0.89%), Phosphate (0.99%), Nickel (0.7%), Manganese (0.4%), and Niobium (0.34%) as the most economically important traded mineral substances⁹ (IBRAM, 2021). Mining was responsible for 4.49% of the Gross Domestic Product in 2021 (ANM, 2022a; IBGE, 2022), and the governments saw the revenues from environmental royalties (including the Financial Compensation for Mineral

⁹ Mineral water was responsible for 1.58%, but it was excluded from this study due to the specificities of its exploration process.

Exploration, CFEM) grow considerably between 2001 and 2021, from 0.35 % to 1.08 % of GDP (Schymura, 2022).

One would expect that, since natural resources are in the center of the Brazilian economy, governmental efforts to mitigate socioenvironmental externalities should also be prioritized. Nevertheless, in compass with the natural resources curse, the magnitude of the Brazilian mining industry contrasts with the deficiencies of its governance system and the prevalence of negative effects.

In the fight against global warming and towards UN SDGs, the improvement of the governance system that enforces already existent environmental laws should be seen as an urgent matter and a feasible sustainability objective, after all, nothing could be more sustainable than a preserved land instead of a transition to a non-vegetated area caused by illegal mining. Albeit sectorial-centered and neo-developmental (Malerba et al., 2012, p. 49), the National Mining Plan 2030 - PNM 2030 (Brazil, 2011) established sustainability and effective governance as two of the three guidelines that should guide actions for the Brazilian mining sector by the year 2030.

Despite that, like many countries that depend economically on mining activities, Brazil has deficient and/or absent governance systems. Brazilian public agency problems include personnel and financial scarcity, professionalization inadequacies, lack of autonomy and overburdening responsibilities (F. M. Euclydes et al., 2022), all of which prevent the necessary institutional development to effectively regulate market externalities.

Shortage of staff, for instance, generates long delays on mining application analysis and an insufficient number of in loco mining tenements inspections (F. M. Euclydes et al., 2022). In addition, Brazil has a continental area and precarious transportation networks in several places, which can make accessing mining areas challenging. Geographic isolation, characterized by low demographic density and difficult access, common features of many

exploration sites, can give the miner a false sense of invisibility, strengthening the hope of impunity in the eventual practice of an environmental crime, thus lowering “illegal costs”.

Within this framework, due to its intrinsic characteristics, legally mining in Brazil requires carrying out financially intensive studies and making investments, enduring lengthy processes of mining permissions, and overcoming all kinds of bureaucratic hurdles. One interested in mining must first apply for a governmental authorization and obtain (prior to installation and operation) environmental licensing. In principle, large mining corporations can better afford environmental licensing costs, and, because of their level of exposure, they should have deeper concerns about complying with laws and regulations. Despite that, 87% of the mining activity in Brazil is carried out by micro and small companies (IBRAM, 2018) and around 10% of all mining applications in Brazil (around 50% for gold) are made for small artisanal mining (ANM, 2021b), which are exempt of prior research¹⁰ and have an area limitation (50ha for individual miners and 1,000ha for miner cooperatives) (Law N° 7805/1989, 1989).

Along with governance issues, in the last years, environmental legislation was overturned, and budget shortfalls and discontinuity hindered field missions (Araújo, 2020). Under Bolsonaro’s administration, especially during the COVID-19 pandemic, 57 legislative acts deregulated or weakened environmental laws in Brazil. There was also significant damage in the most important federal environmental protection agencies, which resulted in a 72% decrease in environmental fines, despite a record level of deforestation (Vale et al., 2021, p. 2). Therefore, Brazil is currently going through a very different scenario from 2016,

¹⁰ Previous geological research to define, evaluate, and determine the feasibility of the economic use of the mineral deposit is required in Brazil (Código de Mineração, 1967, art. 14)

when it was considered a success case by UNEP, with Executive Office of the Presidency and the Federal Police working together with other agencies to fine, seize and prosecute criminals, interdict areas, and confiscate or destroy equipment (Nellemann et al., 2016, p. 12).

Conjunctly, although Brazil has the 12th world's largest economy (The World Bank, 2021), its current level of inequality is dire. As reported by the New Poverty Map (Neri, 2022), in just one year (2020-2021), poorness escalation has driven almost 10 million Brazilians into misery (less than a dollar per day). In 2021, 29,6% of the population (62.9 million) was under the line of poverty in Brazil, the worst scenario since the beginning of the historical series. Inevitably, in the same year, hunger was afflicting 19 million Brazilians (9% of total population) and food insecurity haunted 116.7 million (55% of total population) (Maluf, 2021).

The weakness of the Brazilian state manifests in several ways in the mining industry, with serious implications for inequality and, consequently, for mining-related crimes. Despite the apparent profusion of capital flows, in nations lacking regional development politics focused on redistribution, the positive economic side of mining impacts touches only the market centers, not extraction zones, contributing to the perpetuation of social inequality, promoting poverty, stimulating violence, and destroying territories.

For many Brazilian towns, though, mining – regardless of always being a temporary, finite enterprise – represents the current main economic activity, generating employment and income for populations with few opportunities for human development. As it produces inputs for several segments, mineral activities generate a multiplier effect on labor in other sectors. In Brazil, the mineral extraction sector, excluding oil and natural gas, was responsible for employing 199,075 workers in the fourth trimester half of 2021, indirectly generating 643,656 jobs in the mineral processing industry (ANM, 2021a, p. 13).

In Brazil, the Mineral Exploration Financial Compensation (CFEM), a federal tax designed to counterbalance the damage caused by mineral exploration, imposes a toll of 1% to 3.5% on the mine sales. The income is shared by the Union (3%), State (25%), and municipalities (65%) where the activity takes place (Lei N° 8001/1990, 1990), but it's not always translated into socio-environmental benefits (A. C. P. Euclydes, 2013, p. 1090; L. F. da Silva et al., 2017, p. 5). The fact that CFEM spending is discretionary (Law N° 7990, 1989) and nontransparent (Caitano et al., 2021, p. 10; Rodrigues & Anjos, 2018, p. 309) is among the causes of redistribution unsuccess.

Social vulnerabilities, combined with criminal impunity of the State and private agents alike (Décary-Secours, 2021; Kaufhardt, 2021), and high violent crime rates (Cerqueira, 2021) composes a dangerous operational setting to public agencies operation. Also, the fact that mining is an important source of income for governments and entire communities, may help the maintenance of dark spots, defined by Factor (2019, p. 2) as geographic regions where communities suffer with crimes that are not reported to the police and do not appear in criminal statistics either because of government inefficiency or a lack of reporting from the members of the community. Ultimately, governance deficiency, in turn, generates business risks, environmental crimes, and mining disasters, such as the ones caused in Mariana, by Samarco, in 2015, and in Brumadinho, by Vale, in 2019 (Freitas et al., 2019; Penido, 2018), killing hundreds of people.

Mining in the Brazilian Caatinga. Research¹¹ on mining-related crimes in Brazil has been addressing environmental effects of mineral exploration inside the Amazon biome (e.g. Barroso & Campos Mello, 2020; Mallett et al., 2021; Spiegel et al., 2012) and the recent

¹¹ Classified into the first quartile of SCImago Journal & Country Rank (<http://www.scimagojr.com>).

tragedies involving mining dams (Goncalves Ribeiro & Rezende, 2015; Miranda & Marques, 2016; Ruchkys et al., 2019). These themes are important for improving the efforts of environmental crime prevention, but Brazil has other five biomes besides the Amazon: Atlantic Forest, Caatinga, Cerrado, Pantanal and Pampa (IBGE, 2021) - which have their specific importance and preservation needs, but have been less explored by academic researchers.

The Caatinga is a unique semi-arid biome in the Brazilian Northeast, the region with the highest levels of poverty (Neri, 2022), hunger (Maluf, 2021), and violence (Cerqueira, 2021) in the country. Home to 27 million people, 4,963 plant and 1,182 animal species (Brazil, 2022), the biome covers 10% of the national territory, reaching 1,209 municipalities and nine (9) states (IBGE, 2021). With approximately 74% of its area required for mining between 2010 and 2020 (ANM, 2021b), Caatinga has played a significant role in Brazilian mineral trade, particularly with the production of chromium, iron, nickel, gold, and vanadium in Bahia, copper in Bahia and Alagoas, and manganese in Ceará (ANM, 2022a).

In 2021, eight out of the most economically important minerals explored in Brazil were prominent in mining applications inside municipalities totally within Caatinga. Along with clay and quartzite, they comprised the ten most required minerals in the region (see Table 3), accounting for around 83% of the 79.2 thousand mining tenements applications (which represents 9.1% of the total mining applications of the country).

Table 3

The 10 most required substances of Brazil in 2021.

Substance	Mining applications - Caatinga	Mining applications share – Caatinga/Brazil
Iron ores	11,856	35.92%
Granite	9,761	12.14%
Sand	7,574	7.08%
Clay	6,062	7.6%
Limestone	5,857	15.64%

Gold	5,852	3.21%
Copper ores	5,643	19.29%
Quartzite	5,353	34.82%
Manganese ores	4,374	24.22%
Phosphate	3,515	17%
TOTAL	65,847	

Note. This table, assembled by the author, showcases the ten most sought-after substances in Brazil in the year 2021. It lists each substance alongside two key metrics: the number of mining applications specific to the Caatinga biome and the proportion of these applications relative to the total across Brazil. The data underpinning this analysis was sourced from the National Mining Agency - ANM (2021b).

Admittedly, a search on mining-related crimes in the Caatinga on international databases (Scopus and Web of Science) returned no results, while mining-related searches on the biome refers mainly to its effect on living organisms (Da Silva et al., 2005; C. E. D. L. Lins et al., 2007; C. E. L. Lins et al., 2006; Mergulhão et al., 2010; J. M. Silva et al., 2021; Teixeira-Rios et al., 2013).

Preventing mining-related crimes: the role (and limitations) of police institutions

From the limitation of scientific management (Taylor, 1998) to the range of systemic models (Capra & Luisi, 2016), organizational theory evolved to recognize the inherent complexity of human relationships of collaboration, ethics, conflict, and resistance, which became the object of academic study and practical management. Skills linked to learning, , and innovation have become critical success factors, and technology is the means by which all solutions are made feasible, especially those involving complex or wicked problems (Hawryszkiewicz, 2016), such as crime.

Considering the organizational perspective, there seems to have been a convergence between political evolution – which crowned democracy as model of government– and scientific – which brought the concept of power to the center of the debates (Clegg, 2009).

According to Rose and Miller (1992), modern democratic states have abandoned the utopia of

complete social control, accepting that human organizations have their own naturalities, rules, processes and internal forms of self-regulating power.

In liberal states, power is confronted by human rights and the government, by a handful of processes outside its reach, beyond politics, which can only be administered by a complex network of relationships. Hence, as democracy advanced in the world, traditional control mechanisms became obsolete (Rose & Miller, 1992). This applies particularly to positivist governance systems based on binomials, such as hierarchy and discipline.

Social governance extrapolates political actions (bureaucracy, policing, surveillance). Given the impossibility and ineffectiveness of direct external control, the government is forced to develop technologies to exercise power at a distance over the private sphere of the modern world. In the field of public administration, there is a growing need to invest in agile, organic structures capable of using technology, creativity, learning, and innovation to keep up with the social evolution rhythm.

Complex phenomena, like crime, require holistic comprehension and management. This implies to transcend the mechanistic paradigm and to adopt the ecologic premise that the living beings nature is not on the matter but in their connections, which form an inseparable web of relations (Capra, 1997). It is necessary to attack the causes of the problem, which are multifactorial, controlling for the risk of the factors that create it in each level of the social ecosystem¹². This demands efforts to develop tools of governing at a distance capable of promoting self-regulation and engagement.

Inside this new paradigm, security solutions must be built together with civil society, not for them – risking to fail due to detachment of reality – or for them – because,

¹² As described by Ferreto & Romero (2009), which defend an ecological model to approach violent behavior.

paraphrasing Garriott (2013), in criminal societies, crime is seen as much as a problem as it is a solution. Police governance has, indeed, evolved towards the narrowing of ties with the community and the strengthening of public participation. Community policing initiatives around the world support this impression (Lum, 2009; Goldstein, 1987; MacDonald, 2002; Adams et al., 2002; Gill et al., 2014; Factor, 2019).

Based on this argument, it can be said that police work, more than open itself, must encourage social participation in favor of a more just and peaceful society. To be effective, policing has to adapt to the reality of the region and be seen as legitimate and fair, as well as involve community members (Factor, 2019).

Such approach is in harmony with UN 1992 Rio Declaration principle 10, which states that:

Environmental issues are best handled with participation of all concerned citizens, at the relevant level. At the national level, each individual shall have appropriate access to information concerning the environment that is held by public authorities, including information on hazardous materials and activities in their communities, and the opportunity to participate in decision-making processes. States shall facilitate and encourage public awareness and participation by making information widely available. Effective access to judicial and administrative proceedings, including redress and remedy, shall be provided (Antrim, 2019).

This is why modern police governance also implies coordinating the potential for using the police force to meet the specific expectations and needs of communities regarding the preservation of social and natural peace. Through granting access to self-regulation tools, public security actors (especially police and citizens) could organize themselves and create specific solutions to the problems of their regions using legal methods that respect government guidelines.

Enhancing popular participation instruments is essential, which translates into both an increase in citizens' contributions to security and the openness, transparency, and accountability of police institutions, particularly concerning data availability and results - the effective impact of police work on the real world. This research, therefore, seeks to contribute to this realm of governance improvement by elucidating the workings of governance in the context of environmental crimes, particularly through a detailed examination of the roles and impacts of police and regulatory agencies. In doing so, it aims to illuminate the intricate dynamics of governance mechanisms in deterring illegal mining activities, thereby enhancing the understanding of how these entities operate and the extent of their efficacy in the real world.

Criminological approach

Governance systems of modern democratic nations are based on the central point of reference of the neoliberal thought: the homo economicus. According to Lemke (2001, p. 12), the concept evolved to a being that can systematically change the “environment” by counting on the “rational choice” of the individuals. Nowadays, this ideal of freedom and rationality has transformed into an “entrepreneurial unit—a subject of oneself who is encouraged to take calculated risks for the enjoyment of future returns” (Deukmedjian, 2013, p. 65).

This thesis relies on this concept to build a holistic model to understand and prevent illegal mining on the Brazilian Caatinga. As explained, a systemic approach seems more appropriate because it is focused on effectiveness and prevention, not on repression (A. D. Costa, 2020). With a comprehensive understanding of illegal mining, it would be possible to concentrate resources and efforts on improving criminocclusive solutions (which reduce crime risk) (Andresen et al., 2010, p. 348) and reducing criminogenic factors (which intensify crime risk), lowering the chances of the crime to happen.

The proposed model is based on a combination of two main theories of criminology: Classic criminology, represented by Becker's (1968) Rational Choice Theory, and Environmental Criminology, embodied by Cohen & Felson's (1979) Routine Activity Theory.

Classic criminology and the Rational Choice Theory

Rooted deeply in the tenets of Enlightenment thought, classical criminology fundamentally argues that human beings are intrinsically equipped with free will, enabling them to make choices that are rational and deliberate. This concept is very well explored by Becker (1968), who introduced a more sophisticated economic perspective to the field. Becker's theory provides a structured framework for understanding the intricate mechanics behind individual decision-making processes in the context of criminal behavior.

According to Becker's theoretical model, criminal conduct is not a mere act of deviance but rather a product of rational calculation. His perspective posits that individuals engaging in criminal activities weigh the potential outcomes based on their perceptions of success and the consequences thereof. In essence, criminal actions are viewed as deliberate choices made after considering the balance between the potential benefits and associated risks.

Becker's analysis implies that the likelihood of a person committing a crime is significantly influenced by their evaluation of two key factors: the probability of successfully accomplishing the criminal objective and the perceived risk of detection, apprehension, and subsequent punishment. The theory states that an individual is more inclined to commit a crime if the perceived benefits outweigh the anticipated costs. This includes factors such as the likelihood of achieving the criminal goal, the expected gains from the crime, the chances of being caught, and the severity of the potential punishment. In this economic calculation, if

the rewards of the crime seem substantial and the perceived risk of punishment is low, the propensity to engage in criminal behavior increases.

Thus, Becker's (1968) approach to understanding crime highlights the importance of perceived risk and reward in the decision-making process of potential offenders. It underscores the rationale that behind every criminal act lies a thought process, that is influenced by individual perceptions and calculations of potential outcomes. This economic lens on criminological theory not only deepens our understanding of the motives behind criminal behavior, but also suggests critical implications for the development of effective mining-related crime prevention and criminal justice policies.

Interestingly, Becker's (1968) economic conceptualization of crime as an industry, proposes that criminal activities create externalities with significant and widespread costs, particularly impacting the public and private sectors. His theory extends the understanding of the economic consequences of crime beyond the direct outcomes of criminal acts. These broader implications include substantial public expenditures on crime prevention strategies, enforcement measures, the judicial process, and the incarceration system (Becker, 1968, pp. 170–172).

Souza (2021) examined environmental crimes in Brazil employing Gary Becker's theoretical framework, which provided a profound understanding of the dynamics that drive environmental violations. The analysis revealed a pronounced disconnection between Brazil's stringent environmental legislation and its actual enforcement. The primary factors contributing to this enforcement gap include a low likelihood of crime detection, lenient penalties, and a judicial system plagued by delays and inefficiencies. Such conditions cultivate a perception of minimal risk among potential violators, especially within corporate circles, where environmental non-compliance is often viewed as financially favorable compared to the cost of compliance.

Souza (2021) also pointed out that bureaucratic shortcomings and corruption further weaken the enforcement of environmental laws in Brazil. This deficiency reduces the preventive impact of existing rules. The study proposes an enhancement of enforcement strategies through the integration of technological solutions and community participation. Such measures are expected to improve the detection and accurate identification of environmental violations, influencing the cost-benefit analysis for potential offenders.

Moreover, the author emphasizes the need to address the socio-economic drivers behind environmental crimes. Factors like poverty and limited educational opportunities prompt individuals and communities to engage in environmentally damaging practices for immediate economic gain. The study advocates for a comprehensive strategy to combat environmental crimes, encompassing not only rigorous law enforcement and judicial reforms but also widespread societal involvement and increased awareness (Souza, 2021).

Within Becker's theoretical view, the societal and economic impacts of crime are multi-dimensional, entailing both direct costs and indirect effects, such as the erosion of social cohesion and community morale. Understanding these is crucial for formulating a broad-based and effective strategy for crime reduction, which must aim to mitigate not only the immediate consequences of criminal activities, but also their broader economic and social ramifications (Souza, 2021).

Becker's model urges policymakers to contemplate the long-term economic and social outcomes of crime prevention and control measures. It calls for a balanced approach where the costs of criminal justice initiatives are carefully weighed against their potential to reduce crime rates and the associated societal impacts. This requires an economic evaluation of criminal justice policies, considering the interplay between offender behavior, enforcement efficacy, and the overall impact on society. Viewed through this economic lens, crime is

perceived as a phenomenon influenced by a calculated assessment of potential rewards versus the risks and costs involved.

It is important to register that this perspective is also explored, albeit differently, by Clarke and Cornish (1985), who, employing concepts of sociology of deviance, criminology, economics, and psychology, stated that criminal behavior is a rational and purposive choice which unfolds in a sequence of separate stages and decisions. Their perspective, deeply rooted in the sociology of deviance, psychology, and criminology, differs from Becker's primarily in disciplinary orientation and application context. While Becker, an economist, approaches crime from a cost-benefit analysis perspective, viewing criminal activity as a rational decision influenced by potential gains and punishments, Clarke and Cornish dive into the psychological and sociological aspects, emphasizing the purposive and calculated nature of criminal conduct (Clarke & Cornish, 1985, p. 327).

Their model intricately dissects the criminal decision-making process, proposing that it unfolds in a sequence of discrete stages, each necessitating a different set of explanatory theories and variables. This approach suggests that understanding criminal behavior requires more than just an economic analysis of risk and reward; it demands an examination of the individual's psychological state, social influences, and environmental contexts. The "stages of involvement", as outlined by Clarke and Cornish (1985), provide a framework for exploring these various dimensions, recognizing that each stage in the criminal process—from initial contemplation to the actual commission of a crime—may be influenced by distinct factors and motivations.

Regardless, the rational choice perspective primarily emphasizes the calculated motives of the offender, an element that intersects with the Routine Activity Theory's framework (Cohen & Felson, 1979). This theory posits that crime occurs when a motivated offender, a suitable target, and the absence of a capable guardian converge in time and space.

In this context, the offender's rational decision-making is just one facet of the broader dynamics that facilitate the occurrence of crime, alongside the characteristics of the target and the specific conditions of the location where the crime takes place. This convergence of elements is systematically explored within the Routine Activity Theory.

Environmental Criminology and the Routine Activity Theory

According to Andresen (2020, p. 30), environmental criminology encompasses a group of theories that are interested in the immediate circumstances in which crime occur, looking for crime patterns that are based on environmental influences. It is rooted in prevention, and encompasses the Rational Choice Perspective, the Geometry of Crime and the Crime Pattern Theory, and the Routine Activity Theory, which will be employed in the present study as a guideline to ensure a holistic analysis.

The Routine Activity Theory (Cohen & Felson, 1979) postulates that, in the absence of a capable guardian, an offender and a target must come together in a place to create an opportunity for a crime to happen. Eck (1994; Eck & Weisburd, 1995) further augment this theory by introducing three governance elements: a handler, who exerts influence over the offender's actions, and a manager, responsible for overseeing the place; and a guardian who protects the target/victim.

In alignment with the Routine Activity Theory, this study proposes that the prevention of mining-related crimes would necessitate a comprehensive strategy that addresses three facets:

- governance mechanisms for deterring miners;
- desirability and attributes of minerals;
- geographic determinants of the mining tenements.

In the preceding unit, the framework for analyzing the governance of miners was elucidated through the lens of Rational Choice Theory. This section will address theoretical and empirical studies of geographic determinants that modulate the prevalence and spatial distribution of illegal mineral explorations. The following will delineate the theoretical approach employed in this research to scrutinize the desirability attributes of minerals, which serve as the targets for unauthorized extraction activities.

In the realm of environmental crimes, supervising the location of crimes can be difficult. Remote areas can produce considerable logistical challenges for law enforcement agencies, such as difficult terrain and long travel distances. The lack of nearby communities or witnesses may allow illegal miners to operate with less fear of being reported to authorities. These factors can result in delayed responses to illegal mining activities, allowing criminals to conduct their operations with reduced fear of immediate intervention. Accordingly, the remoteness of mining sites can foster a sense of isolation and anonymity for criminals, making it easier for them to evade detection and capture.

Moreover, because mining-related crimes inherit the concentration of mineral deposits from Earth geoformation, they often produce clear "offender convergence settings", regions where offenders meet to perpetrate crimes in similar times and places. Mining-related crimes are known to have clear convergence settings even in the most remote places, such as indigenous reserves in the Amazon, which have a history of predation by environmental criminals (Siqueira-Gay & Sánchez, 2021).

Hence, a comprehensive analysis that also incorporates those geological factors is imperative for an accurate assessment of the risk of mining-related crimes, a necessity that is substantiated by a diverse body of scholarly work. Van Uhm & Nijman (2020) introduced a typology of environmental criminal groups—namely "Green Organized Crime", "Green Opportunistic Crime", and "Green Camouflaged Crime" — that serves as an analytical lens

for understanding mining-related crimes and places. "Green Organized Crime" entities are highly diversified and capable of exploiting mineral-rich locales, while "Green Opportunistic Crime" groups adapt to exploiting mineral opportunities. "Green Camouflaged Crime" organizations embed illegal activities within legal frameworks, complicating governance efforts.

Caplan et al. (2017) employ risk terrain modeling to elucidate the notion of how localized geographic zones exert varying degrees of influence on criminal activities, accentuating the significance of geographically specific locales as epicenters for illicit conduct. By delineating "behavior settings", the model facilitates a multifaceted analysis of specific environmental variables that contribute to the propensity for criminal conduct.

This granular focus enables a more accurate risk assessment by accounting for unique geographic attributes, such as proximity to mineral deposits, road density or urban areas, which can be studied to find out if they catalyze or inhibit illicit activities. Hence, the model underscores the indispensability of integrating geographic variables into risk assessments, advocating that the susceptibility to mining-related crimes is not homogeneously distributed but is contingent upon the distinct geographic features of a particular locale.

Freeman et al. (1996) and Curtis-Ham et al. (2021) explore the spatial intricacies of criminal activities, illustrating that even neighborhoods with initial similarities can exhibit divergent concentrations of criminal activities. Influencing this spatial concentration are factors such as criminal density, which inversely affects the probability of capture, and the spatial extent of criminal activities, indicative of the degree of police engagement. These observations corroborate theories of criminal homology and differentiation, positing that criminals operating in spatial proximity are likely to share greater activity spaces.

The relationship between spatial extent of environmental crimes and police engagement is not straightforward but assumes a complex character. While spatial extent

remains an important variable for understanding the dynamics of criminal activities, its interpretation must be nuanced by considering the inherent attractiveness of mineral-rich areas for criminal exploitation. In such contexts, a high concentration of criminal activities in a small area may not necessarily denote effective policing but could instead signal a hotspot for illegal mining due to the presence of valuable minerals. Thus, the relationship between spatial extent and police engagement becomes more complex and must be analyzed in conjunction with geological factors to accurately assess the effectiveness of law enforcement measures.

Puech (2005) and Johnson & Summers (2014) broaden the discourse to encompass the spatial autocorrelation of crime rates and the role of social cohesion in criminal behavior. The studies underscore that specific categories of crimes exhibit greater localization and that offenders predominantly operate in areas characterized by diminished social cohesion, in proximity to their residences or age-related activity nodes.

The concept of spatial autocorrelation, as discussed by Puech (2005), suggests that criminal activities are not randomly distributed but tend to cluster in specific locations due to a variety of interconnected factors, including the availability of resources, the presence of potential targets, and the level of social cohesion within a community. In the context of mining-related crimes, these motives could explain the preference of illegal miners to explore rural areas near cities, where the accessibility and availability of resources, such as fuel and transportation, facilitate criminal operations.

The geographic proximity of rural areas to urban centers and the presence of well-maintained infrastructure, such as interstate highways and gas stations, for instance, can serve as facilitators for elevated crime rates in these locales (Hakim, 1980; Klaassen, 1985; Martin, 1995). Offenders can find these areas strategically advantageous for blending into the

community or executing swift escapes, thereby contributing to the spatial concentration of criminal activities.

Lastly, rural areas, often characterized by low demographic density, present a governance gap that renders them susceptible to environmental crimes, such as unauthorized mineral extraction (Akella & Cannon, 2004). This vulnerability is exacerbated by systemic issues of underreporting and under-prosecution, often due to conflicts and lack of inter-agency collaboration (Espin & Perz, 2021), or legal constraints, such as short statutes of limitation, which further impede effective enforcement, perpetuating a cycle of environmental degradation (UNCAC, 2022). Because of all that, the decline in official statistics may not necessarily signify a reduction in environmental crimes but rather indicate high latency in reporting and discretionary law enforcement practices (Williams, 2019).

This phenomenon is further layered by the varying levels of social cohesion within rural communities. Jobes (1999) explains that areas with an agricultural economic base and stable populations generally exhibit stronger social bonds, which act as a deterrent to crime. Conversely, rural recreational towns characterized by higher levels of migration and anonymity tend to have weaker social bonds, thereby becoming more susceptible to criminal activities. Thus, the interplay between geographic accessibility, infrastructural amenities, and social cohesion forms a complex matrix that influences the spatial distribution and prevalence of crimes in rural areas.

In conclusion, the geographic and environmental facets are inextricably linked to the genesis and perpetuation of environmental crimes. These facets are sculpted by a multifaceted interplay of variables, including resource availability, social cohesion, and spatial decision-making by offenders. Consequently, an intricate understanding of the local context is indispensable for a comprehensive grasp of the dynamics governing environmental crimes.

As a result of this multifaceted context, the localization aspect is vital in determining the risk of mining-related crimes in a particular area. On the one side, a mining area that is easily accessible and conveniently located reduces transportation costs, infrastructure development expenses, and logistical challenges associated with mining operations. Favorable geographic aspects, such as proximity to transportation routes and existing infrastructure, such as gas stations, can significantly impact the overall efficiency and cost-effectiveness of illegal mining activities.

On the other hand, remote locations can also hinder governmental capabilities of regulation and law enforcement. Criminals operating illegal mining activities often exploit the remoteness of mining areas to their advantage. The lack of nearby law enforcement presence and limited accessibility can make it challenging for authorities to monitor and regulate illegal mining operations effectively. Furthermore, illegal mining activities in remote locations can strain government resources and budgets because establishing and maintaining law enforcement infrastructure, surveillance systems, and patrols in such distant areas is costly and resource intensive.

The CRAVED Approach: Theoretical Underpinnings and Practical Implications in Environmental Crimes. The CRAVED approach was built upon both Routine Activity Theory (Felson, 2017) and the Rational Choice Perspective (Clarke & Cornish, 1985) based on the premise that the higher the market attractiveness of a product, the more likely it is to become the object of theft. Since in Brazil mining-related crimes are also a form a theft (usurpation from the Union), using the CRAVED approach is appropriate.

This specific method is centered on the assumption that not all targets have the same risk of being objects of a crime (Clarke, 1999) since "hot products" are subjected to a higher

risk because they are easily Concealable, Removable, Available, Valuable, Enjoyable and Disposable (CRAVED).

According to Clarke (1999, pp. 23–25), the concealability of an item increases the risk of theft because it provides criminals with opportunities to carrying out the theft without attracting attention and not being easily recognizable afterwards. Also, higher risks are linked to easy-to-move products: a small ingot of silver has a higher propensity of being stolen than a 600-pound block of the metal (Clarke, 1999, p. 25).

Availability is explained by Clarke (1999, pp. 23–24) in three levels. At the macro-level, if only existing products can be stolen, the popularization of products will raise the risk of theft. At meso-level, the more criminals have access to the product, the more likely it will be stolen. Finally, at the micro-level, products in plain view have a higher risk of being stolen (Clarke, 1999, p. 25).

More expensive products also have a higher risk of being stolen, especially if they represent better profits if sold than kept (like five-year-old cars that are worth more if their parts are sold separately than the car as a whole). Complementarily, products that can be enjoyed (used) by the criminal (like televisions) and are easy to dispose of (sell) are more likely to be stolen (Clarke, 1999, pp. 24–25).

Pires and Clarke (2012) have then broken the concept of availability into Abundant and Accessible, creating the CRA(A)VED model. Abundancy refers to the relative prevalence or availability of a particular target. Items that are abundant are more likely to be targeted by criminals as they are widely distributed and can be found easily. Accessibility focuses on the ease of access to the target. Targets that are easily accessible, either due to their location or lack of security measures, are more likely to be targeted by criminals.

Also, Moreto and Lemieux (2015) further develop the approach accounting for wildlife product variations along illegal wildlife market processes establishing a new model

called CAPTURED (Concealable, Available, Processable, Transferrable, Useable, Removable, Enjoyable, and Desirable). The revised model (Moreto & Lemieux, 2015, pp. 314–315) retains four elements from the original CRAVED model - Concealable, Available, Removable, and Enjoyable – but Valuable and Disposable were transformed into Desirable, which represents the traditional and socio-cultural significance of wildlife products beyond their monetary value, and Transferable, indicating the ease with which these products can be moved and exchanged.

Finally, the authors added two new elements to the original CRAVED model (Moreto & Lemieux, 2015, p. 315): Processable and Usable. The former emphasizes the need for altering or modifying some wildlife products to enhance concealability, removability, transferability, enjoyability, or desirability. How a product is processed varies based on the item, actors' objectives, and the ultimate destination or purpose that a processed wildlife product is intended to serve. The latter relates to the perishability or market longevity of a wildlife product. Whether a product can be used directly affects other elements in the model, such as enjoyability and desirability. For instance, a spoiled caviar or a deceased parrot have no use to consumers.

The CRAVED method (and its CRA(A)VED and CAPTURED variations) has already been used to examine the risk of environmental "products" being a criminal target in areas such as illegal fishing (Petrossian & Clarke, 2014; Tabar et al., 2021), wildlife trafficking and poaching (Pires, 2015; Pires & Clarke, 2012; Pires & Petrossian, 2016; Romero-Vidal et al., 2020), timber (Baker, 2003), livestock theft (Sidebottom, 2013), and the relation between human trafficking and illegal fishing (Moreto et al., 2020).

VALUED: Unraveling the Specificities of Mining Attractiveness Beyond CRAVED and CAPTURED Perspectives. No study to date has used CRAVED to analyze the vulnerabilities of mining-related products for theft. Hence, for the purposes of this study,

due to the particularities of mineral explorations, some concepts of the CRAVED model were adapted, and some were replaced to create a framework to analyze the propensity to mine in a given area. This new model carries the acronym VALUED. A description of each of the VALUED elements is provided in Table 4.

Table 4

VALUED elements

Element	Definition
Valuable	Refers to the economic worth and significance of the mineral substance, measured by its monetary value in the market.
Abundant	Indicates the plentiful and substantial presence of the mineral, suggesting a high quantity available in the Earth's crust.
Localized	Describes the favorable and convenient geographic aspects of the mineral deposit, making it easily accessible for extraction and development.
Usable	Reflects the mineral's capability to be used without further processing.
Explorable	Represents the ease with which the mineral can be extracted from the earth, making it feasible for mining exploration and extraction activities.
Disposable	Refers to the ease of selling the extracted mineral in the market.

Note: Table 4, developed by the author, categorizes key elements in mineral economics under the acronym VALUED. It defines each term - Valuable, Abundant, Localized, Usable, Explorable, Disposable - in relation to its significance in the mineral market, presence in the Earth's crust, geographic factors, processing requirements, extraction feasibility, and market disposition.

The value of a mineral is highly significant for criminals operating illegal mining activities as it directly influences the potential profits they can gain from their illicit operations. Mineral commodities, such as gold and diamonds, are more exposed to illicit trade and other forms of crime due to their ease of trading and high-value returns (TRACIT, 2019), which corroborates the need to include the value of the substances in our model.

It is important to register that the value of a mineral substance incorporates the concept of concealability, as minerals are commodities whose price is often determined by their mass (with fewer exceptions like mineral water and oil). Therefore, the more valuable a substance is, the easier it becomes to conceal. For instance, a kilogram of gold is highly valuable and worth concealing, while the same amount of sand is not as valuable and thus, less likely to be concealed.

The abundance of a mineral substance was also judged important to determine how likely it will be available to extract and process by criminals. High abundance also lowers the extraction costs per unit, which can lead to more cost-effective mining operations and increased profitability for mining enterprises. Finally, since abundant minerals can offer a continuous supply source for illegal miners, after learning how to mine that specific mineral, abundance means a reduction in the risk of depletion and insurance of a steady stream of "stolen" goods for criminals.

The "localized" aspect in the VALUED model is a focused construct, aimed at capturing the specific geological traits of a mineral deposit that make it easily accessible and, therefore, more susceptible to illegal mining activities. Since it focuses on the mineral substance itself, this dimension does not encompass broader geographic or governance factors but is solely concerned with the mineralogical characteristics that influence the feasibility of extraction.

For instance, the depth of the mineral deposit is a crucial factor in this context. Shallow deposits that are easily reachable from the surface are more likely to be targeted for illegal extraction due to the reduced need for specialized equipment and expertise, which, in turn, lowers the operational costs and complexities. Such deposits are particularly attractive for small-scale illegal miners who may not have access to advanced extraction technologies. Similarly, the geological formation of the deposit, such as its occurrence in placer deposits or vein formations (Revuelta, 2018, Chapter 2), can also influence its attractiveness for illegal mining. Deposits that are part of easily extractable geological formations are more likely to be targeted due to the straightforwardness of the extraction process. Consequently, these should receive a higher rating on the Localized element.

The usability of a mineral without further processing is also relevant in determining its immediate market demand and potential utilization. Minerals that can be directly used

without extensive processing could hold higher appeal to criminals due to their immediate applicability, since they provide a quicker return on investment and reduced operational complexities, which reduces the risk of being caught.

The ease of exploration of minerals is a fundamental aspect in assessing the mining potential of a given area. Minerals that are easily explorable, with straightforward extraction processes and favorable geological conditions, are more attractive to mining since lower exploration and extraction costs increase the feasibility and profitability of criminal projects, encouraging investment and development in illegal mining. Hence, illegal miners focus on minerals with easy extraction processes because it enables them to swiftly exploit valuable mineral resources and evade detection by law enforcement authorities.

Lastly, the concept of disposability in the VALUED model refers to the ease of selling the extracted mineral in the market. In Brazil, as indicated by the Organization for Economic Co-operation and Development (OECD, 2022), there is an inadequate regulation of the mining sector, which has serious issues related to transparency and accountability. Notably, the absence of market regulation for mineral sales leads to potential opportunities for corruption and rent-seeking activities.

Until 2023, even gold, one of the few minerals with selling control, faced a paradox. Despite the requirement that gold extracted from *garimpo* areas be sold as a financial asset to a Securities and Exchange Brokerage Firms (Compensação Financeira pela Exploração de Recursos Minerais - DTVM), authorized by the Central Bank, the reality presented a stark contrast. In practice, the precious metal made its way to "commercial" establishments, traded as a mere commodity, relying solely on the seller's word and the buyer's presumed good faith (Manzolli et al., 2021). This oversight had unintended consequences, enabling illegally extracted gold to freely circulate under the pretense of being legal. However, in May 2023, the Supreme Federal Court (STF) intervened, suspending the rule that presumed the legality

of acquired gold and the good faith of the purchasing legal entity, recognizing the need to combat illegal *garimpo* in the Amazon and indigenous lands (STF, 2023).

The illicit trade of illegally extracted minerals poses significant challenges for law enforcement and regulatory authorities (UNODC, 2023, Chapter 4). In Brazil, the absence of stringent market controls creates an opportunity for criminals to exploit the loopholes in the system and freely sell the illicitly acquired minerals to both domestic and international markets. Once the illegal extraction is completed, stolen minerals can be easily introduced into the market without proper documentation or traceability.

It is known that the price of the substance directly influences the intensity and probability of illegal mining activities (Siqueira-Gay & Sánchez, 2021, p. 28). This is because the gross gain is in the center of a mining decision (Guj, 2008). Likewise, minerals that are readily marketable and have established demand are also more desirable for mining activities. If high disposability can ensure a constant flow of revenue for mining companies, reducing storage costs and minimizing financial risks associated with unsold inventories, for criminals mining illegally, the concept of disposability is even more critical, as it determines the ease of selling the stolen minerals in the market and not getting caught.

By integrating Value, Abundance, Localization, Usability, Explorability, and Disposability into our model, we gain a comprehensive understanding of their significance for legal mining in a specific area and can deduce the potential for illegal mining elsewhere. Each element holds substantial weight in shaping the appeal of mining activities, thereby aiding law enforcement in effective planning and strategizing.

Materials and Methods

Becker (1968) defended that the public security governance system, as well as the size and form of punishments, directly affect the occurrence of crimes, since changing these variables alters criminal's perception about the probability of success of his future endeavors. To Becker's model, Ehrlich (1973) added controls for legal and illegal income opportunities, creating the so-called Becker-Ehrlich model, described below in its usual logarithmic form (Entorf & Spengler, 2000):

$$\ln(\text{crime rate}) = \beta_0 + \beta_1 \ln(\text{deterrence}) + \beta_2 \ln(\text{income}) + \beta_3 \ln(\text{other influences}) + u$$

In this study, the risk of illegal mining in the Caatinga biome is evaluated through a synergistic approach that combines this classical econometric model and environmental criminology. Specifically, the foundational elements of the Routine Activity Theory—governance over miners as the offender, desirability of minerals as the target, and geographic aspects of mining tenements as the place—are reconfigured as sets of variables in an adapted Becker-Ehrlich econometric model.

Hence, grounded in the theoretical foundations of the Becker-Ehrlich model, operationalized through the Routine Activity Theory's triadic framework—offender, target, and place—the econometric model for investigating illegal mining risk can be articulated as follows:

$$\begin{aligned} \text{Illegal mining} = & \beta_0 + \gamma_1 (\text{Governance Over Miners}) + \gamma_2 (\text{Target Suitability}^{13}) \\ & + \gamma_3 (\text{Place Suitability}) + u \end{aligned}$$

Where:

¹³ Which was considered a proxy for opportunities for illegal income.

$$\begin{aligned}
\gamma_1(\text{Governance Over Miners}) &= \beta_1(\text{Police Investigations}) \\
&+ \beta_2(\text{Environmental Fines}) + \beta_3(\text{Mining Fines}) \\
&+ \beta_4(\text{Opportunities for Legal Income}) + \beta_5(\text{Process Duration}) \\
\gamma_2(\text{Target Suitability}) &= \beta_6(\text{Opportunities for Illegal Income}) \\
\gamma_3(\text{Place Suitability}) &= \beta_7(\text{Roads}) + \beta_8(\text{Gas Stations}) \\
&+ \beta_9(\text{Urban Area}) + \beta_{10}(\text{Mineral Occurrences}) + \beta_{11}(\text{Legal Mining})
\end{aligned}$$

This adapted model is tested employing ArcGIS Pro 3.1, and using Generalized Linear Regression (GLR) as the analytical method, further augmented by the inclusion of spatial lag controls to account for the spatial distribution/autocorrelation of data. After gathering all data collected from 2010 to 2020, the values were spatially aggregated using the arithmetic mean for each cell. In alignment with the original equation proposed in the Becker-Ehrlich model, where all variables are expressed in natural logarithmic form, after aggregation, a natural logarithmic transformation was applied to all variables.

Upon employing four distinct models of logarithmic transformation and conducting statistical tests, the formula

$$f(x) = \begin{cases} \ln(x + 1) & \text{if } x > 0 \\ -\ln(|x| + 1) & \text{if } x < 0 \\ 0 & \text{otherwise} \end{cases}$$

emerged as the most appropriate for the dataset under investigation. This formula not only produced statistically sound results but also maintained the original sign of the variables¹⁴, an essential feature for preserving the integrity and interpretability of the analysis. Particularly, the transformation was effective in normalizing the data distribution, thereby aligning it

¹⁴ In particular, the variable of Relative Distance to Average Income (RDAI), since negative values within this variable signify a diminished landscape for legal income opportunities.

closely with the assumptions of Gaussian distribution essential for parametric statistical analyses. In addition, it was effective in mitigating outliers, which ensured that the data set was well-suited for subsequent econometric analyses.

Population

The study employed a methodological framework focused on individual cells of 10 km² that formed a comprehensive grid covering the 936 municipalities exclusively located within the Caatinga biome. This unit of analysis was chosen to address endogeneity issues and ensure both robustness and comprehensiveness in the evaluation, a decision informed by the work of Berman et al. (2017). The population under investigation included 33,990 cells, each containing mining tenements that required the extraction of one of the ten most prevalent minerals as listed in the ANM database (Clay, Copper, Gold, Granite, Iron, Limestone, Manganese, Phosphate, Quartzite, Sand) during the period from 2010 to 2020.

Independent Variables

The following procedures were necessary to operationalize the independent variables for governance over miners, target and place suitability, and other controls.

Governance mechanisms for deterring miners

Federal Police Investigations. To create a variable for mining-related federal crimes, it was necessary to analyze all environmental crimes investigations concluded by Brazilian Federal Police between 2010 and 2020¹⁵. Data cleaning involved renaming variables and

¹⁵ Access to Federal Police statistical data was granted through process number 08420.007405/2020-9.

adding labels to describe the data, recoding string variables into appropriate numeric and date variables, standardizing municipality names, adding official municipality IDs, removing duplicates, translating to English and classifying each environmental crime article and law (n=172) as pertaining to one specific category (Cultural heritage, Environmental Administration, Fauna, Fishing, Flora, Generic, Health, Historical heritage, Land, Mining, Pollution, Related), masking case IDs, aggregating data to count cases and arrests by municipality and year, selecting only crimes from closed cases, and joining the aggregated data to a GIS shapefile of municipalities to enable spatial analysis.

The investigation analysis outcome was a descriptive dataset which enabled the specific examination of these environmental crime categories, providing a reliable source of information regarding environmental crime deterrence.

For the purpose of analytical robustness, all crimes related to the 12 categories were initially isolated and subsequently aggregated by case to construct a singular dataset that spans all categories of environmental crimes over multiple years. Within this framework, the mining category serves a specific function: it groups cases related to mining-related usurpation, as outlined in Article 2 of Law 8176/1991, and illegal mining, as specified in Article 55 of Law 9605/1998. These crimes are often committed concurrently and constitute the majority of cases, accounting for 99.1%. Additional crimes, such as mining within public forests or protected areas under Article 44 of Law 9605/1998, and unlicensed mining as per Article 21 of Law 7805/1998, were also included in the analysis, although they represent a mere 0.9% of the total cases.

Consequently, should a singular investigation encompass all four delineated categories of mining-related offenses, it would be represented as a solitary entry within the dataset.

Table 5*Mining-related crimes in Brazil between 2010 and 2020*

Article	Law	Frequency	Percent	Valid Percent	Cumulative Percent
21	7805/1989	46	0.2	0.2	0.2
44	9605/1998	162	0.7	0.7	0.9
55	9605/1998	10,212	45.1	45.1	46.0
2	8176/1991	12,228	54.0	54.0	100.0
	Total	22,648	100.0	100.0	

Note. Table 5, constructed by the author, presents a quantitative analysis of mining-related crimes in Brazil from 2010 to 2020. It systematically tabulates the frequency and percentage distribution of crimes under specific legal articles from Laws 7805/1989, 9605/1998, and 8176/1991. The table provides a detailed breakdown, including valid and cumulative percentages, culminating in a comprehensive view of the prevalence of these crimes over the decade. The underlying data for this analysis were sourced from statistics provided by the Federal Police.

In the analysis executed within this investigation, data were systematically aggregated within a grid framework, each cell representing a 10 km² spatial unit and the average value between 2010 and 2020. For instance, where the data were originally gathered at the level of municipalities, intersections between the grid cells and these administrative units were calculated to present the data accordingly.

In the spatial analysis, municipalities are represented by multiple grid cells, each of which assumes the value attributed to the municipality as a whole. For example, should a municipality undergo two investigations in a given year, all grid cells entirely within that municipality would assume the value of "two."

However, complexities emerge when grid cells intersect with multiple municipalities. A mere summation or average of federal police mining cases would misrepresent the true spatial distribution. To address this challenge, a weighted mean, founded on the proportional area of each intersecting municipality within a grid cell, was employed to allocate federal police mining cases more precisely to each cell.

$$\text{Weighted Mean} = \frac{\sum_{i=1}^n (x_i \times w_i)}{\sum_{i=1}^n w_i}$$

The weighted mean is calculated to work even when some part of the cell is inside a municipality with no data (null) or 0. For example, consider a cell (id. n. 108087), where one part of this cell intersects a municipality that had no federal police mining cases and occupies 53.16% of the cell's total area. Another part of the same cell intersects a different municipality that had 2 federal police mining cases and occupies 46.84% of the cell's total area. The weighted mean for federal police mining cases in this cell is calculated as follows:

$$\text{Weighted Mean for cell id. n. 108087} = \frac{\left(0 \times \frac{53.16}{100}\right) + \left(2 \times \frac{46.84}{100}\right)}{\frac{53.16}{100} + \frac{46.84}{100}} \approx 0.94$$

Environmental fines and interdictions. The acquisition and cleaning of Fines from Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) data were conducted through a series of methodologically structured steps, aimed at ensuring both spatial and temporal relevance for the research focus on the Caatinga biome between 2010 and 2020. Initially, the data was downloaded from IBAMA's Geoserver using a Web Feature Service (WFS) request ¹⁶. Subsequently, the dataset underwent a spatial clipping process, wherein only the fines points that fell within the municipalities completely inside the Caatinga biome were retained.

Following the spatial filtering, a new field, 'year_fined' was added to the dataset. This field was populated by extracting the year information from an existing field and converting it into an integer format. Finally, a temporal filter was applied to select only the fines data from the years 2010 to 2020.

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To summarize the data, a selection was made from the "IBAMA_fines_2010_2020" layer based on the year under consideration. This selection was then used to create a new feature layer, which served as the input for the SummarizeWithin tool. This tool was employed to summarize the selected IBAMA fines within a predefined grid network (grid_net). The resulting output was stored in a new feature class, specifically named to reflect the year of the data.

Subsequently, the field "Point_Count" in each of these yearly feature classes was renamed to correspond to the year, thereby facilitating easier identification and subsequent analyses. Finally, a join operation was performed to associate the summarized IBAMA variable, indicating the count of IBAMA fines for each year, with the main grid layer.

Finally, when a person is fined by IBAMA due to environmental law infractions, he is also subject to have the area where the illegality took place interdicted, and his assets seized. Hence, in the same context and also applying a similar approach, data on IBAMA area interdictions (and consequent seizures) were incorporated into the dataset.

Mining-related fines. In this research, the data from the National Mining Agency (ANM) serves as the foundational framework for all subsequent analyses involving other variables. The study is particularly focused on illegal mining activities conducted within mining tenements that lack the requisite legal title issued by the ANM, thereby failing to complete the permission cycle. Given that all subsoil minerals are the property of the Union, prospective miners are obligated to initially request a mining tenement from the ANM. Following this, they must secure the necessary environmental licenses. Only upon obtaining these licenses should they return to the ANM to request the formal mining title. The issue arises when miners neglect to complete this licensing process, opting instead to commence exploration solely with the demarcated mining polygon and environmental license or not even that.

In the initial phase of the research, significant attention was devoted to the cleaning and preparation of ANM data. The raw data, replete with inconsistencies and missing values, underwent a transformation process to make it suitable for subsequent analyses. The first step involved the data load and cleaning of various elements, including different types of events, mining titles, minerals and their respective uses, as well as miners, mining companies, and types of mining processes and stages. This phase was marked by the identification and removal of duplicate entries and the rectification of erroneous or incomplete data. The preparation ensured that the data was not only accurate but also tailored to address the research questions posed in this study, such as counting how many fines (serious administrative faults) or administrative infractions (less serious administrative offences) a mining tenement suffered during the period of one year, or which was the state of a given mining tenement in a specific year.

The next stage focused on calculating new variables that would be instrumental in the subsequent stages of the research. Initially, variables were designed to flag mining processes that had incurred fines or administrative infractions. Both types of events serve as indicators of regulatory breaches but differ in their severity, legal implications, and financial consequences.

Fines are more severe forms of regulatory action, often resulting from substantial violations of mining laws or environmental standards. The event IDs corresponding to fines usually have labels that include terms like "Multa" (Fine), "Infração" (Infraction) that were "Publicada" (Published), among others. Such events often lead to financial penalties and may even precipitate legal actions against the mining entity, including crime investigations.

Contrastingly, administrative infractions are lesser forms of non-compliance that may not result in financial penalties. These are formal records of minor breaches, often procedural in nature. The event IDs representing administrative infractions often include terms like

"Administrative" "Procedural" "Notice" or "Warning" that were also published, signifying that these are not as severe as fines but still indicate a level of non-compliance.

To ascertain the active status of mining tenements between 2010 and 2020, variables were created to identify the year a tenement became inactive and the date of a process's last event. Furthermore, variables were designed to flag processes that had any event post-2009 and to mark those with valid titles after 2009. The latter was particularly critical for determining the legality of mining activities during specific years.

In addition, a series of variables were crafted to count the number of titles between 2010 and 2020, correct expiration dates and delete irrelevant titles. This was followed by the creation of variables to calculate the number of authorized mining days per year, a novel metric that aggregates the legal status of multiple mining tenements per cell.

The next segment of the ANM workflow shifted the analytical lens to the geospatial domain. Layers were created for both active and inactive mining polygons within the Caatinga. These geospatial layers were then enriched with the ANM information gathered in form of variables using SPSS, after which cases with missing data were removed. Subsequently, layers were established to distinguish between legal and illegal mining polygons per year. This would permit the measurement of soil transitions within legal mining areas and areas where mining was prohibited, the proxy used as illegal mining metric in this study.

Finally, mining tenements were summarized using the pairwise intersect tool to accurately preserve variables. This approach was necessitated by the often-diminutive size of mining tenements relative to the 10 km² cells used for spatial analysis. Consequently, even if a mining tenement was only partially intersected by a grid cell, the entire fine was attributed to that cell. This is because the approach focused on sum-based aggregation rather than proportional distribution of the fines.

This methodological choice is particularly relevant given the varying sizes of mining tenements. While it may introduce a form of spatial bias, where fines could be overrepresented in certain grid cells, it ensures that the total number of fines is accurately captured in the spatial summary. The approach is designed to provide a comprehensive picture of ANM fines, prioritizing the complete aggregation of fines over a proportional distribution that could dilute the impact or presence of these fines in smaller mining tenements.

Existing mining tenements were selected on a year-to-year basis and various attributes were summarized per cell, including the total number of administrative infractions and fines, the total mining tax paid, the area in hectares and the number of tenements.

Additionally, the average was used to gauge the type of entity responsible for the mining tenements, to estimate the age of the process, and the number of legal mining days (with a score of 365 indicating full legal permission for all tenements in a cell for that year). These variables are instrumental in analyzing the likelihood of a tenement becoming a target for illegal mining activities.

Lastly, a distinct grid was formulated specifically to isolate the ten substances of interest and to calculate VALUED metrics.

Legal Income. In Becker's economic approach to crime, legal income opportunities act as pivotal factors influencing individual incentives to engage in either lawful or unlawful activities. However, given the complexity of directly quantifying these opportunities, a proxy measure is essential. To this end, the variable "Relative Distance to the Average Income" (RDAI) was employed, drawing on the notion that higher municipal GDP relative to the national average serves as an indicator of more abundant legal income opportunities.

If inequality and government inefficiency is disregarded, elevated GDP levels not only signify greater economic development, but also correlate with advanced infrastructure

and public services, creating an environment conducive to lawful economic activities. This, in turn, offers viable alternatives to unlawful pursuits, such as illegal mining. Therefore, RDAI was utilized to evaluate the potential influence of legal income opportunities on mining-related crimes.

The creation of the independent variable for legal income, inherent to the Becker-Ehrlich model, involved the integration of multiple datasets and their subsequent transformations to generate a robust indicator that encapsulates the economic aspects of the municipalities in question.

In the first phase, conducted using SPSS, two primary datasets were imported: the population data from 2010 and the population data spanning from 2011 to 2020. Post-import, these datasets are sorted by a common identifier, namely the code ('Cód'), and merged to form a comprehensive dataset named 'pop'. The original variables are renamed for clarity, converting the years to specific variables such as 'pop_2010', 'pop_2011', and so forth.

Following this, the Gross Domestic Product (GDP) dataset for the years 2010-2020 was acquired and merged with the 'pop' dataset using the same municipality identifier. Variables were renamed to reflect their nature and year—'pib_2010', 'pib_2011', and so on. Consequently, a derived variable, GDP per capita, was computed for each year by dividing the annual GDP by the corresponding population. These newly created variables were named 'gdp_2010', 'gdp_2011', etc.

Moreover, the method proceeded to calculate the "Relative Distance to the Average Income" (RDAI) for each year. This was achieved by using the formula:

$$\text{RDAI} = \frac{\text{GDP per capita of the respective municipality} - \text{Brazilian GDP per capita}}{\text{GDP per capita of the respective municipality}}$$

The calculated RDAI values for each year were stored as new variables, such as 'rdai_2010', 'rdai_2011', and so on.

In the second phase, data was imported into the GIS environment. A feature class was generated from an existing layer of municipalities completely within the Caatinga biome, and the SPSS data was joined to this new feature class. This resulted in a final dataset that combined geographic and economic indicators, including the computed RDAI values, rendering it valuable for geospatial analyses in the context of legal income across municipalities.

To attain a nuanced understanding of RDAI (Relative Distance to the Average Income) across geographic areas, the same weighted average methodology that had been applied to the Federal Police data was employed. This method offered an accurate representation of border cells, which usually encompass multiple administrative or jurisdictional regions. The weighted average value accounted for the proportionate area of each cell, thereby ensuring a more precise calculation of RDAI values.

Desirability and Attributes of Minerals

As explained in the introduction, this study introduces the Mining-related Illegal Income (MRI) variable, an metric derived from the VALUED methodology, to address the complexity of measuring illegal income opportunities. This new variable transcends the limitations of using GDP per capita as a sole indicator by incorporating elements from Becker's rational choice analysis and the CRAVED model. The MRI variable enables a nuanced identification of regions prone to illegal mining activities, thereby offering a robust analytical tool for understanding the economic incentives behind criminal behavior.

The initial phase was dedicated to the calculation of the average VALUED score for each mineral substance for each year in the range of 2010 to 2020. This average was derived from the arithmetic mean of six distinct elements, namely Valuable, Abundant, Localized, Usable, Explorable, and Disposable, each contributing to the overall VALUED score for a

given mineral in a specific year. The operationalization of each constituent element within the VALUED metric is elaborated in the section entitled "Independent Variables", but the mathematical representation of this average VALUED score is encapsulated in the following equation:

$$\text{AvgVALUED}_{m,t} = \frac{V_t + A + L + U + E + D_t}{n}$$

Where m represents the mineral substance under consideration, and t denotes the specific year ranging from 2010 to 2020 and:

- V_t : Valuable score for the year t ;
- A : Abundant score, which is constant across years;
- L : Localized score, also constant across years;
- U : Usable score, constant across years;
- E : Explorable score, constant across years;
- D_t : Disposable score for the year t .

The subsequent stage involves the computation of the "Relative Risk" for each mineral substance within a specific geographic cell. This is accomplished by multiplying the VALUED score for each mineral by its corresponding area percentage within the cell for a particular year t :

$$\text{RelativeRisk}_{m_i,t} = \text{AvgVALUED}_{m_i,t} \times \text{PercentArea}_{m_i,t}$$

Where m_i denotes the i^{th} mineral substance in the set of the 10 most required mineral substances in the Caatinga¹⁷ and t represents the year. Following the computation of the Relative Risk for each mineral, the next step is to derive the Average Relative Risk (AvgRR) for the cell. This AvgRR is calculated as the arithmetic mean of all Relative Risks for the minerals in that particular cell for the year t :

$$\text{AvgRR}_t = \frac{\sum_{i=1}^n \text{RelativeRisk}_{m_i,t}}{n}$$

The terminal phase of this analytical process concentrates on the calculation of the Mining-Related Illegal Income (MRI) for each cell, specifically for each year t . The MRI is derived by multiplying the Average Relative Risk (AvgRR) with the aggregate of the percent areas for all minerals within that cell for the year t :

$$\text{MRI}_t = \text{AvgRR}_t \times \left(\sum_{i=1}^n \text{PercentArea}_{m_i,t} \right)$$

¹⁷ The use of m_i rather than m adheres to established mathematical conventions pertinent to the treatment of sets or sequences. Specifically, the subscript i functions as an index, delineating the i^{th} element within a set or sequence. This index ranges from 1 to n , where n signifies the aggregate number of elements in the set. Within the ambit of this research, m_i designates the i^{th} mineral substance in a predetermined set comprising 10 distinct mineral substances. Utilizing m in isolation could engender ambiguity, as it might suggest a generalized applicability to any m , devoid of any contextual placement within a set or sequence. Conversely, when summing across a set of mineral m 's, indexing them as m_i is the conventional approach. It is imperative to clarify that the subscript i does not denote an "ith mineral" per se. Rather, it serves as a numerical identifier for each unique mineral within the set under consideration. This indexing is instrumental in maintaining an organized account of individual minerals when multiple substances are in focus.

VALUED. The operationalization of the VALUED variables required analyzing data for each of the 10 minerals regarding all the aspects of the model: Valuable, Abundant, Localized, Usable, Explorable, and Disposable.

In the specific context of the VALUED dataset, it was necessary to normalize the values that were based on existing datasets (e.g. value), transforming the different measures regarding the substances into a 1-10 scale, representing the range of mineral values. The goal was to enable more effective comparisons and assessments of their relative significance among themselves and the other VALUED variables. In practical terms, the normalization process ensured that each mineral's measure was presented on an equitable scale, irrespective of its initial magnitude.

When performed, the normalization procedure followed a systematic approach:

- **Identification of Reference Points:** The initial step involved determining the minimum (Min) and maximum (Max) values for each specific substance within the timeframe of 2010 to 2020. These reference points established the range within which normalization would take place.
- **Calculation of Deviation:** The extent of deviation of each individual value (Value_i) from the minimum reference point (Min) was calculated as follows:

$$\text{Deviation}_i = \text{Value}_i - \text{Min}$$
This provided a measure of how far each value was from the minimum.
- **Determination of Normalization Factor:** The range between the maximum (Max) and minimum (Min) values was designated as the normalization factor (Norm_Factor): $\text{Norm\_Factor} = \text{Max} - \text{Min}$.
- **Normalization Calculation:** The normalized value (Normalized_i) for each individual value was then computed using the formula: $\text{Normalized}_i = 1 + ((\text{Deviation}_i / \text{Norm\_Factor}) * 9)$. This formula ensured that the values were

transformed onto a scale of 1 to 10, with due consideration to their relative position within the range.

Finally, all analyses considered the minimum effort required to explore the mineral, as in small artisanal mining context. For instance, sand can be mined industrially - using heavy equipment and exploring more valuable deposits like quartz sand (Vatalis et al., 2014) or heavy mineral sands (Bisht & Martinez-Alier, 2023) – or artisanally – with one person, a shovel and a horse-drawn cart.

Valuable. The value of each substance was calculated dividing total "US\$ FOB" (Free On Board) by the net weight in kg using exports data from Comex Stat, a system for querying and extracting data from Brazilian foreign trade which extracts, each month, detailed data on Brazilian exports and imports from SISCOMEX¹⁸. The normalization process was executed across distinct years for each specific mineral substance because the principal aim was not to engage in a comparative evaluation of prices among the selected minerals. Instead, the emphasis was placed on scrutinizing the temporal variations in prices between 2010 and 2020, with a particular focus on assessing their potential impact on illegal mining activities.

The precise value increments that encapsulate the value addition needed to trigger a unit change on the normalized scale that corresponds to each mineral are described in Table 6.

Table 6

Value addition needed to trigger a unit change on the normalized scale of the Valuable factor

Mineral	Increment Value (US\$/kg)
Clay	0.0433
Copper	0.1033
Gold	1845.01
Granite	0.0433

¹⁸<http://comexstat.mdic.gov.br/en/sobre>

Mineral	Increment Value (US\$/kg)
Iron	0.0433
Limestone	0.0111
Manganese	0.0433
Phosphate	0.0133
Quartzite	0.0267
Sand	0.0244

Note. Table 6, authored by the researcher, delineates the incremental value needed to effectuate a unit change on the normalized scale of the Valuable factor for various minerals. It enumerates these values in US dollars per kilogram for the studied minerals. The calculations are based on raw data accessible at <http://comexstat.mdic.gov.br/en/geral/40962>.

Abundant. Abundance values are presented in Table 7. The metric was operationalized through Brazilian mineral reserves, which serves as a dual-faceted indicator. Using mineral reserves as a proxy measure for abundance provides a nuanced understanding of a mineral's attractiveness for criminal exploitation, while also shedding light on its economic viability. Hence, a comprehensive analysis was conducted to ascertain the reserves of the ten minerals from 2010 to 2020, offering a glimpse into the mineral wealth of the nation. Each unit change on the normalized scale from 1 to 10 corresponds to a change of 1/9 of the Norm_Factor ($=51.000.000.000 - 2.400 = 50.999.997.600$ tons). Consequently, each unit increment on the normalized scale is equivalent to 5.6 billion tons.

Table 7

Normalized Abundance and Estimated Reserves of Key Minerals in Brazil

Mineral	Normalized abundance	Brazilian reserves
Clay	1	Although not present in Brazilian Mineral Summaries, according to Salum's (2018) report on the socioeconomic and environmental diagnosis of small-scale mining in Brazil, the country has reserves of approximately 2.67 billion tons of clay.
Copper	1	With reserves of approximately 11.8 million tons, copper holds a specific, albeit smaller, role in Brazil's diverse mineral matrix (IBRAM, 2018).
Gold	1	A precious metal, gold's reserves in Brazil are estimated at 2,400 tons (IBRAM, 2020).
Granite	2	An essential ornamental rock, granite's reserves are intertwined with other varieties like quartzite. The total reserves for ornamental rocks, including granite, stand at 6 billion tons (Brasil, 2018).
Iron	6	A cornerstone of Brazil's mineral exports, iron reserves are estimated at 29 billion tons (IBRAM, 2020).

Mineral	Normalized abundance	Brazilian reserves
Limestone	10	Essential for various industries, limestone's reserves in Brazil are pegged at 51 billion tons. The data, sourced from Lima & Neves' (2012) report, offers a comprehensive view of limestone's significance.
Manganese	1	With reserves of 140 million tons, manganese's role in Brazil's mineral matrix is undeniable, as indicated by the IBRAM (2020) report.
Phosphate	1	Essential for agriculture, phosphate reserves in Brazil are estimated at 315 million tons (IBRAM, 2020).
Quartzite	2	Similar to granite, quartzite's reserves are considered within the broader category of ornamental rocks, with total reserves estimated at 6 billion tons (Brasil, 2018).
Sand	10	While no official data on sand reserves in Brazil was found, its significance is undeniable. Given its vast consumption globally, sand's reserves are wrongly considered unlimited, as highlighted by UNEP and GEAS (2014). Because of that, for the purposes of this study, sand reserves were equaled to the biggest known reserve in the dataset, limestone, with 51 billion tons.

Note. Table 7, compiled by the researcher, presents the normalized abundance and estimated reserves of key minerals in Brazil. The table details both the normalized abundance and specific data on Brazilian reserves for each mineral.

Localized. In operationalizing the concept of 'localization' within the context of mineral reserves in Brazil, the study employed the geological environments and their respective accessibility scores (1-10) as indicators for each mineral substance. Average accessibility scores were calculated based on these environments, serving as a quantifiable metric for the ease (10) or difficulty (1) of access to these mineral reserves.

The average accessibility score for each mineral is derived from the logistical factors that influence the feasibility of mining operations. High average accessibility scores indicate that the mineral is found in geological environments that are logistically convenient for extraction (e.g. near Earth's crust). Conversely, low scores suggest that the mineral is located in geological settings that are less accessible (e.g. deep rocks), posing challenges for both legal and illicit mining activities.

The index also took into consideration the geological environments present in the Caatinga biome, which are strongly associated with crystalline shields (which cover most of the area), sedimentary deposits, karstic landscapes, and ecotones. Ecotones are areas where

different ecosystems meet, and, in these sub-regions, fluvial, lacustrine, and alluvial plains settings are more common than in the rest of the biome (J. M. C. D. Silva et al., 2017, p. 89).

Table 8

Metrics for Geological Environments Accessibility of Key Minerals in Brazil

Substance	Accessibility of Geological Environments	Localized*
Clay	Alluvial Plains (10), Coastal Plains (10), Fluvial (7), Karst Landscapes (7), Lacustrine (7), Laterites (7), Riverbanks (10), Sedimentary Deposits (8)	8
Copper	Intrusive Igneous Rocks (1), Metamorphic Rocks (3)	2
Gold	Alluvial Plains (10), Crystalline Shields (8), Fluvial (7), Intrusive Igneous Rocks (1), Metamorphic Rocks (3), Riverbanks (10)	7
Granite	Crystalline Shields (8), Intrusive Igneous Rocks (1)	5
Iron	Banded Iron Formations (2), Cretaceous Basins (6), Intrusive Igneous Rocks (1), Laterites (7), Metamorphic Rocks (3)	4
Limestone	Coastal Plains (10), Cretaceous Basins (6), Karst Landscapes (7), Lacustrine (7), Limestone Plateaus (8), Paleozoic Marine Sequences (7), Sedimentary Deposits (8), Tufa and Travertine (6)	7
Manganese	Banded Iron Formations (2), Intrusive Igneous Rocks (1), Laterites (7), Metamorphic Rocks (3), Sedimentary Deposits (8)	4
Phosphate	Coastal Plains (10), Cretaceous Basins (6), Lacustrine (7), Paleozoic Marine Sequences (7), Sedimentary Deposits (8)	8
Quartzite	Cretaceous Basins (6), Crystalline Shields (8), Metamorphic Rocks (3)	6

Substance	Accessibility of Geological Environments	Localized*
Sand	Alluvial Plains (10), Beaches (10), Coastal Plains (10), Cretaceous Basins (6), Dunes (10), Fluvial (7), Lacustrine (7), Paleozoic Marine Sequences (7), Riverbanks (10), Sedimentary Deposits (8)	9

Note. Based on geological environments described by Costa et al. (2010), Evans & Holm-Denoma (2018), Jones et al. (2019), Kekelia (2021), Penha (2017), Revuelta (2018), Adamek et al. (2021), Adeleke (2023), Ayuk et al. (2020), Bisht & Martinez-Alier (2023), Cobbing (2000), Coimbra & Freire (2021), Echavarria (2014), Fubelli & Dramis (2023), Hackney et al. (2021), Hook (2019), Igarapé Institute & Interpol (2021), Iyer & Hamza (2019), Le Tourneau (2021), Lopes et al. (2013), Maciel et al. (2022), Maniçoba et al. (2020), Manning (1995), Matavelli et al. (2015), Moon et al. (2006), Nascimento (2003), Salum (2018), Silva et al. (2017), UNEP & GEAS (2014). * The average was calculated and then rounded to the nearest whole number.

Usable. In the confluence of environmental criminology and mineral economics, this usability index emerges as an indispensable metric for gauging the ease with which minerals can transition from their raw state to a product ready to be sold, but it is particularly salient when assessing the vulnerability of various minerals to illegal mining activities. Minerals requiring fewer processing stages are inherently more susceptible to illicit extraction and subsequent sale.

The core of the scoring mechanism lies in the deduction of points based on the presence of processing indicators. Specifically, if a certain type of processing is needed to make that substance "usable", two points were subtracted from the usable score of 10, symbolizing the pinnacle risk of becoming a target for theft due to the mineral's inherent capability to be directly sold without the need for processing. If only sometimes that processing is needed, one point was removed. If the result was zero (manganese) or negative (copper), it was rounded to the minimum value (usable=1).

The rationale for operationalizing the "Usable" variable on a 1-10 scale was rooted in the need to quantify processing of the illegally explored substances, encompassing the tasks described in **Table 9**.

Table 9*Processing Steps Typically Required for the Sale of Illegally Extracted Minerals*

Processing	Explanation	Substances
Washing	Removal of impurities and separation of the mineral from other materials like soil or rock	Gold
Crushing	Fragmentation of the mineral into smaller pieces to facilitate further processing	Copper, Iron, Phosphate, Manganese (Sometimes)
Grinding	Reduction of the mineral to a fine powder, typically to augment surface area for ensuing processes	Copper (Sometimes), Iron (Sometimes), Phosphate (Sometimes), Manganese (Sometimes)
Polishing	Creation of a smooth surface, predominantly for aesthetic applications	Granite (Sometimes)
Calcination	Controlled heating of the mineral to induce a chemical transformation	Limestone (Sometimes)
Separation	Isolation of the desired mineral from impurities and other mineral constituents	Gold, Copper, Iron, Phosphate, Manganese
Chemical Processes	Utilization of chemicals for mineral extraction or modification	Gold
Smelting/Refining	Melting or purifying the mineral for further use	Gold (Sometimes)
Cutting	Shaping the mineral, usually for construction or ornamental use	Granite, Quartzite (Sometimes)

Note. Categorization based on the mineral processing described by Adeleke (2023), Revuelta (2018), Gupta & Yan (2016). The need for processing was determined based on interviews with experts and an analysis of advertisements on the online platform mfrural.com.br.

Gold, with a usability score of 3, necessitates multiple stages of processing, including washing, amalgamation usually using mercury, and sometimes smelting or refining. It is not typically sold in its raw, extracted form, but a sponge-like state, making it less susceptible to illegal mining activities. Copper, Iron, Phosphate, and Manganese, with scores between 5 and 6, are generally sold in bulk, often directly from the extraction sites¹⁹. These minerals predominantly undergo size reduction through crushing and separation processes, but manganese sometimes undergoes even fewer processing steps, limited mainly to sieving, which accounts for its higher usability score of 6.

¹⁹ Online platforms like mfrural.com.br have hundreds of ads selling these minerals in bulk.

Granite, Limestone, and Quartzite, with usability scores between 7 and 9, fall into the high usability category. Granite can be manually extracted with a hammer and a chisel, but is occasionally subjected to cutting and polishing. Sometimes, limestone is calcined at the extraction site, enhancing its utility for industrial applications like cement production. Quartzite is often commercialized in its raw form but may be cut for specialized applications such as flooring.

Finally, Clay and Sand, both with perfect usability scores of 10, require the least amount of processing. Clay is typically sold in its raw form to ceramic manufacturers, requiring no prior processing. Sand can be directly extracted and sold for various applications, including construction, also without any need for further processing.

Table 10

Usability Index

Mineral	Usability
Clay	10
Sand	10
Limestone	9
Quartzite	9
Granite	7
Manganese	6
Copper	5
Iron	5
Phosphate	5
Gold	3

Note. The need for processing was determined based on interviews with experts and an analysis of advertisements on the online platform mfrural.com.br.

Explorable. Within the VALUED framework, explorable means to measure the degree of ease associated with extracting a mineral from the Earth. This factor holds significant implications for comprehending the allure of a mineral in the context of both legitimate and illicit mining endeavors. In order to concretely define this factor, two pivotal components were analyzed: grade and equipment costs. Each of these constituents underwent

an assessment, yielding scores on a scale from 1 to 10. The culmination of these scores was employed to establish the overall "Explorable" score attributed to each mineral.

Grade quantifies the quality needed for some mineral deposit be deemed viable, specifically examining whether the mineral concentration renders it economically practical for extraction. Mineral grades, such as of Copper (0,5%), Phosphate (24%), Manganese (35%), Limestone (45%), and Iron (62%) were normalized to 1, 3, 4, 5 and 7 respectively (Haldar, 2013, p. 38). Minerals for which grade is not a crucial factor received higher scores, as their quality is based on other characteristics such as grain size (for sand and quartzite), plasticity (for clay), and the presence of defects or fissures (for granite) (Bisht & Martinez-Alier, 2023; Cobbing, 2000; Grimaldi & Cura, 2009; Haldar, 2013; Jones et al., 2019; Moon et al., 2006; Vatalis et al., 2014). This is because they can be directly exploited in bulk.

Finally, equipment costs scrutinize the financial investment essential for procuring the requisite machinery and equipment to facilitate mineral extraction. A higher score signifies diminished costs, thereby augmenting the mineral's appeal for mining undertakings by even small artisanal miners. clay, granite, sand, and quartzite secured a score of 10 because they necessitate minimal equipment-related expenditures.

Table 11

Explorability Metrics for Key Minerals in Brazil

Mineral	Feasible Grade	Cost of Equipment	Explorable
Clay	10	10	10
Copper	1	5	3
Gold	1	4	3
Granite	10	10	10
Iron	7	5	6
Limestone	5	6	6
Manganese	4	5	5
Phosphate	3	5	4
Quartzite	10	10	10

Mineral	Feasible Grade	Cost of Equipment	Explorable
Sand	10	10	10

Note. Table 11 provides an assessment for the chosen minerals, incorporating variables such as feasible grade, cost of equipment to create and average Explorability measure. The estimations are grounded in the research carried out by the author, drawing on studies by Moon et al. (2006), Haldar (2013), Jones et al. (2019) Bisht & Martinez-Alier (2023), Cobbing (2000), Grimaldi & Cura (2009), Vatalis et al. (2014).

Disposable. The total mineral production in Brazil was used as a metric for the "Disposability" facet within the VALUED model, since it was considered a pragmatic strategy to gauge the inherent ease with which extracted minerals can be effectively marketed. Data availability and the fact that the volume of production often reflects a high demand for the mineral, which means a strong marketability, justified the choice.

Furthermore, within the context of Brazil's mining sector, which is characterized by regulatory gaps and transparency issues, high production levels might encompass minerals explored through illicit means. To illustrate the point, the report titled "Legalidade da Produção de Ouro no Brasil" (Manzoli et al., 2021) provides significant insights into Brazil's mining sector, demonstrating the prevalence of regulatory gaps and transparency issues, as well as indicating that 28% of gold production in 2019 and 2020 was deemed irregular, despite being one of the few minerals that have their commerce controlled by the government. High production levels are evident, with 174 tons of gold traded during 2019-2020, but 49 tons were mined from areas with irregularities. Thus, the production volume metric provides a useful indicator of the potential for illegally mined substances to enter the market.

To operationalize the volume of mining production in Brazil, data from IBGE's PRODLIST²⁰, a comprehensive list that serves as a detailed compilation of goods and

²⁰ <https://www.ibge.gov.br/en/statistics/technical-documents/statistical-lists-and-classifications/17175-list-of-industrial-products.html?=&t=o-que-e>.

industrial services captured in the Annual Survey of Industry (PIA) – Product, was used.

Again, the exact monetary increments required to effectuate a one-unit alteration on the normalized scale, specific to each mineral, are delineated in **Table 12**.

Table 12

Value addition needed to trigger a unit change on the normalized scale of the Disposable variable

Mineral	Increment Value (US\$ thousand)
Clay	9.392,58
Copper	310.364,37
Gold	178.280,81
Granite	41.001,44
Iron	2.753.380,93
Limestone	113.409,83
Manganese	22.645,03
Phosphate	271.738,45
Quartzite	3.765,04
Sand	22.000,76

Note. The raw data is available on “Tabela 5806 - Produção e vendas dos produtos e/ou serviços industriais, segundo as classes de atividades e os produtos - Prodlist Indústria 2013” (<https://sidra.ibge.gov.br/tabela/5806>) and “Tabela 7752: Produção e vendas dos produtos e/ou serviços industriais, segundo as classes de atividades e os produtos - Prodlists Indústria 2016 e 2019” (<https://sidra.ibge.gov.br/tabela/7752>). Values in US\$ correspond to the original currency used by the source.

Geographic determinants of the mining tenements

In the Becker-Ehrlich model, deterrence and income are the primary variables employed to understand criminal behavior. The model postulates that crime is likely to occur when perceived benefits, commonly monetary in nature, surpass the associated costs, including the probability of apprehension and the magnitude of punishment. However, to achieve a nuanced understanding of the spatial and temporal dimensions of mining-related crimes, this research augmented the model by incorporating variables from environmental criminology, particularly those aligned with the Routine Activity Theory.

Hence, in addition to the VALUED methodology, which centers on the minerals that constitutes the target of criminal endeavors, the Becker-Ehrlich equation was enhanced by

variables accounting for the spatial context. In summary, these additional variables—roads length, number of gas stations, CPRM mining occurrences, and urban area—enrich the Becker-Ehrlich model by providing a more comprehensive framework to understand the multifaceted nature of mining-related crimes. Each of these variables brings a unique spatial dimension that can influence both the propensity to commit a crime and the effectiveness of deterrence mechanisms, thereby making them essential for a more nuanced analysis in environmental criminology.

Roads Length. The extent of road networks within a region could serve as an enabler for both crime and law enforcement. For criminals, a well-connected road network might provide easier access to targets and facilitate quicker escape routes, thereby reducing the perceived cost of committing a crime. On the other hand, law enforcement agencies could also benefit from a robust road network to improve their response times. Thus, the length of roads is a dual-faceted variable that can impact the occurrence and deterrence of criminal activities.

To generate a comprehensive dataset of roads relevant to the study area, multiple steps were undertaken to download, filter, and process the road network data. Initially, the entire South America road network was downloaded from the OpenStreetMap Project as a PBF file. To delineate the specific area of interest—the Caatinga region—a ".poly" file was generated using the "osmpoly_export" tool, which was subsequently employed to clip the broader South America dataset.

The road types included in the study were carefully chosen based on their relevance to the region and the specific focus on mining activities. The categories 'motorway,' 'trunk,' 'primary,' 'secondary,' 'tertiary,' 'unclassified,' 'residential,' and 'track' were selected. These

road types were identified and extracted using QGIS's²¹ "select by expression" function, followed by exporting the selected features to shapefile format.

Once these road types were isolated, the final step involved using the PairwiseClip function to clip these road segments by the Caatinga municipalities, ensuring that only the roads within or intersecting the study area were included in subsequent analyses. This resulted in a new geodatabase feature class that encapsulated only the road segments pertinent to the study, thereby offering a detailed and spatially relevant dataset for examining the relationship between road infrastructure and illegal mining activities within the Caatinga biome.

The summarization technique was employed to aggregate the lengths of roads within each cell of the grid. Initially, the length of each road segment within the cell was calculated and summed to yield the total road length in kilometers for that particular cell. This aggregated metric was then appended to the grid as a new attribute. The field initially generated as "sum_Length_KILOMETERS" was renamed to "roads_km" for easier identification and interpretation. This field stores the cumulative length of roads, measured in kilometers, for each cell within the grid. Subsequently, this attribute was joined to the main grid, thereby integrating the summarized road lengths into the primary analytical framework. This information is static, representing the state of the road network as of the data's download (September 2021).

Number of Gas Stations. In the realm of illegal mining activities, the presence of gas stations plays a decidedly unique role. Given that illegal mining involves the extraction and

²¹ QGIS was selected instead of ArcGIS for this study due to the fact that the webserver of Open Street Maps was already configured for use with QGIS, offering a more streamlined integration.

swift transportation of mineral resources, the availability of fuel becomes a logistical cornerstone for these unauthorized operations. Illegal miners may rely on these gas stations to power their machinery and vehicles, ensuring uninterrupted operations and facilitating rapid movement of illegally obtained resources. In this regard, gas stations can serve as vital nodes in the supply chain of illegal mining, providing the fuel necessary for the various phases of the operation, from extraction to transportation.

In the initial phase of the variable creation, data pertaining to gas stations were acquired from the Open Street Map Project (OpenStreetMap, 2021). This was achieved through the use of the QuickOSM (Gustry, 2023) plugin for QGIS, which facilitated the extraction of relevant data based on predefined geographic and amenity criteria.

The summarization procedure computed the aggregate number of gas stations situated within each grid cell, and this computed attribute was subsequently appended to the grid. The automatically generated field name "Point_Count," which emerged as a result of the summarization operation, was renamed to "gas." This field encapsulated the total count of gas stations within each grid cell. Importantly, this data is static, representing the state of gas stations as of the time they were downloaded in September 2021.

CPRM Mining Occurrences. In accordance with the Geological Survey of Brazil (CPRM, 2021), a mining occurrence is defined as a natural concentration of a mineral or group of minerals, in quantities sufficient to be economically viable. These occurrences, therefore, represent critical focal points for economic development, but they also become highly attractive targets for various forms of illegitimate activities, notably illegal mining. The economic viability of these sites, underscored by the presence of valuable minerals, can act as a magnet for organized crime groups, thereby heightening the propensity for criminal activities in areas proximate to these mining occurrences.

Additionally, mining operations, by their nature, often draw a transient workforce. Such a population may lack robust social ties to the local community, which could have implications for social cohesion. The absence of strong social bonds can inadvertently create an environment conducive to crime, as the conventional social deterrents may be weaker or entirely absent. Thus, the presence of CPRM mining occurrences inherently influences the socio-economic and criminogenic landscape of the regions in which they are situated.

The creation of the CPRM variable involved a multi-step process to distill the data into a format amenable for comprehensive risk assessment within the Caatinga biome. Initially, mining occurrence data were procured from the Geological Service of Brazil (CPRM, 2021). These data, also static in time, underwent a spatial restriction process to retain only those occurrences inside municipalities entirely encapsulated within the Caatinga biome.

Following the spatial restriction, the data were then aggregated to align with the existing grid system that frames the study area. This was accomplished by summarizing the points of interest within each grid cell, thereby creating an aggregate variable that encapsulates the frequency of mining occurrences within these specific geographic units (10km² cell).

Finally, field alterations were conducted to rename the aggregate count of points as "cprm_poi", thereby providing an explicit description of the data source and what the variable represents. Once renamed, this newly created variable was incorporated into the existing data structure by joining it with the primary grid layer, ensuring that each cell in the grid is supplemented with the corresponding CPRM data.

Urban Area. While the initial stages of mineral extraction predominantly occur in rural or secluded locations, the subsequent phases of the mining supply chain are often deeply entwined with urban centers. These hubs serve as marketplaces for the commercialization of

various minerals, thereby acting as the end nodes in the supply networks that may involve both legal and illegal mining activities.

Beyond serving as marketplaces, urban areas also play a pivotal role as sites for the processing of extracted minerals. The availability of specialized equipment, skilled labor, and other essential resources makes these urban centers indispensable to the mining industry. In addition to these utilities, the concentration of logistical and administrative capabilities within urban areas further facilitates the operational aspects of mining, possibly including those that are illicit.

Moreover, the presence of what was captured by satellites as "urban areas" within rural settings often signals a level of infrastructure that is indispensable for the functioning of the mining industry. These areas, though not urban in the conventional sense, may house essential facilities, such as temporary worker accommodations, equipment storage, and even processing units. Their existence in proximity to mining tenements could therefore be interpreted as indicative of an infrastructure network that supports mining activities.

In this vein, the role of urban areas extends beyond mere geographic locations to become intricately linked operational nodes in the mining supply chain. Their importance in facilitating various stages of mineral extraction, processing, and commercialization makes them a relevant variable in the risk assessment model for mining-related crimes. Therefore, the inclusion of urban areas as a variable not only complements other geographic factors but also provides critical insights into the structural elements that could potentially facilitate illegal mining activities.

The variable for urban areas is derived from MapBiomass (2023) transition raster, a source that will be comprehensively detailed in the "Dependent Variable" section. This variable is characterized by both temporal and spatial fluctuations. To encapsulate these dynamics, an iterative methodology was applied, covering a time frame from 2010 to 2020.

The first step involved implementing a selective filtering process on the baseline spatial raster, specific to each year under study, within the Caatinga biome. A set of pre-determined values was employed to isolate pixels representing transitions to, as well as the persistence of, urban zones. These selected areas were then converted from raster to polygon format to facilitate subsequent operations.

Upon completion of the polygon conversion, an aggregation step was undertaken. Utilizing the existing grid that frames the study area, the urban polygons were summarized within each grid cell. This operation served to create an aggregate variable that encapsulates the extent of urban areas in hectares for each grid cell, thereby producing a dataset that could be readily integrated into the broader risk assessment framework. This aggregation was performed iteratively for each year in the dataset, thereby allowing for a temporal analysis of urban expansion or contraction within the study area.

Lastly, metadata adjustments were carried out to ensure the newly created variable was both descriptive and aligned with the existing data schema. Specifically, the field originally designated as "sum_Area_HECTARES" was renamed to "urban_{year_str}" to reflect the specific year and the nature of the data it represents.

It is important to register that, in assessing the risk factors associated with illegal mining activities, the spatial relationships between various geographic features cannot be overlooked. Among these, the potential autocorrelation between gas stations and urban areas raises compelling questions for the research design. Gas stations are, fundamentally, point-based measurements; they denote specific locations rather than expansive areas. This quality sets them apart from urban areas, which are measured as continuous zones of varied dimensions. Consequently, while both gas stations and urban areas may be viewed as markers of human activity and development, their spatial attributes diverge sufficiently to warrant separate consideration.

The point-based nature of gas stations offers insights that an area-based measure like urban zones cannot capture. For instance, the density and distribution of gas stations may reflect the routes most frequented for transportation of mineral resources, thus serving as a proxy for potential sites of illegal mining activities. Conversely, urban areas provide a measure of generalized human activity, but they lack the granularity to capture such specific patterns.

Turning to the relationship between roads and urban areas, one encounters another layer of complexity. While urban areas inherently capture paved roads within their boundaries, they fall short of accounting for the unpaved roads that often serve mining tenements. This distinction is not merely semantic; it has substantive implications for the study, particularly given that mining tenements are predominantly located in rural settings. These rural locations are commonly connected by a network of unpaved roads, which are not reflected in the data pertaining to urban zones.

In this context, both roads and urban areas become essential variables in the risk assessment model. Roads, particularly those that are unpaved, serve as the lifelines for mining tenements, offering the only means of access to and from these remote locations. Their inclusion in the model thus complements the data on urban areas by providing a more comprehensive representation of the transportation network that facilitates mining activities. This dual inclusion enriches the model, enabling it to capture the nuanced spatial dynamics that underlie the risk of illegal mining in the Caatinga biome.

Legal mining. The process for prospective miners to perform lawful mining operations begins with the requirement of a mining tenement delineation with the ANM. This initial step is crucial as it lays the foundational legal groundwork for subsequent legal (and illegal) mining activities. Next, the procurement of environmental licenses is mandatory, as it ensures the incorporation of environmental considerations into the mining regulatory

framework. After acquiring the environmental licenses, the process reaches its culmination with the formalization of the mining title by the ANM, fully legitimizing operations within the stipulated tenement, time, and quantity.

Legal mining tenements are the specific areas where the ANM authorized mining activities during the specified timeframe. Hence, in the present study, the variable designated as "Legal Mining" is intrinsically linked to this operational and regulatory framework governed by Brazil's National Mining Agency (ANM). The focus is to investigate the role of the area of explorations (TNVS) inside mining tenements that maintained a valid mining title for at least one day between 2010 and 2020 - which corresponds to the variable `nl_leg_mean` - on illegal mining.

The integration of this variable into the analytical model anticipates a notable issue: the granting of a legal title to a mining tenement inherently includes permission for exploration and commercialization of the mineral resources. This creates an unintended opportunity for illegal miners to exploit the established infrastructure to sell illicitly mined minerals. Concurrently, legal miners may integrate illegally sourced minerals into their output, purchasing at a lower cost than that of lawful extraction and subsequently marketing these as their own legally mined products.

The correlation between legal and illegal mining also arises from factors such as the presence of valuable mineral deposits and existing mining infrastructure that can be exploited illegally. Consequently, in regions where legal mining activities are more prevalent, one could argue that there is a greater likelihood that unauthorized individuals or groups may attempt to exploit these resources outside the bounds of the law.

In addition, the presence of valuable mineral deposits in areas with active legal mining operations can serve as a tempting target for illegal activities. These deposits may attract individuals seeking to exploit them for personal gain without adhering to the necessary

legal and environmental regulations. Moreover, existing mining infrastructure, such as machinery and facilities, can facilitate illegal explorations by providing convenient access to markets and resources for unauthorized mining operations.

Thus, the "Legal Mining" variable encapsulates the dynamics of regulatory compliance and non-compliance within the mining sector (e.g. when legal miners mix illegal minerals into their legal outputs). It offers a critical lens for evaluating adherence to, or deviation from, legally established mining protocols. In doing so, it provides a chance to better understand the mining activities occurring around legally designated tenements and their potential role in facilitating illegal mining operations.

Other Controls

Given that the dependent variable was constituted by a select array of soil transition types within mining tenements, the inclusion of both the area and number of mining tenements as control variables in the equation became a methodological necessity. These controls served to adjust for the influence exerted by the spatial extent and prevalence of mining tenements on the dependent variable, enhancing the model's analytical robustness.

To compute these controls, two variables were generated for each year within the study's temporal scope, designated as $\text{area}_{\text{year}}$ and pct_{year} . The first variable encapsulated the cumulative area in hectares of mining tenements for each respective year, obtained through the summation of individual tenement areas. This variable served to account for the spatial extent of mining activities, thereby offering a nuanced understanding of its influence on the dependent variable.

Conversely, the pct_{year} variable was calculated as the cumulative count of mining tenements for each year. This was achieved through the summation of individual tenement instances within the dataset. This variable adjusted for the sheer prevalence of mining

tenements, an aspect that potentially correlates with the frequency of soil transitions within these tenements.

It is worth noting the intricacy of ascertaining the operational status of a mining tenement in a 11-year time series, which presented a methodological challenge. Given the dynamism inherent to mining operations—ranging from regulatory approvals to potential "availability"²² or closure — a static snapshot of mining tenements completely inside the Caatinga would not suffice. Exclusively filtering tenements based on their active status at the time of data download would also not be enough, as it would introduce a temporal bias into the dataset. For instance, tenements active in 2010 could have transitioned into inactivity in the intervening years, thereby no longer being pertinent to the current scope of the study.

To address this issue, the dataset was subjected to a temporal analysis focused on detecting the beginning and finishing date of each mining tenement. Event types (n=2478), notably those representing regulatory cessation or expiration, were meticulously examined to determine the start or end of a mining process.

The first criterion aimed to isolate tenements that had undergone events post-2009, thereby ensuring current relevance. Subsequently, a focus was placed on tenements with titles active between 2010 and 2020, further refining the dataset by temporal specificity. A synthesized approach was then employed to include tenements that satisfied either of the two preceding conditions: experiencing events after 2009 or holding active titles between 2010

²² A procedure by ANM to select new candidates for mining projects previously granted to others but returned to the agency due to reasons like application rejection, title expiration, mine abandonment, or relinquishment of mining rights (<https://www.gov.br/anm/pt-br/acao-a-informacao/disponibilidade-de-areas>).

and 2020. Simultaneously, an exclusionary tactic was implemented to remove tenements that had ceased to be operational.

A specialized variable denoted the year of inactivation, achieved through a set of predefined event IDs that were coded representations of various forms of inactivation, such as regulatory cessation, natural expiration, or other forms of termination. By retaining only the most recent inactivation event for each tenement, the study ensured the elimination of irrelevant, inactive tenements from the dataset while assuring that active tenements were preserved.

Lastly, a variable capturing the date of the most recent event for each tenement was employed. This variable, termed "last_event" served as a corroborative mechanism, further fine-tuning the dataset by flagging the current operational status of each tenement. The methodology employed for the summarization of these variables was congruent with the procedures delineated for mining-related fines from the National Mining Agency, as explicated in the Section "Independent Variables". Through this intricate process, the study achieved a temporally accurate and operationally relevant selection of 46,618 mining tenements, from laying a robust foundation for subsequent analyses.

For reasons analogous to those articulated for the variables pertaining to the area and number of mining tenements, the same soil transitions that served as proxies for mining-related crimes were utilized to construct another control variable ($outside_{year}$). This variable quantified the area of such transitions occurring outside any mining polygon, encompassing even those not included in the current study (e.g. requiring exploration of other substances or more than one mineral). This inclusion was imperative to ensure that the transitions observed within untitled mining tenements were not merely reflective of natural occurrences, such as weather phenomena, thereby enhancing the robustness of the analytical framework.

Dependent variable

The core issue this empirical research found about mining-related crimes was the identification and operationalization of a reliable dependent variable. Traditional methods such as police investigations, often seen as the go-to metric for crime rates, are implicated in a paradox: rational choices made by police can lead to a disproportionate focus on 'high-risk' areas or populations, resulting in an inflation of recorded criminal activity (Harcourt, 2005). Aligning with the Brazilian law enforcement context, an increase in police activity can also result in a higher discovery of crimes, leading to an inflation of recorded crime rates within the region.

Brazil's substantial mining sector is often riddled with unreported activities, making it an elusive target for quantitative analysis. The CFEM dataset, which serves as a repository for mining-related tax information since 2002, only captures the contours of legal mining operations. Within this dataset, a mere 40,915 mining tenements have been registered as probable sites of mining activity, representing a scant 8% of the 485,969 mining processes initiated since 2002 (256,011 that became inactive and 229,958 that were active in 2023). Metrics produced by governmental agencies, such as ANM shutdown orders or IBAMA interdictions, are inherently biased. Specifically, these metrics are often influenced by external factors, such as political interests and budgetary constraints. In the search for an unbiased dependent variable, MapBiomas data emerged as the most promising.

Nevertheless, after a preliminary evaluation, it was possible to conclude that the method used by MapBiomas to detect mining explorations on the caatinga biome has improved on the collection 7, but it is still under development. The Caatinga biome has an official area of 84,445,300 ha but, according to the most recent data available on Mapbiomas online platform (MapBiomas, 2023b), only 9,147 ha (0,1% of the Caatinga) would have been mined between 2010 and 2020. This contrasts with the fact that approximately 50% of the

biome was required for mining and 24% have been licensed to mineral exploration between 2010 and 2020.

Table 13

Geographic extents of the current investigation

Item	Area (ha)	Proportion to study area	Proportion to Caatinga
Caatinga	84,445,300	121%	-
Study area (municipalities completely inside Caatinga)	69,620,940	-	82%
Area required for mining (2010-2020)	42,646,732	61%	50%
Licensed mining tenements in operation (2010-2020)	21,336,437	30%	24%
Total active mining tenements* (2010-2020)	72,537,482	104%	85%
Mapbiomas Mining Area (2010-2020)	9,147	0.013%	0.011%

Note. The data for the study area is from Brasil | Cidades e Estados |, by IBGE, 2019, (<https://www.ibge.gov.br/cidades-e-estados>). The data for mining tenements is from SIGMINE, Mining Geographic Information System, by ANM, 2023, (<http://sigmine.dnpm.gov.br>). *Accounting for overlapped mining tenements.

To further support the deficiencies of MapBiomas data regarding mining in the Caatinga biome, an exploratory analysis that juxtaposed CFEM and MapBiomas data unearthed clear incongruities. Specifically, Currais Novos, the municipality distinguished for having the highest mining production in Rio Grande do Norte—amounting to 371,949 tons of minerals in addition to 459,032 m³ of other mineral substances—during the specified period (ANM, 2022b), was paradoxically recorded as having zero mining area in the MapBiomas dataset (2023b). As a matter of fact, MapBiomas recorded a scant 12 hectares allocated to mining exploration across the entire Rio Grande do Norte State during the decade spanning from 2010 to 2020.

The area that is the object of interest of this research, encompassing only the 963 municipalities completely inside the Caatinga, has 69,620,940 ha, which represents 82% of

the biome. A preliminary exploratory analysis based on pixel counting²³ demonstrates that Mapbiomas is improving, but still lacks the capacity to generalize the use of the soil for mining in the biome Caatinga.

Table 14

Count of pixels of land use transitions to mining inside municipalities completely inside Caatinga between 2010 and 2020

Label	Pixel Value	Area (ha) 2010 - 2020		
		Col. 6	Col.7.1	Difference
Mining to Mining	3030	45,926	87,415	90%
Savanna Formation to Mining	0430	1,042	1,036	-1%
Mosaic of Uses to Mining	2130	427	354	-17%
Pasture to Mining	1530	440	334	-24%
Other Temporary Crops to Mining	4130	92	141	53%
Grassland to Mining	1230	139	65	-54%
Urban Area to Mining	2430	112	61	-46%
Other non-Vegetated Areas to Mining	2530	557	52	-91%
River, Lake and Ocean to Mining	3330	152	32	-79%
Forest Formation to Mining	0330	33	11	-67%
Rocky Outcrop to Mining	2930	10	3	-71%
Other Perennial Crops to Mining	4830	4	1	-84%
Total		48,934	89,503	

Note. Data from MapBiomas Collection 7 Transition Maps, by Mapbiomas, 2022, October 25, (https://mapbiomas.org/en/colecoes-mapbiomas-1?cama_set_language=en).

²³ Considering that MapBiomas raster have a 30 m resolution, by counting the number of pixels and multiplying per 900, it was possible to roughly estimate the area in square meters.

This discrepancy not only calls into question the accuracy of the data but also underscores the necessity of scrutinizing multiple soil transitions for a more comprehensive and reliable understanding of the mining landscape. In response to this critical exigency, a proxy was formulated, anchored in the same data repository—specifically MapBiomass Collection 7—which encompasses an array of 36 distinct land-use classifications.

MapBiomass transition raster pixels have values composed by the soil usage in the year before and after: $(ID \text{ year } 1 \times 100) + ID \text{ year } 2^{24}$. By analyzing eleven years of soil transition in the region, 374 combinations of these 36 values were found, and 30 were chosen to compose the proxy. Because of the evident remote sensing image similitude with mineral explorations, in addition to all transitions to mining, all changes from forest and non-forest natural formation to Rocky Outcrop (29) and Other Non-Vegetated Areas (25) from 2010 to 2020 were selected, as presented in detail in Appendix B.

Transitions from rocky outcrop to rocky outcrop, non-vegetated areas to non-vegetated areas and between each other were excluded because of the probability of not representing a significant change in reality. Also, only transitions to mining, rocky outcrop and non-vegetated areas that happened in Caatinga were chosen. Consequently, the aggregate area corresponding to the selected transitions that constitute the mining proxy for the decade spanning from 2010 to 2020 has 506,703.15 ha or 416,401.52 if not overlayed (see Appendix E).

²⁴ According to MapBiomass (2023a):

303 = forest that remained forest

315 = forest that has been converted to pasture

1515 = pasture that remained pasture

1524 = pasture that has been converted to urban infrastructure.

Added to the initial area of mining, the estimated proxy area has grown by 5,539%, which corresponds to 0.6% of Caatinga and 0.7% of the studied region. After assuring a more robust variable composition, a table was constructed to reclassify all other pixel as null (0, 'nodata'), creating a reclass table containing only the selected transition values: all soil transitions to mining, every transformation from forest and non-forest natural formation to Rocky Outcrop (29) and Other Non-Vegetated Areas (25). In the absence of precise and reliable geospatial data, all these Transition to Non-Vegetated Soil (TNVS) inside mining tenements without at least one day of mining permission during that year were considered illegal mining for the purposes of this study.

In order to provide a comprehensive understanding of mining exploration activities, both legal and illegal, distinct layers were created for each type of mining exploration. The creation of a legal exploration layer served as a critical first step, facilitating the isolation of legally sanctioned mining activities from those that are not. All TNVS within mining tenements that had at least one day of a valid mining title during the given year were deemed as legal. Through an inverse selection mechanism, all TNVS that lay inside tenements lacking a legal mining title were considered illegal.

In the next step, a layer containing all active mining tenements between 2010 and 2020 was then created to serve as a comprehensive repository of all mining claims and rights in the study area regardless of the substance it required to explore. This was necessary to allow a selection of TNVS that were outside any mining polygon, which were also saved as a distinct layer to compose a control variable.

Finally, the quartet of Mapbiomas transitions sets—namely outside exploration, legal, no-title, and urban areas—were subjected to a spatial summarization from the year 2010 to 2020, focusing specifically on the total area in hectares. These newly computed fields were then systematically integrated into the primary grid as out_{year} , leg_{year} , no_title_{year} and $urban_{year}$.

In addition, the average between years was calculated for each one of these fields, providing a comprehensive mean value that reflects temporal changes in land use across the respective categories from 2010 to 2020.

Plan of Analysis

In this study, Becker's rational theory of crime is applied to assess mining-related crimes, with a focus on weighing the benefits against the costs of criminal activities. Deterrence is measured through variables such as mining-related investigations, fines imposed by the National Mining Agency (ANM), and fines by the National Environmental Agency (IBAMA). The economic approach emphasizes the role of legal and illegal income opportunities in influencing crime. Legal income opportunities, reflected in higher municipal GDP levels, are seen as positive incentives that provide lawful paths for income generation, potentially deterring criminal behavior. Conversely, illegal income opportunities, difficult to measure directly, are suggested to be indirectly indicated by the VALUED approach, attracting potential criminals with more lucrative targets.

Adapted from the CRAVED approach to assess mineral substances' desirability as targets for usurpation, this methodology aligns with Becker's rational choice analysis, focusing on how the desirability of minerals influences the decision-making process of illegal miners. The newly developed mining-related illegal income (MRI) variable offers deeper insights into the relationship between income, criminal opportunities, and crime rates. Furthermore, the criminogenic potential of mining tenements (places) in relation to illegal mining activities is operationalized using indicators like road length, gas stations, urban area, and mining deposit volume. This multi-variable approach provides a nuanced understanding of the spatial factors contributing to the likelihood of illegal mining activities.

After defining the variables, the initial phase of the analytical process was dedicated to resolving spatial correlation challenges by generating appropriate spatial lag variables.

These spatial lags serve as a robust foundation, ensuring the rigor of all subsequent analyses within the adapted Becker-Ehrlich model. This preparatory step is pivotal for the integrity of the model, especially considering the complex spatial dynamics inherent to the 936 municipalities fully encapsulated within the Caatinga biome.

Spatial dependence

This study adopted a k-nearest neighborhood structure, specifically set at eight neighbors. This choice was driven by the need to capture a comprehensive perspective of spatial dependencies across the 10km² cell grid. The Cluster and Outlier Analysis algorithm, part of the ArcGIS Spatial Statistics Toolbox, was utilized to operationalize these methodological considerations, thereby enhancing both the reliability and validity of the spatial analyses conducted in this dissertation. The selection process is detailed below.

This research primarily focuses on areal data²⁵, which refers to spatial data observed over regular or irregular grid cells, such as municipalities or census tracts. Areal data analysis aims to quantify the spatial patterns of an attribute through a specific neighborhood structure while accounting for spatial effects. This is particularly relevant for examining such phenomena as illegal mining activities, since the analysis of such a complex issue demands

²⁵ Beyond areal data, there exist three additional types of spatial data analysis. Spatial point pattern analysis is instrumental in fields like disease mapping for identifying spatial clusters and their associated risk factors. Geostatistical analysis, prevalent in geological sciences, uses point-referenced data and distance-based functions to measure spatial dependence. Finally, spatial interaction data analysis models flows between origins and destinations and is commonly employed in transportation planning and migration studies. Each approach serves to elucidate different facets of spatial configurations and interactions (Chi & Zhu, 2020, pp. 5–6).

data from a variety of sources often aggregated to different administrative or geographic units (Chi & Zhu, 2020).

However, in the quest to investigate the spatial patterns, the necessity of accounting for spatial autocorrelation is paramount, since it poses challenges to traditional statistical analyses that assume independence among observations (Anselin, 1995). Here, it is important to differentiate the main concepts regarding this issue, because while spatial autocorrelation, spatial dependence, and spatial heterogeneity are often used interchangeably, they possess nuanced differences.

Spatial autocorrelation is the correlation of a variable with itself through space, assessing how similar or dissimilar objects are in different locations. It is necessary for evaluating the "independence of observations" assumption, a prerequisite for conducting valid statistical analyses, as it determines whether the observed values in one location are independent of the values in neighboring cells. It is often used for Exploratory Spatial Data Analysis (ESDA) and is measured by indexes like Moran's I. Spatial heterogeneity refers to the non-uniform distribution of attributes across the spatial unit. Spatial dependence, on the other hand, is more commonly used in spatial regression modeling and pertains to the interdependence of the response variable and/or model residuals across locations (Chi & Zhu, 2020). Such dependence is particularly prevalent in areal data, where the values observed in one unit are influenced by neighboring units. This phenomenon can bias standard regression estimates if not appropriately accounted for, thus necessitating a control variable for spatial dependence (Chi & Zhu, 2020).

To address the issue of spatial dependence, areal data regression modeling often uses neighborhood structures, which can be of two types: distance-based or contiguity-based (Chi & Zhu, 2020). Distance-based neighborhood structures also offer two principal methodologies to address the inherent irregularity of areal units commonly encountered in

social science research (such as municipalities). One involves designating a specified number of nearest neighbors for each areal unit, while the other focuses on defining a distance band within which the centroids of areal units are considered to be neighbors.

On the other hand, contiguity-based structures define neighbors based on shared boundaries or vertices, with variations such as the "rook's case" (boundaries touch) and the "queen's case" (boundaries or vertices touch) offering different levels of contiguity. These structures are particularly straightforward to implement on a regular grid – such as the one used in this research – and can extend to higher-order neighbors (Chi & Zhu, 2020).

In this study, the adoption of a contiguity-based neighborhood structure for a global assessment, specifically the "queen's case," is deemed appropriate due to its straightforward applicability to the research's regular grid. Given that the study employs a grid with cells measuring 10km² each, a single contiguous neighborhood would comprise 90km². Considering that the average area of the municipalities under study is 743km², approximately 8 of these contiguous neighborhood units would suffice to encapsulate the municipal area in its entirety.

These neighborhood structures must transition from a theoretical construct to an operational entity through their conversion into spatial weight matrices. These matrices contain spatial weights that correlate with a designated variable—be it the response variable or regression errors—across the adjacent 10km² cells, in alignment with the pre-defined neighborhood structure (distance or contiguity).

According to Chi & Zhu (2020), the terminologies "neighborhood structure" and "spatial weights matrix," though sometimes used interchangeably in existing literature, fulfill discrete yet interlinked functions in this research framework. The former acts as an overarching conceptual roadmap, while the latter functions as a detailed operational manual, specifying the computational steps necessary for the analytical rigor of the spatial regression

model deployed in this study. Thus, the conversion from the chosen theoretical neighborhood structure (contiguity, queen's case) to an operational spatial weights matrix is not merely procedural but fundamentally critical to the rigor and validity of the spatial analyses conducted in this dissertation.

Traditional linear regression assumes that errors are independently and identically distributed (i.i.d.), a condition that is often violated when spatial dependencies exist within the data. Without accounting for such dependencies, the model would require an unsustainable number of parameters—exceeding the sample size—and thus would be analytically infeasible. By introducing a spatial lag variable as a control in the model, the issue of spatial dependencies was addressed. The variable was created based on a spatial weights matrix, constructed according to the 'queen's case' neighborhood structure, thereby capturing the spatial interdependencies among observations. This allowed for the variance-covariance matrix of either the response variable or the regression errors to be formulated as a function of a manageable set of estimable parameters relative to the sample size, thereby enabling a rigorous and analytically feasible spatial analysis (Anselin, 1995).

Despite being central to the efficacy of the spatial regression models employed, the selection of an appropriate spatial weights matrix is non-trivial, particularly in areas with strong spatial heterogeneity, as seen in environmental criminology and mineral economics. This complexity is further compounded by the Modifiable Areal Unit Problem (MAUP), especially evident in distance-based spatial weights matrices that necessitate the setting of threshold values. Specifically, small threshold values can lead to an overabundance of areal units without neighbors, while large values may produce excessively large neighborhoods. Moreover, distance-based approaches typically result in a paucity of neighbors in rural areas and an excess in urban areas.

While Aldstadt and Getis (2006) offer the multidirectional optimal ecotope-based algorithm (AMOEBA) for identifying optimal spatial weight matrices²⁶, and Zhu et al. (2010) advocate for a regularization method, the selection often depends on the specific research context. In the present case, the variability inherent of a spatial regression using a 10km² cell grid covering only areas where some mining tenement existed between 2010 and 2020 leads to disparate weight sums across cells. Several cells do not have eight contiguous neighbors, some no neighbor at all.

To mitigate the problems arising from this, the research adopted a row-standardized approach for the spatial weights matrix, in line with established methodologies (Anselin, 1995). By dividing each cell by the sum of its respective row, the resulting matrix facilitates a weighted average attribute of neighbors, thereby enhancing the interpretability and analytical rigor of the model. This row-standardization technique is consistently applied throughout the spatial analyses conducted in this study, ensuring a coherent and meaningful interpretation of the results.

This procedural step functioned as an implicit form of regularization, constraining the range of spatial weights and ensuring their summation to unity for each observational unit. Such a measure balanced the influence of each unit's neighbors, effectively mitigating the potential for outliers in the data set to disproportionately skew the model's estimates.

²⁶ The "ecotope-based" aspect of AMOEBA focuses on identifying subregions of spatial association within the data. The algorithm is multidirectional, searching for spatial association in all specified directions from one or more "seed" spatial units, and is optimal in revealing the most local scale of spatial association present in the data. Essentially, it aids in demarcating clusters of related spatial units, termed "ecotopes", based on their spatial relationships and associations (Aldstadt & Getis, 2006).

Consequently, the model was not only sensitive to spatial dependencies but also achieved this sensitivity in a manner that was statistically robust and less susceptible to the idiosyncrasies of the specific dataset under investigation. Thus, the utility of row-standardization, serving as a form of regularization, was substantiated through its capacity to enhance both the reliability and validity of the model's analytical outcomes.

Table 15

Summary of Spatial Relationships Matrix

Spatial Relationships	Distance/Neighbors	Spatial Connectivity (%)	Average Number of Neighbors	Minimum Number of Neighbors	Maximum Number of Neighbors
Fixed Distance	25 km	0.36	121.47	8	211
	50 km	1.27	432.13	14	776
	75 km	2.64	899	38	1627
	100 km	4.41	1498.29	62	2575
Inverse Distance	25 km	0.36	121.47	8	211
	50 km	1.27	432.13	14	776
	75 km	2.64	899	38	1627
K-Nearest Neighbors	8	0.02	8	8	8
	16	0.05	16	16	16
	50	0.15	50	50	50
	250	0.74	250	250	250

Spatial Relationships	Distance/Neighbors	Spatial Connectivity (%)	Average Number of Neighbors	Minimum Number of Neighbors	Maximum Number of Neighbors
	500	1.47	500	500	500

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation.

Spatial matrices generated using fixed and inverse distances at a radius of 75 km and beyond, as well as k-nearest neighbors approaches incorporating 250 and 500 neighbors, have engendered warning notifications concerning excessive memory allocation. This raised salient questions regarding computational efficiency and resource utilization, factors that are paramount in large-scale spatial analyses.

As the distance parameter or the number of neighbors escalated, a concomitant rise in spatial connectivity was palpable. Nonetheless, elevated levels of spatial connectivity are not universally advantageous for mining-related crimes investigations and were evaluated in the context of the specific analytical objectives. Within the purview of fixed and inverse distance matrices, the number of neighbors exhibited a broad range of variability. This contrasted to k-nearest neighbors methods, which furnished a consistent number, an attribute that may be interesting to the analytical framework employed, which will be approached in more detail below.

Also because of heterogeneity of the multiple data used in the present study, the limitations of global metrics like Moran's I and Geary's c for detecting spatial patterns and diagnosing spatial autocorrelation had to be acknowledged. These metrics, while useful for assessing homogeneous regions, proved inadequate for analyzing data across areas characterized by multiple spatial regimes (Anselin, 1996).

Table 16 encapsulates the performance metrics of various Global Moran's I spatial autocorrelation models, scrutinized Expected Index, Variance, z-score, and p-value.

Table 16

Summary of Global Moran's I Spatial Correlation

Spatial Relationships	Moran's Index	Expected Index	Variance	z-score	p-value
Fixed Distance 25km	0.999	0.00	0.00	1312	0.00
Fixed Distance 50km	0.996	0.00	0.00	2504	0.00
Fixed Distance 75km	0.991	0.00	0.00	3656	0.00
Fixed Distance 100km	0.985	0.00	0.00	4751	0.00
Inverse Distance 25km	0.999	0.00	0.00	1056	0.00
Inverse Distance 50km	0.997	0.00	0.00	1801	0.00
Inverse Distance 75km	0.995	0.00	0.00	2456	0.00
K-nearest 8	1.000	0.00	0.00	380	0.00
K-nearest 16	1.000	0.00	0.00	538	0.00
K-nearest 50	0.999	0.00	0.00	951	0.00
K-nearest 250	0.996	0.00	0.00	2127	0.00
K-nearest 500	0.992	0.00	0.00	3011	0.00

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation.

The values of Moran's I were close to 1 across all conceptualization methods, signaling a strong positive autocorrelation, indicating that similar values were spatially clustered. The z-scores were notably elevated, and the p-values were consistently zero, corroborating the statistical significance of the spatial patterns identified. This rendered the Moran's I values not just quantitatively large but also statistically robust.

Given the near-uniform high values of Moran's I, the choice between different spatial conceptualization methods had to be determined by other analytical requirements, considering the computational efficiency and the specific spatial scale of interest, rather than differences in Moran's I itself.

To address these limitations, Local Indicators of Spatial Association (LISA) were employed as a more nuanced tool for spatial analysis (Anselin, 1995; Cliff et al., 1981; Getis,

1995) These indicators provided a framework for identifying localized spatial dependencies and heterogeneities regarding the dependent variable (no_title) in the spatial regression model. This methodological choice served to illuminate localized spatial patterns and clusters that are critical for a nuanced understanding of the phenomena under study.

Specifically, using Local Moran's I, a range of spatial lags were generated to scrutinize the inherent spatial correlations in the dataset under varying parameters: Fixed Distance of 25km and 50km, Inverse Distance of 25km and 50km, and K-nearest neighbors encompassing 8, 16, 50, 250, and 500.

Table 17

Local Moran's I Main Statistics

Condition	LMiIndex			LMiZScore			LMiPValue
	Min	Max	Std. Dev.	Min	Max	Mean	Mean
Fixed Distance 25km	-3.80	24.00	0.71	-20.06	19.66	0.97	0.08
Fixed Distance 50km	-3.95	8.05	0.33	-20.26	20.19	0.98	0.06
Inverse Distance 25km	-3.61	37.78	1.09	-19.27	24.82	1.09	0.08
Inverse Distance 50km	-3.29	28.44	0.68	-20.95	26.21	1.23	0.07
k-Nearest 8	-4.18	141.89	2.57	-22.36	24.20	0.65	0.18
k-Nearest 16	-3.82	88.23	1.88	-23.85	22.31	0.76	0.14
k-Nearest 50	-3.62	30.45	1.02	-19.61	21.65	0.93	0.10
k-Nearest 250	-3.87	10.28	0.41	-20.51	22.32	1.03	0.06
k-Nearest 500	-3.78	7.42	0.29	-20.57	19.26	0.99	0.06

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation.

The metrics of LMiIndex, LMiZScore, and LMiPValue provided evidence for dissecting the spatial autocorrelation within a dataset. The Local Moran's I Index, or LMiIndex, serves as a tool for gauging local spatial autocorrelation for individual observations within their respective neighborhoods. Unlike its global counterpart, which offers one single measure for the entire dataset, the LMiIndex facilitates the exploration of localized variations. High positive values in this index are indicative of observations with neighboring observations of comparable values, thereby forming a spatial cluster.

Conversely, negative values signal a dissimilarity between an observation and its immediate spatial context. In this research, under the "k-Nearest 8" condition, a maximum LMiIndex of 141.89 and minimum of -4.18, with a standard deviation of 2.57, highlight statistically significant spatial clusters.

Complementing the LMiIndex is the Local Moran's I Z-Score (LMiZScore), which performs the task of standardizing the Local Moran's I values. This standardization is instrumental in assessing the statistical significance of the autocorrelation by delineating how many standard deviations an observation's LMiIndex is from the mean. A Z-score in close proximity to zero is indicative of a spatial pattern that approximates randomness. On the contrary, elevated positive or negative Z-scores are demonstrative of statistically significant clusters or outliers. Here, the inverse distance of 50km had the most statistically significant spatial clusters, with a range of 47 between the extremes, but followed closely by the k-Nearest 8 condition, with a maximum LMiZScore of 24 and a minimum of -22.

Adding an additional layer of statistical rigor is the Local Moran's I P-Value (LMiPValue), employed for the critical task of testing the null hypothesis that spatial randomness prevails in an observation's neighborhood. A low P-value, typically below the 0.05 threshold, allows for the rejection of the null hypothesis and validates the statistical significance of the spatial pattern. In the dataset under investigation, it is salient that the mean P-value exceeds the 0.10 threshold across two conditions delineated in the table: k-nearest 8 and 16.

While this might be seen as a failure to robustly reject the null hypothesis of spatial randomness, such an interpretation would be overly simplistic. A mean P-value above 0.10 does not necessarily negate the presence of spatial clusters; rather, it implies a more complex spatial arrangement. Specifically, this elevated mean P-value suggests that a considerable portion of the cells in the dataset demonstrate a random spatial distribution, even as localized

clusters with low p-values do exist. Therefore, the higher mean P-value should not be misconstrued as an absence of spatial clustering but should be understood as indicative of a more intricate spatial pattern that includes both clustered and randomly distributed observations. Hence, among the approaches used in the spatial autocorrelation analysis, even the k-nearest 8 neighborhood, which presented the lowest average p-value (0.18), had 14,697 (43%) of the 33,990 cells that composed the studied population presenting significant p-values (<0.1).

After understanding the apparent spatial pattern presented by the several approaches, the spatial lag variable was sourced from the natural logarithm of illegal mining average area within the cell between 2010 and 2020 (nl_no_title), the dependent variable explained below. This variable functions as a control for spatial autocorrelation, thereby mitigating the risk of confounding correlations that could distort the interpretation of the causal links between variables. The table below shows a comparative analysis of the spatial lags created.

Table 18

Spatial lags main statistics

Condition	Mean	Standard Deviation	Range	Interquartile Range	Skewness	Kurtosis
Fixed Distance 25km	0.00	0.34	3.33	0.39	1.95	8.83
Fixed Distance 50km	0.00	0.23	1.74	0.32	0.96	3.76
Inverse Distance 25km	0.00	0.38	4.17	0.38	2.42	12.32
Inverse Distance 50km	0.00	0.28	3.07	0.34	1.72	8.07
k-Nearest 8	0.01	0.64	9.04	0.38	3.66	22.35
k-Nearest 16	0.01	0.56	5.85	0.39	3.11	16.15
k-Nearest 50	0.00	0.42	3.30	0.38	2.25	9.20
k-Nearest 250	0.00	0.26	1.76	0.36	1.12	3.93
k-Nearest 500	0.00	0.21	1.20	0.30	0.82	3.27

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation.

The k-nearest 16 and k-nearest 8 conditions exhibited the most pronounced standard deviation, signaling a heightened level of variability within the dataset. This increased variability is particularly advantageous for identifying spatial patterns associated with illegal

mining activities. Furthermore, the k-nearest 8 condition demonstrated the broadest range, capturing the dataset's most extreme values, thereby offering a more comprehensive understanding of the spatial distribution.

These conditions also manifested elevated levels of skewness, kurtosis, and an increased number of outliers, indicating a distribution markedly deviating from normality. While such a distribution could potentially disrupt the underlying statistical assumptions requisite for regression analyses, it concurrently suggests that these conditions are most apt for capturing the spatial extent and magnitude of illegal mining clusters.

Following the same logic proposed by Anselin (1995), this dissertation opts for a k-nearest neighborhood structure, deliberately set at 8 neighbors. This choice was motivated by the intent to capture the most comprehensive view of spatial dependencies across the 10km² cell grid, which is even more pronounced in areas with strong spatial heterogeneity. Utilizing 8 neighbors also aligns with the traditional "queen's case," encompassing all adjoining cells—those sharing either a boundary or a vertex—and offers a broad lens through which to understand spatial interdependencies and autocorrelations (Anselin, 1995; Chi & Zhu, 2020).

Generalized Linear Regression

In the initial stage of this research, an Exploratory Regression served to assess the viability of the planned combination of explanatory variables. However, an issue of non-normality in the residuals significantly undermined the validity of the model generated using Ordinary Least Squares (OLS) regression. This issue was initially attributed to the zero-inflated nature of the dependent variable, which in this study represents the occurrence of mining-related crimes. In many spatial cells within the study area (24,067 or 70% of the total), the occurrence of such crimes is zero, thereby leading to a disproportionate number of zero values in the dataset.

The subsequent model, an Exploratory Regression on a dataset with only positive dependent variables, was an attempt to rule out the zero-inflation issue as a contributing factor to the non-normality of residuals. However, even in this modified dataset, the models continued to fail the Jarque-Bera test for normality. This persistent failure suggests that zero-inflation may not be the sole reason for the observed non-normality; other model misspecifications, potentially including non-linear relationships among variables, could be contributing to the problem.

While spatial lag controls and weights matrices were effective in addressing spatial autocorrelation, as confirmed by non-significant Global Moran's I values, these techniques were not designed to manage the issue of non-linear relationships. Therefore, the shift to Generalized Linear Models (GLM) became imperative, as this choice offered the analytical flexibility to model non-linear relationships and accommodate various distributional forms for residuals, providing a more robust and reliable analytical framework.

It is important to note that the Exploratory Regressions were not without merit. These models were instrumental in evaluating issues of collinearity among variables, demonstrating it was not a problem (see Appendix F for VIF measures). Thus, while the Exploratory Regression models served a purpose in the initial stage, the transition to GLMs was essential for overcoming their limitations and achieving a more rigorous analytical outcome.

Results and Discussions

Preliminary Data Analysis and Exploration

This section elucidates the preliminary steps taken to ensure the data's suitability for subsequent analyses. Given that, as explained in the plan of analysis, a transformation to natural logarithm had to be performed, this section primarily aims to provide descriptive statistics of the variables before and after transformation. For all variables, the number of observations was the same (N=33,990), and there were no missing observations. In addition to main statistics, a correlations matrix (Appendix F) was calculated to aid the analysis.

Finally, distribution Graphs can be found in Appendix J and all statistical analyses in this section, including the calculations of skewness and kurtosis, were conducted using the Data Engineering tool from ArcGIS Pro 3.1. According to Esri (2023), skewness is calculated as the third moment (the average of the cubed data values) divided by the cubed standard deviation, while kurtosis is calculated as the fourth moment (the expected value of the data values taken to the fourth power) divided by the fourth power of the standard deviation..

Descriptive Statistics for Illegal Mining

In this subsection, the focus is on the raw statistical attributes of illegal mining activities, comparing the original variable (no_title_mean) with its natural logarithm-transformed variant (nl_no_title). This assessment aims to gauge the extent to which logarithmic transformation can serve as an effective tool for data normalization, in line with the objectives laid out in the plan of analysis.

Table 19

Descriptive statistics of the illegal mining variable

	Min	Max	Sum	Mean	S.D.	Variance	Skewness	Kurtosis
no_title_mean	0.00	101.34	4831.29	0.14	1.08	7.56	45.82	3205.21
nl_no_title_mean	0.00	4.63	2714.38	0.08	0.24	2.97	5.66	50.46

Note. Table 19, derived from the author's doctoral research, presents descriptive statistics for illegal mining variables. Variables include 'no_title_mean' (Mining tenements area in hectare) and 'nl_no_title_mean' (Area of transitions to mining, non-vegetated areas and rocky outcrops outside mining tenements in hectare).

The statistical properties of the original variable (no_title) demonstrated high skewness and kurtosis values, signifying a significant deviation from a normal distribution. This trend was indicative of the presence of many zero values, thereby substantiating the hypothesis that illegal mining activities were not pervasive across all studied areas. Such a skewed and leptokurtic distribution posed potential biases in downstream statistical analyses that presupposed data normality.

In contrast, the logarithmic transformation of the variable (nl_no_title_mean) led to noteworthy improvements in data dispersion and distributional characteristics. The mean decreased to 0.08, while the standard deviation and variance were substantially reduced to 0.24 and 2.97, respectively. Even though both original and transformed variables exhibited elevated skewness and kurtosis, the transformation yielded significantly lower values for these metrics. Hence, while not entirely normalizing the data distribution, the logarithmic transformation improved its statistical properties, rendering it more apt for subsequent analytical procedures.

The correlation coefficients between the dependent and independent variables serves as an extension of the preliminary descriptive statistics, offering nuanced insights into the complex relationships that underpin illegal mining activities, particularly in the Brazilian Caatinga biome, the focal area of this dissertation. In this sense, the moderate positive correlation²⁷ between illegal and legal mining ($r = 0.56^*$) lends empirical support to the notion that areas with legal mining activities may also be susceptible to illegal mining. This finding adds nuance to the risk assessment model proposed in this dissertation by

²⁷ * p-value<0.5

highlighting the role of legal mining operations as potential facilitators of unauthorized activities.

Also important, the correlation ($r = 0.13^*$) with opportunities for illegal income (MRI) is another indication of the composite variable's important role. This coefficient suggests that the attractiveness of the mineral plays a modest role in influencing illegal mining activities. This observation challenges existing theoretical frameworks that often attribute more significant influence to these factors, thereby suggesting that they may not be the primary drivers in the context of the Caatinga biome.

Furthermore, the dependent variable displayed weak positive correlations with the area of mining tenements ($r = 0.13^*$), which was expected, since the transitions that compose the proxy for illegal mining happen exclusively inside the area of mining tenements. Finally, the correlation with the metric for the same transitions outside mining tenement (nl_out_mean) ($r = 0.22^*$) highlights the importance of controlling for these areas. This relationship validates the inclusion of this control variable in subsequent multivariate models and underscores its significance in isolating the effects of the predictors under investigation.

Collectively, these correlation coefficients enrich the foundational understanding of the determinants of illegal mining activities and reveal a lack of significance regarding the actions of the agencies responsible for deterring mining-related crimes, which did not present relevant correlations. Despite that, the initial statistics offered valuable directional cues for further multivariate analyses and provided empirical support to the multi-faceted dynamics contributing to illegal mining, as proposed in the risk assessment model of this dissertation.

Descriptive Statistics for Variables Encompassing Governance Over Miners

The governance variables relevant to mining activities presented distinct statistical characteristics that warrant detailed interpretation, as shown in Table 20.

Table 20*Descriptive Statistics for Variables Encompassing Governance Over Miners*

	Min	Max	Sum	Mean	S.D.	Skewness	Kurtosis
mean_mining_r	0.00	2.82	3903.30	0.11	0.24	5.22	44.98
mean_ibama	0.00	40.09	749.91	0.02	0.30	84.68	10039.93
mean_sum_aau	0.00	1.09	49.00	0.00	0.02	22.67	804.14
mean_sum_afs	0.00	1.82	2310.91	0.07	0.14	2.99	15.54
mean_r dai	-5.90	0.41	-98246.80	-2.89	1.11	0.40	2.56
nl_pf_mean_mining_r	0.00	1.34	3188.52	0.09	0.16	2.89	15.81
nl_ibama_mean	0.00	3.72	506.09	0.01	0.09	13.46	291.54
nl_anm_mean_aau	0.00	0.74	44.40	0.00	0.02	18.18	475.05
nl_anm_mean_afs	0.00	1.04	1992.34	0.06	0.11	2.36	9.39
nl_mean_r dai	-1.93	0.34	-44475.56	-1.31	0.34	1.24	4.66

Note. Table 20, derived from the author's doctoral research, provides descriptive statistics for governance-related variables in mining. The table includes variables such as 'mean_mining_r' (Average year of the start of mining processes), 'mean_ibama' (Number of environmental fines), 'mean_sum_aau' (Number of mining administrative infractions), 'mean_sum_afs' (Number of mining fines), 'mean_r dai' (Relative distance to average GDP), 'nl_pf_mean_mining_r' (Number of mining-related federal police investigations), 'nl_ibama_mean' (Number of IBAMA environmental fines), 'nl_anm_mean_aau' (Number of ANM mining administrative infractions), 'nl_anm_mean_afs' (Number of ANM mining fines), and 'nl_mean_r dai' (Relative distance to average income). This tabulation provides a comprehensive statistical foundation for evaluating governance aspects in the mining sector.

The Federal Police's involvement in environmental crime investigations represents a critical deterrence mechanism within the government's enforcement agencies. Given their exclusive jurisdiction as the federal government's judiciary police, their investigations bear significant weight, as they can result in a myriad of punitive measures, including imprisonment. It is against this backdrop that a more exhaustive descriptive analysis is warranted, using the raw data that was not subject to any kind of aggregation or transformation.

From 2010 to 2020, environmental units of the Federal Police have concluded a total of 48,964 investigations, spanning 3,501 municipalities across Brazil. Within the area of study, which comprises 936 distinct municipalities, 399 of these have been the sites for 1,567 environmental investigations. In terms of the nature of criminal infractions, 78,784 environmental crimes were investigated in Brazil during this period. The majority were related to flora, accounting for 23.7%, closely followed by mining-related crimes at 23.2%.

Within the Caatinga, a total of 3,545 environmental crimes were investigated. Here, mining-related crimes²⁸ were notably prevalent, constituting 30.8% of the cases, while flora-related crimes accounted for 21.3%.

That being said, the grid-transformed variable `mean_mining_r`, representing 450 mining-related police investigations closed between 2010 and 2020 in the analyzed area, exhibited a mean value of 0.11 and a standard deviation of 0.23. The skewness and kurtosis values of 5.221 and 41.988, respectively, indicated a positively skewed and leptokurtic distribution. These statistics indicates that police investigations were predominantly infrequent, with the data skewing towards areas with fewer or no investigations.

In contrast to `mean_mining_r`, its log-transformed version, `nl_pf_mean_mining_r`, had a mean of 0.09 and a standard deviation of 0.16. The skewness and kurtosis values for the transformed variable were 2.89 and 15.81, respectively, which suggests a less skewed and less leptokurtic distribution compared to the original. The variance for the log was also lower, at 1.69, compared to 2.05 for `mean_mining_r`. In summary, the log transformation of the variable related to mineral crimes mitigated the distribution's skewness and kurtosis, making the data more normalized whilst still maintaining its original characteristics.

In addition, a weak positive correlation ($r = 0.03^*$) with the dependent variable (`nl_no_title_mean`) suggests that Federal Police investigations had limited interaction with

²⁸ It is crucial to delineate the distinction between the number of crimes and the number of investigations. One investigation can encompass multiple crimes, and conversely, certain crimes may be interconnected, particularly in the domain of mining, as previously elucidated. Therefore, although 450 mining-related investigations were conducted in the Caatinga biome, these investigations inevitably incorporated a greater number of mining-associated offenses, along with other environmental and non-environmental transgressions.

illegal mining. Interestingly, police cases were prevalent on places with higher GDP, as demonstrated by a moderate correlation with the variable RDAI ($r=0.38^*$).

For IBAMA²⁹, representing the 8,031 environmental-related fines applied by the agency in the studied area between 2010 and 2020³⁰, the raw average data was highly skewed (84.68) and leptokurtic (10038.40). This extreme concentration suggested that environmental fines were concentrated and not uniformly imposed across the areas under study.

For the transformed variable `nl_ibama_mean`, representing the natural logarithm of the original IBAMA variable, the mean value stood at 0.01 with a standard deviation of 0.09. The skewness and kurtosis figures were 13.46 and 291.54, respectively. While these values were significantly reduced compared to the raw IBAMA variable, they still indicated a positively skewed and leptokurtic distribution. The skewness value, albeit lower than its raw counterpart, still implies a concentration of data towards areas with fewer fines.

The kurtosis value of 291.54, although considerably less than the raw IBAMA data, continues to suggest the presence of extreme values or outliers. Thus, even after the

²⁹ In the empirical analysis, various metrics pertaining to Ibama were scrutinized for their potential influence on the dependent variable. However, most of these indicators failed to reach a level of statistical significance. The singular exception to this trend was the metric concerning the mean values of fines concomitant with area interdictions. This variable manifested statistical relevance in one of the models under review, a matter that will be discussed below.

³⁰ In the same temporal frame, a total of 17,620 fines were administered by IBAMA in municipalities fully encompassed by the Caatinga biome. This variance is attributable to the selection criteria for the grid cells, which were chosen on the basis of possessing an active mining tenement.

transformation, the IBAMA variable still underscores the existence of areas where environmental fines are disproportionately focused, thereby mirroring the patterns observed in the raw data. Correlations analyses revealed a weak link between IBAMA environmental governance and illegal mining ($r=0.02$) and a tendency to focus on urban areas ($r=0.47$ with nl_urban_mean).

In the governance landscape delineated by the Brazilian Mining Agency, an unambiguous disparity manifests between the enforcement mechanisms of Administrative Fines (AFS) and Administrative Infractions (AAU). The aggregate of 8,751 mining fines levied against selected mining tenements, when superimposed onto a grid, revealed a mean value of 0.07. Conversely, the 463 administrative infractions produced a negligible average of 0.001. This stark dichotomy accentuates the outsized role that fines play in the regulatory framework. Furthermore, the raw data for AFS and AAU indicate skewness values of 2.99 and 22.67, respectively, coupled with kurtosis values of 15.54 and 804.14.

These statistics infer that while mining fines are somewhat infrequent but dispersed across a broader spectrum, administrative infractions are exceedingly rare and highly concentrated in specific instances or locales. This condition is reflected in the correlation matrix, which shows a weak relationship between these variables with illegal mining (0.04^* for AAU and 0.05^* for AFS). Interestingly, a higher correlation was found with legal mining (0.07^* for AAU and 0.06^* for AFS), reinforcing the role of ANM as a regulatory agency dedicated to overseeing miners with permits, and not as an administrative enforcement tool focused on repressing illegal mining.

The higher standard deviation for AFS, as opposed to AAU, merits a nuanced examination. One conceivable explanation for this greater dispersion is the recurrent imposition of fines, often targeted at habitual offenders or locales notorious for repeated violations. Additionally, fines are more prevalent in the context of illegal mining activities,

which are geographically disparate. This is demonstrated by relevant associations with the area of mining tenements ($r=0.28^*$ with `nl_anm_mean_area`) and the VALUED composite variable MRI ($r=0.34^*$) contrasting with a weaker link with legal mining ($r=0.6^*$ with `nl_leg_mean`). On the other hand, legal mining tenements, rarer (no relevant correlations were found) and more often subject to administrative infractions (since only legal mining can lose deadlines, etc.), contribute to the lower dispersion in AAU, possibly indicative of a more uniform enforcement.

Finally, the raw variable for the relative distance to the average national GDP (RDAI), which is a proxy for legal income opportunities, displayed skewness and kurtosis values close to zero (0.40 and 2.56 respectively), indicating a more symmetrical distribution. The mean value, however, was negative (-2.89), which represents well the general socioeconomic vulnerability faced by the majority of municipalities in the Caatinga.

For the transformed variable RDAI, the mean value is -1.31 with a standard deviation of 0.34. The skewness and kurtosis figures are 1.24 and 4.66, respectively, revealing the concentration of data towards municipalities with lower opportunities for legal income. The kurtosis value of 4.66 is indicative of a distribution closer to normality. After the transformation of the RDAI variable, the mean recalibrated to -1.31, accompanied by a standard deviation of 0.34. Notably, the skewness and kurtosis figures ascended to 1.24 and 4.66, respectively. These values were revelatory of a data distribution that leaned towards municipalities characterized by constrained legal income opportunities. The kurtosis value of 4.66, exceeding the standard normal distribution kurtosis of 3, signified a leptokurtic distribution.

In summary, the data delineates a governance landscape characterized by a multiplicity of enforcement priorities among different regulatory bodies. Correlational analyses augment this complexity, demonstrating that elevated levels of fines and

investigations do not consistently correspond with geographic areas exhibiting a high prevalence of illegal mining activities. Therefore, the descriptive statistics serve not merely as an explanatory account, but also as a foundational basis for subsequent multivariate analyses designed to dissect these multifaceted interactions.

Descriptive Statistics for Target Suitability

The MRI variable, which represents illegal income opportunities generated from minerals available in the cell by demonstrating how suitable the mineral is to crime, displayed a mean value of 2.75 with a standard deviation of 2.73. The skewness and kurtosis values were 1.61 and 7.11, respectively, indicating a right-skewed distribution with a heavier tail compared to a normal distribution. This suggests that most municipalities in the Caatinga biome have relatively low levels of opportunities for illegal income from mining, but outliers significantly raise the mean. This distribution could be influenced by the factors encapsulated in the VALUED model, such as the value and abundance of minerals, their localized nature, and their usability and disposability.

Upon logarithmic transformation, the log-transformed variable exhibited statistical properties that were closer to a normal distribution. The mean reduced to 1.08, and the standard deviation decreased to 0.70. Moreover, the skewness and kurtosis values changed to 0.13 and 1.99, respectively, suggesting a more symmetrical and platykurtic distribution. This transformation likely made the data more amenable for subsequent analytical procedures, while still preserving the underlying structure and relationships in the data.

Table 21

Descriptive Statistics for Target Suitability

	Min	Max	Sum	Mean	S.D.	Variance	Skewness	Kurtosis
mean_mri	0.00	27.88	93642.22	2.75	2.73	0.99	1.61	7.11
nl_mean_mri	0.00	3.36	36743.03	1.08	0.70	0.65	0.13	1.99

Note. Table 21, produced as part of the doctoral research, displays descriptive statistics for variables assessing target suitability in mining. It includes 'mean_mri' and 'nl_mean_mri', raw and log-transformed measures

reflecting the attractiveness of minerals as targets for illegal activities. The table covers minimum, maximum, sum, mean, standard deviation, variance, skewness, and kurtosis of these variables.

Finally, the strong correlation with $nl\_anm\_mean\_area$ ($r=0.91^*$) underscores the inextricable link between the size of mining tenements and the propensity for minerals to be targeted for illicit activities. Similarly, the moderate correlation with mining-related fines and the average year of the processes active in the area suggests that the VALUED approach correctly captured the suitability of mineral as a target for crimes.

Descriptive Statistics for Place Suitability

The variables pertaining place suitability, essential for understanding the spatial dimensions contributing to the propensity and deterrence of mining-related activities, exhibited varied statistical characteristics that invite comprehensive interpretation.

Table 22

Descriptive Statistics for Place Suitability

	Min	Max	Sum	Mean	S.D.	Variance	Skewness	Kurtosis
mean_cprm_poi	0	47	8019	0.24	1.00	4.22	13.64	368.01
mean_gas	0	10	628	0.02	0.21	11.39	19.92	594.83
mean_roads_km	0	197	237891	7.00	9.77	1.40	4.98	50.25
mean_urban	0	869	125057	3.68	27.00	7.34	13.49	244.44
leg_mean	0	439	7646	0.22	4.73	21.03	57.35	4071.57
nl_cprm_poi_mean	0	4	4025	0.12	0.34	2.90	3.41	16.75
nl_gas	0	2	355	0.01	0.10	9.63	11.19	149.00
nl_roads_km	0	5	52246	1.54	1.09	0.71	-0.09	2.04
nl_urban_mean	0	7	7237	0.21	0.86	4.04	4.36	21.98
nl_leg_mean	0	6	2319	0.07	0.26	3.79	8.92	123.93

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation. The table includes variables such as 'mean_cprm_poi' (Brazilian Mineral Research Company Points of Interest), 'mean_gas' (Number of Gas Stations), 'mean_roads_km' (Total length of roads in km), 'mean_urban' (Urban area in hectare), and 'leg_mean' (Legal mining exploration area in hectare). Similar log-transformed variables as 'nl_cprm_poi_mean', 'nl_gas', 'nl_roads_km', 'nl_urban_mean', and 'nl_leg_mean' are also presented.

The variable `mean_cprm_poi`, representing the 8,019 mining occurrences as identified by the Geological Survey of Brazil, exhibited a mean value of 0.24 and a standard deviation of 1.00. The skewness and kurtosis values stood at 13.64 and 368.01, respectively. This right-skewed and leptokurtic distribution suggests that mining occurrences are infrequent but concentrated in specific locales, thereby delineating "hot spots" where mining activities—both legal and illicit—are likely to be prominent. Although still positively skewed and leptokurtic, the log transformation considerably mitigated both skewness and kurtosis, making the data more normalized while retaining its original characteristics.

For the variable `mean_gas`, representing 628 gas stations in the area, the mean value was 0.02, and the standard deviation was 0.21. Consequently, the skewness and kurtosis figures were 19.92 and 594.83, respectively, which can be attributed to the infrequent distribution of fueling points across nearly 34,000 cells. As expected, the log-transformed version, `nl_gas`, significantly tempered these values, thereby making the data less skewed and less leptokurtic.

It is noteworthy that gas stations have a robust correlation with urban areas ($r = 0.47^*$ with `nl_urban_mean`), and a moderate one with `nl_roads_km` ($r = 0.20^*$), which – not-surprisingly - attests that the existence of gas stations is closely associated with urban development and road networks. A lesser obvious relationship is the correlation between gas stations and IBAMA fines ($r=0.39^*$), which could suggest that gas stations owners are an important offender of environmental regulations.

Regarding the 237,891 kilometers of roads that connect municipalities in the Caatinga, denoted by the variable `mean_roads_km`, the mean value was 7.00, accompanied by a standard deviation of 9.77, skewness of 4.98, and kurtosis of 50.25. Interestingly, its log-transformed counterpart, `nl_roads_km`, exhibited a mean of 1.54 and a standard deviation of 1.09, with skewness and kurtosis values of -0.09 and 2.04, respectively. The log

transformation reversed the skewness direction and brought the kurtosis closer to a normal distribution, signifying a more balanced data distribution. Regardless, the variables encompassing the roads revealed an area with a relatively robust ground transportation infrastructure that is closely aligned with urban development patterns ($r=0.42$ with `nl_urban_mean`).

The variable `mean_urban`, one of the only two place-related variables that exhibited temporal variation (along with legal mining), accounted, in 2020, for an area of 382,367 hectares in the study region, constituting approximately 0.54% of the studied area. The grid aggregated mean was 3.68 with a standard deviation of 27.00, and the skewness and kurtosis stood at 13.49 and 244.44, respectively. These figures indicate a substantial spatial concentration. Its log-transformed version, `nl_urban_mean` had a mean of 0.21 and a standard deviation of 0.86. The skewness and kurtosis were 4.36 and 21.98, respectively.

Similar to the other variables, the log transformation of 'urban' mitigated the skewness and kurtosis, making it less extreme while still retaining a positively skewed and leptokurtic nature. In addition to the already mentioned relevant correlations, urban areas were also associated with higher levels of economic development ($r=0.12$ with `RDAI`).

The variable `leg_mean` was a result of the 21,522 mining polygons that had at least one day of a valid legal mining title between 2010 and 2020, totalizing 21,336,437 ha (30% of the studied area). It represents the same set of transitions that formed the proxy to control for illegal mining and mining outside tenements, totalizing approximately 54 thousand different explorations that encompass 26,702 ha.

Transposed to the grid, the variable exhibited substantial variability and extremities in its distribution. It spanned a range from 0 to 439, with a total sum of 7,646, presented a mean of 0.22 and a high standard deviation of 4.73, indicating wide dispersion. The very high skewness (57.35) and kurtosis (4,071.57) values pointed to a pronounced right-skewed and

leptokurtic distribution, suggesting a concentration that demonstrated that legal mining was spatially clustered indeed.

After applying the logarithmic transformation, the resultant `nl_leg_mean` showed a normalization in its statistical properties. The range was reduced to 6, with a total sum of 2,319. The mean dropped to 0.07, and the standard deviation decreased to 0.26, indicating a tighter data distribution. The variance was lowered to 3.79. Most importantly, the skewness and kurtosis values significantly decreased to 8.92 and 123.93, respectively, reflecting a successful normalization of the distribution.

In summary, the log transformations of the place suitability variables yielded distributions that were less skewed and less leptokurtic compared to their raw counterparts. Despite this, the transformed variables continued to highlight areas of concentration, suggesting that the underlying spatial patterns remained largely consistent. This normalization proved to be particularly useful for subsequent multivariate analyses, where assumptions of normality and linearity were often required.

Generalized Linear Regression Results and Discussions

The undertaking of 22 Generalized Linear Regressions was the empirical method that scrutinized the hypotheses posited. The models encompassed a range of variables pertaining to governance aspects and the suitability of the mineral and mining tenement for crime. Each model was designed to incorporate different subsets of variables representing each group, thereby allowing to understand their collective and individual impacts on the dependent variable: the incidence of illegal mining. The models' predictive power and overall fit were evaluated through the coefficients of determination (R^2) and Akaike Information Criterion (AIC). The results can be found in Appendix G, but Table 23 encapsulates the core findings adequately.

Also, it is important to register that, according to Roback and Legler (2021, Chapter 5) GLMs flexibly accommodate various distributions, using a canonical link function to relate predictors linearly to the response variable, including non-normal types like in this Gaussian model. The Gaussian GLM's identity link function models the mean response directly from predictors, enhancing traditional linear regression to cover diverse data. This study's Gaussian GLM, detailed in the appendix through tables of residuals and outliers, alongside normal distribution curve graphs, demonstrates this versatility, effectively handling the data and supporting the robustness of the model against outliers.

Table 23*Quantitative Assessment of Governance, Target, and Place Aspects in GLR Models*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Model Characteristics					
R ²	0.32	0.47	0.48	0.48	0.48
AIC	-14233.75	-23198.59	-23306.77	-23314.75	-23299.94
Governance Aspects					
nl_anm_mean_myp	0.01*** (0.00)	-0.00 (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
nl_mean_r dai	-0.01*** (0.00)	-0.01** (0.00)	-0.01** (0.00)	-0.01** (0.00)	-0.01** (0.00)
nl_ibama_mean				0.01 (0.01)	0.01 (0.01)
nl_pf_mean_mining_r					0.00 (0.01)
nl_anm_mean_aau					0.04 (0.06)
nl_anm_mean_afs					-0.01 (0.01)
nl_anm_mean_fines				-0.01 (0.01)	
nl_ibama_interdict_mean_value				0.01*** (0.00)	
Target Aspect					

nl_mean_mri	0.02*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Place Aspects					
nl_leg_mean	0.50*** (0.00)	0.33*** (0.00)	0.33*** (0.00)	0.33*** (0.00)	0.33*** (0.00)
nl_roads_km	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
nl_cprm_poi_mean					0.00 (0.00)
nl_gas					-0.01 (0.01)
nl_urban_mean					0.00 (0.00)
Control Variables					
nl_anm_mean_area			0.009*** (0.00)	0.009*** (0.00)	0.009*** (0.00)
nl_out_mean			0.029*** (0.00)	0.028*** (0.00)	0.028*** (0.00)
sl_knearest8		0.163*** (0.00)	0.159*** (0.00)	0.160*** (0.00)	0.160*** (0.00)

Notes. Table 23, derived from the author's doctoral research, provides results from Generalized Linear Regression (GLR) models examining illegal mining. Variables are classified into Governance Aspects (such as 'nl_anm_mean_myp': Average year of the start of mining processes, 'nl_mean_rdai': Relative distance to average GDP), Target Aspect ('nl_mean_mri': Mineral Suitability Index), and Place Aspects ('nl_leg_mean': Legal mining tenements area in hectare, 'nl_roads_km': Total length of roads in km), along with Control Variables ('nl_anm_mean_area': Mining tenements area in hectare, 'nl_out_mean': Transition area outside mining tenements in hectare). Each model incorporates these variables to evaluate their impact on illegal mining. The table assesses model performance using R² and Akaike Information Criterion (AIC). Statistical significance is indicated by asterisks (p-value<0.05**; <0.001***).

The table elucidates the empirical dimensions of the study's analytical framework by operationalizing variables necessary to test the research hypotheses. The intentional omission of control variables in Models 1 and 2 served a specific analytical purpose: to accentuate the pivotal role that neighborhood effects and area-specific variables play in shaping the outcome of illegal mining activities. Mining tenements often crossed the borders of the 10km² cells of the grid and overlaid other polygons. The proxy for illegal mining is composed by the same transitions of legal mining and mining outside polygons. The absence of these controls markedly influenced the coefficients and signals of key variables, notably nl_anm_mean_myp and nl_leg_mean.

In the absence of controls, the variable `nl_anm_mean_myp`, which represents the average year of the initiation of mining processes, exhibited a positive coefficient. This positive skew was later rectified in subsequent models that incorporated control variables, where the sign of the coefficient inverted. Similarly, the coefficient for `nl_leg_mean`, denoting the area of legal mining, exhibited a pronounced increase when controls were absent, suggesting a skewed interpretation of its relationship with illegal mining activities.

Thus, the deliberate exclusion of control variables in the initial models underscores the crucial necessity of accounting for spatial and area-specific factors. Failure to do so not only skewed the coefficients but also misrepresented the underlying dynamics that contribute to illegal mining activities.

The integration of control variables in Models 3 through 5 led to a stabilization in both predictive power and model fit, as evinced by the relatively consistent R^2 and AIC values. The subsequent introduction of additional variables into Models 4 and 5 did not notably modify these indices, indicating a saturation point in the models' explanatory capacities. Importantly, many of these additional variables failed to achieve statistical significance, thereby reinforcing the robustness of the variable set utilized in Model 3. This model not only maintained a level of predictive accuracy nearly on par with that of Models 4 and 5, as validated by analogous R^2 and AIC values, but it also did so without incorporating statistically insignificant variables. Hence, while Model 4 showed a marginally improved AIC, Model 3 is posited as the optimal model in explicative terms. Nonetheless, the inclusion of variables in Models 4 and 5 was crucial for hypothesis testing, despite their limited impact on the model's statistical indicators.

In spite of that, the fluctuation in the statistical significance of variables across the models underscores the contextual and contingent nature of these determinants. While the variations may provide preliminary insights into the factors influencing the dependent

variable, they are insufficient for drawing substantive conclusions regarding the efficacy of existing governance structures. To that end, a nuanced examination of each variable, situated within the framework of the stated hypotheses and conceptual aspects, is imperative for a more comprehensive understanding of the factors influencing illegal mining. This in-depth analysis will be undertaken in the subsequent sections.

Evaluation of Governance Mechanisms in Deterring Illegal Mining Activities

The first hypothesis (H₁) posited that effective governance mechanisms, including mining and environmental governance, and law enforcement activities, would serve as significant deterrents to illegal mining, which was not substantiated by the empirical data. Drawing upon extant literature that underscores the role of a capable guardian in the deterrence of criminal activities, this hypothesis aimed to scrutinize the potency of governance structures in mitigating mining-related crimes.

However, the empirical evaluation of this hypothesis revealed a contradictory scenario. Model 3, which exhibited a plateau in its explanatory power as evidenced by stabilized R² and AIC values, demonstrated that the introduction of variables representing various governance mechanisms did not significantly alter these metrics. This is indicative of the ineffectiveness of such mechanisms, a conclusion further substantiated by the absence of statistical significance in the coefficients corresponding to variables such as fines and police investigations.

Table 24

Governance Results Across Generalized Linear Regressions

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Governance Aspects					
nl_anm_mean_myp	0.01*** (0.00)	-0.00 (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
nl_mean_RDAI	-0.01*** (0.00)	-0.01** (0.00)	-0.01** (0.00)	-0.01** (0.00)	-0.01** (0.00)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Governance Aspects					
nl_ibama_mean				0.01 (0.01)	0.01 (0.01)
nl_pf_mean_mining_r					0.00 (0.01)
nl_anm_mean_AAU					0.04 (0.06)
nl_anm_mean_AFS					-0.01 (0.01)
nl_anm_mean_fines				-0.01 (0.01)	
nl_ibama_interdict_mean_value				0.01*** (0.00)	

Notes. This table presents Table 23 results pertaining to Governance Aspects independently. The dataset is derived from scholarly research conducted for the completion of this doctoral dissertation and focuses on elucidating the efficacy of governance mechanisms in deterring illegal mining. Variables are organized under the category of Governance Aspects, each representing a different form of deterrence or governance measure. The table showcases the results from multiple Generalized Linear Regression (GLR) models—Model 1 (no controls), Model 2 (only spatial autocorrelation control), Model 3 through Model 5 (all controls and different independent variables)—to measure the effect on the dependent variable, which is the incidence of illegal mining. Included are 'nl_anm_mean_myp' (Average year of the start of mining processes), 'nl_mean_RDAI' (Relative distance to average GDP), 'nl_ibama_mean' (Number of IBAMA environmental fines), 'nl_pf_mean_mining_r' (Number of mining-related Federal Police investigations), 'nl_anm_mean_AAU' (Number of ANM mining administrative infractions), 'nl_anm_mean_AFS' (Number of ANM mining fines), and 'nl_ibama_interdict_mean_value' (Sum of the values of the seizures applied alongside the interdiction of areas that were target of environmental infractions). Statistical significance is denoted by asterisks (p-value<0.05**; <0.001***). Standard errors for each coefficient are indicated in parentheses.

This failure of governance mechanisms in deterring illegal mining activities stands in stark contrast to traditional criminological theories that emphasize the importance of a capable guardian. For instance, the Routine Activity Theory, which often serves as a theoretical underpinning for environmental criminology, would suggest that effective governance should inhibit illegal activities by increasing the perceived risk and potential costs for would-be offenders.

The empirical evidence generated by the Generalized Linear Regression models suggests a systemic failure of governance mechanisms, a finding that deviates from the theoretical expectations set forth by criminological paradigms such as the Routine Activity

Theory. As elucidated by Model 5, which was rigorously verified against eight alternative models featuring diverse variables and spatial lags (see Appendix G), Federal Police investigations in the domain of mining (nl_pf_mean_mining_r) were not statistically significant. Likewise, composite variables accounting for the sum total of environmental investigations (nl_pf_sum) and the subsequent quantification of environmental damage (nl_pf_sum_value_ca) also failed to yield significant results.

In addition, administrative infractions and fines imposed by the National Mining Agency (ANM), represented by variables nl_anm_mean_aau and nl_anm_mean_afs, as well as their aggregate measure, nl_anm_mean_fines, demonstrated no substantial impact on deterring illegal mining activities, even when tested in various combinations across 11 models (see Appendix G).

Finally, the work of IBAMA revealed to have the most promising of deterrence effects. Although the average number of fines resulted in constant insignificance across 9 models, the value associated to the assets that were confiscated by the occasion of interdictions had an impact on reducing 1% of illegal mining where it was done. Despite minimum, the effect was the only statistically significant among deterrence mechanisms.

On a bigger scale, the relative distance to the average income, represented by the variable RDAI, was always significant, albeit also in a small scale. Like IBAMA interdictions, a unit increase in economic development reduced illegal mining by 1%, which represents evidence for investing in socioeconomic improvement of the communities inside Caatinga as a prevention strategy for illegal mining.

Finally, hypothesis 1.1 received partial empirical support, indicating that the length of the mining permit process does exert some influence on the incidence of illegal mining activities. However, the marginal effect size and the inversion of the sign across models warrant a more nuanced interpretation. These findings suggest that the relationship between

the duration of the mining process and illegal mining is complex and likely subject to conditional factors not encapsulated in the current model. Consequently, further empirical scrutiny is requisite to elucidate the intricacies of this relationship.

In summary, the results indicate a pressing need for a reevaluation of current governance mechanisms, given their apparent failure to act as effective deterrents against illegal mining activities. This finding is not merely an empirical anomaly but an issue that necessitates a substantive rethinking of governance strategies and frameworks in the realm of environmental criminology.

Evaluation of Target Suitability

The second hypothesis (H₂) posited that the suitability of the mineral itself as a target for criminals, represented by the variable *nl_mean_MRI*, would influence the incidence of illegal mining activities. This hypothesis drew on the precepts of Rational Choice Theory, which focus on the cost-benefit analysis, and Routine Activity Theory, which posits that the presence of a suitable target is one of the fundamental pillars that precipitate criminal activities.

Table 25

Target Suitability Results Across Generalized Linear Regressions

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Target Aspects					
<i>nl_mean_MRI</i>	0.02*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)

Notes: This table presents Table 23 results pertaining to Target Suitability independently. The table encapsulates the results from multiple Generalized Linear Regression (GLR) models— Model 1(no controls), Model 2 (only spatial autocorrelation control), Model 3 through Model 5 (all controls and different independent variables)—to measure the effect of the suitability of the mineral as a target for criminals, represented by *nl_mean_MRI* (Mineral Suitability Index), on the dependent variable, which is the incidence of illegal mining. Statistical significance is denoted by asterisks (p-value < 0.001***).

The empirical evaluation of this hypothesis lends unequivocal support to its premises. Across the 22 tested models (see Appendix G), target suitability exhibited statistical significance, substantiating its role as a potent determinant in the incidence of illegal mining

activities. Importantly, the coefficient associated with `nl_mean_MRI` remained stable across the models, thereby reinforcing its robustness as an influential factor. This consistency in the models attests to the variable's persistent relevance, even when controls and additional variables are absent (despite skewing results).

The explanatory power of the VALUED approach was somewhat diluted when aggregated among 10 different substances, 11 years and 10km², but its constancy suggests that illegal mining activities are indeed influenced by the minerals available in a given area, a proposition that aligns well with the theoretical foundations of environmental criminology. The VALUED approach served well as a proxy for the attractiveness of a target, thereby validating the notion that its suitability is a key determinant in the occurrence of illegal mining activities. The evidence implies that mitigating the attractiveness of these targets, rendering illegal mining more difficult or less profitable, could be an effective avenue for policy intervention.

Evaluation of Place Suitability

To address Hypothesis 3 (H₃) and its sub-hypothesis (H_{3.1}), the Generalized Linear Regression models incorporated a set of variables representing the geographic and infrastructural attributes of mining tenements. These variables, collectively categorized under Place Aspects, include the area of legal mining (`nl_leg_mean`) and urban areas (`nl_urban_mean`), the total length of roads (`nl_roads_km`), and the number of CPRM mining occurrences (`nl_cprm_poi_mean`) and gas stations (`nl_gas`). The analytical results are encapsulated in Table 26.

Table 26

Place Suitability Results Across Generalized Linear Regressions

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Place Aspects					
<code>nl_leg_mean</code>	0.50*** (0.00)	0.33*** (0.00)	0.33*** (0.00)	0.33*** (0.00)	0.33*** (0.00)
<code>nl_roads_km</code>	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)

nl_cprm_poi_mean	0.00 (0.00)
nl_gas	-0.01 (0.01)
nl_urban_mean	0.00 (0.00)

Notes: This table presents Table 23 results pertaining to Place Suitability independently. The dataset originates from scholarly research conducted for the completion of this doctoral dissertation and aims to elucidate the geographic determinants influencing illegal mining activities: 'nl_leg_mean' (Legal mining tenements area in hectare), 'nl_roads_km' (Total length of roads in km), 'nl_cprm_poi_mean' (Brazilian Mineral Research Company Points of Interest), 'nl_gas' (Number of Gas Stations), and 'nl_urban_mean' (Urban area in hectare). Variables are classified under the category of Place Aspects, each representing a different geographic or infrastructural attribute of mining tenements. The table presents results from multiple Generalized Linear Regression (GLR) models— Model 1(no controls), Model 2 (only spatial autocorrelation control), Model 3 through Model 5 (all controls and different independent variables)—to measure their effect on the dependent variable, which is the incidence of illegal mining. Statistical significance is denoted by asterisks (p-value<0.001***). Standard errors for each coefficient are indicated in parentheses.

Hypothesis 3 posited a positive correlation between the geographic and infrastructural attributes of mining tenements and the frequency of illegal mining activities. This hypothesis is substantially corroborated by the empirical results, albeit with some caveats.

Variables that represented infrastructure, such as gas stations and urban areas were insignificant, but roads were systematically significant, despite the low impact. Mineral occurrences were also not important to illegal mining. However, legal mining was consistently the most important driver of illegal mining across all models. Hence, the sub-hypothesis 3.1, which posited that the presence of legal mining activities serves as a criminogenic catalyst for illegal mining, is accepted. The consistency of this variable across the models suggests that legally authorized mining activities indeed potentiate illegal mining by providing the necessary infrastructure and human capital.

In summary, the empirical analysis lends considerable support to Hypothesis 3 and its sub-hypothesis. While some spatial variables did not achieve statistical significance, the consistent significance of key variables like nl_leg_mean and nl_roads_km reaffirms the criminogenic role of geographic and infrastructural attributes in illegal mining activities. These findings not only validate the theoretical underpinnings of the Becker-Ehrlich model

but also extend its scope by incorporating spatial determinants, thereby contributing to a more nuanced understanding in the domain of environmental criminology.

Conclusions

In the culmination of this research, it became evident that the landscape of illegal mining activities in the Brazilian Caatinga is a complex tapestry, woven from a myriad of governance, target, and place-related determinants. The disquieting inefficacies within existing governance systems resonate with the broader academic discourse on the limitations of global governance mechanisms in mitigating environmental degradation, particularly in the mineral extraction sectors. The risk assessment model introduced in this study serves as an incipient yet robust attempt for critically evaluating these governance structures.

The empirical rigor applied to scrutinize the effectiveness of governance mechanisms provides a clear picture of their deterrent capacities. In stark contrast to the tenets of environmental criminology, which accentuate the role of a capable guardianship, the governance systems in place in the Brazilian Caatinga are visibly failing to deter illegal mining activities. This systemic failure is not an empirical anomaly but a substantive lacuna that urgently calls for a complete review and update of current deterrence instruments.

In this line of thought, the insights gleaned from Becker's economic theory of criminal behavior can be directly applied to understand the rising trend in mining-related crimes in Brazil, particularly in the context of ineffective deterrence. The theory elucidates that criminal actions are the outcome of rational calculations, where potential offenders weigh the benefits against the risks. In scenarios where the deterrence mechanisms — such as the likelihood of being caught and the severity of punishment — are perceived as weak or ineffective, the scale tips in favor of committing the crime. This lack of effective deterrence results in a higher perceived probability of success and lower risk of punitive consequences, thereby encouraging criminal activities.

Therefore, the Brazilian surge in mining-related crimes could arguably be attributed to this imbalance in the risk-reward calculus. When individuals involved in or considering

illegal mining perceive that the rewards (economic gain, resource acquisition) significantly outweigh the risks (legal repercussions, social condemnation), their propensity to engage in such activities increases. This is particularly relevant in regions where governance and law enforcement mechanisms are either lax or inefficient, exacerbating the issue. The findings of this study underscore the urgent need for strengthening the deterrence framework — enhancing detection methods, ensuring stricter enforcement of laws, and imposing more severe penalties — to realign the risk-reward ratio against the perpetration of mining-related crimes.

The study also delved into the intricacies of target suitability, employing the VALUED approach encapsulated by the MRI variable. Although the VALUED approach presents a somewhat diluted account due to its aggregation across multiple minerals, its empirical validation is unequivocal. The robustness of the MRI variable, evidenced through its consistent statistical significance across multiple models, underscores its potential as a valuable tool for both academic exploration and policy formulation.

The results align seamlessly with the theoretical constructs of Rational Choice Theory and Routine Activity Theory, thereby fortifying its academic credibility while also offering actionable insights for policy interventions. In addition, since the VALUED approach incorporates the price fluctuations of minerals, the research also provides more evidence that the value of the mineral has a direct influence on the size of illegal mining. In addition, these results reinforce the work of Bezzola et al. (2022, p. 3).

However, the most salient insights are arguably gleaned from the place-based analyses. The spatial dimensions of illegal mining, particularly in locales with active legal mining operations, emerged as a potent criminogenic catalyst. These findings are in congruence with extant literature that advocates for place-based strategies in environmental

management and contribute a nuanced layer to the Becker-Ehrlich model by incorporating spatial variables.

Thus, the study not only corroborates but also enriches existing theories within the realms of environmental criminology and mineral economics. It sheds light on the multifaceted nature of illegal mining activities and provides a compelling case for the reevaluation and redesign of the mineral sector governance structures. The empirical findings extend not just theoretical validation but also practical pathways for the formulation of targeted and effective policy interventions.

Both the immediate implications and future trajectories of these findings are far-reaching, extending beyond the academic realm to influence policy decisions and stakeholder strategies. The exigency for innovative, empirically substantiated, and theoretically robust governance mechanisms has never been more pronounced, especially in the context of escalating environmental challenges.

In this regard, the paradigm shift defended in the literature used as framework for this research, which demands understanding and managing complex social issues like crime, moving from traditional enforcement models to more inclusive, participatory, and interconnected approaches, gains importance. The failure of the current deterrence strategies emphasizes the need for governance systems that are adaptive, innovative, and rooted in ethical frameworks, focusing on the empowerment of communities and collaborative strategies.

Integrating economic concepts like the opportunity for income into environmental criminology theories, the results presented in this research demonstrate the synergy potential between these different perspectives. They underscore the importance of addressing crime as a multifaceted and interconnected problem, which demands governance models that integrate

diverse perspectives and knowledge areas, aligning with the principles of democracy, transparency, and public participation.

On this matter, this doctoral dissertation acts as an initial step and a reference point for future research efforts focused on addressing the multifaceted challenge of deterring crimes against nature within a holistic framework. Within the Brazilian context of environmental crimes, while there exists a clear mandate for law enforcement, the priority must unequivocally shift to the realm of evidence-based prevention strategies. This approach not only aligns with the multifaceted nature of the issue at hand but also ensures a more comprehensive, sustainable, and democratic response to environmental crimes, thereby enriching the discourse in environmental criminology and mineral economics.

Limitations

Limitations in this research stem primarily from methodological constraints and data availability. While the study employed an 11-year data set, aggregated on a year-by-year basis, the final analysis was conducted using the averaged values spanning from 2010 to 2020. This exclusion of the temporal dimension invariably compromises the richness of the dataset, leaving substantive information unexplored.

Similarly, computational constraints presented another significant limitation. Specifically, the inability to process a matrix comprising 34,000 by 34,000 cells across an 11-year period on a conventional 32GB memory laptop posed a methodological constraint. A computational endeavor of this magnitude would require a specialized machine capable of handling this kind of computational calculation, a resource not readily available for this research.

Furthermore, the utilization of Mapbiomas data as a proxy for illegal mining activities introduced a considerable degree of imprecision. The aggregation of sparse mining data with rocky outcrops and non-vegetated areas generated a substantial amount of noise in the dataset. The absence of more precise synthetic aperture data, and the unavailability of digital elevation models (DEMs) that could facilitate year-by-year tracking of mining excavations, led to the reliance on Mapbiomas data.

An additional limitation emerges from the methodological constraints dictated by the inclusion of gold among the top ten most demanded substances according to the National Mining Agency (ANM). This inclusion mandated that gold be a part of the array of substances scrutinized in this research, which, in turn, posed challenges to the efficacy of the VALUED approach. The scale employed by the VALUED approach, which quantifies the value of minerals from 1 to 10, had to be adapted to mitigate this constraint. Specifically, the study resorted to a temporal self-comparison for each substance over the 11-year period, as

opposed to utilizing their intrinsic market values. This adaptation was necessitated by the fact that, if actual market values were used, gold would invariably secure a ranking of 10 each year, consequently relegating all other substances to a rank of 1. Such a scaling discrepancy would fundamentally invalidate the metric's ability for nuanced differentiation among mineral values. This limitation, therefore, raises questions about the robustness of the VALUED approach in adequately capturing the intricate economic dimensions that contribute to the phenomenon of illegal mining, which could easily be the most important of all.

These limitations, while constraining the scope and interpretive power of the findings, also delineate avenues for future research endeavors, equipped with more advanced computational resources and refined datasets.

Future Studies

While the limitations of this study constrain its scope and interpretive power, they concurrently define avenues for future scholarly investigations. One critical area for subsequent research is the detailed examination of temporal dynamics that influence illegal mining activities. Owing to the methodological constraint of utilizing averaged data spanning the years 2010 to 2020, subsequent scholarly undertakings could leverage finer-grained, temporally sensitive analyses. This would enable the illumination of intricate temporal patterns that bear consequential implications for governance mechanisms and regulatory schemas. In this regard, advanced methodologies such as spatial panels or deep learning-based time series forecasting models could be employed to re-analyze the existing dataset, thus providing a more nuanced understanding of the temporal dynamics at play.

Indeed, the methodological constraints imposed by computational limitations in this study underscore the critical need for enhanced computing capabilities in future research endeavors. Utilizing specialized computing infrastructure capable of processing larger matrices would obviate current limitations, thereby affording researchers the latitude to undertake more complex, nuanced analyses. Such computational advancements would particularly facilitate the exploration of the intricate spatial and temporal dimensions that govern illegal mining activities.

The deployment of advanced computational resources would serve to enrich the robustness of analytical models, thereby enabling a more comprehensive capture of the complexities that characterize illegal mining. This, in turn, would provide a more granular understanding of the multifaceted factors at play, which could be pivotal in the crafting of targeted and effective policy interventions. Enhanced computational capabilities would thus not only broaden the scope of academic inquiries but also substantially elevate the practical

applicability of research findings in the realms of environmental criminology and mineral economics.

Furthermore, the contextual specificity of this study, focused on the Brazilian Caatinga, invites broader geographic inquiries. Other Brazilian biomes, such as the Amazon and Atlantic Forest, present themselves as fertile grounds for the replication and validation of the analytical approach employed herein. Comparisons with other mineral regions, such as Alaska in the United States, or African Savannas would also be interesting. Such geographic expansions would not only contribute to the generalizability of the study's findings but also enrich the comparative understanding of how different environmental settings mediate the phenomenon of illegal mining.

Moreover, a pivotal avenue for future inquiries lies in the enhancement of the precision of proxies employed to assess illegal mining activities. The current study necessitated the utilization of Mapbiomas data, a decision that inadvertently introduced significant noise into the analytical framework. Subsequent research endeavors would benefit from the exploration and incorporation of more refined datasets. This could entail the use of synthetic aperture data to produce digital elevation models (DEMs) with the capacity to facilitate the tracking of mining excavations on a year-by-year basis. The adoption of such advanced datasets would substantially augment the accuracy and reliability of models designed to capture the intricacies of illegal mining activities. Within this context, NASA's Global Ecosystem Dynamics Investigation (GEDI) project emerges as a promising candidate for such empirical tests.

The VALUED approach, despite serving as an innovative conceptual framework for dissecting the economic dimensions intrinsic to illegal mining activities, simultaneously delineates avenues for methodological refinement. Subsequent scholarly pursuits could focus on the examination of individual minerals, eschewing the temporal self-comparison method

employed in this study in favor of actual market valuations. Such an approach would not only enrich the comparative evaluation of mineral values but would also elevate the methodological robustness of the VALUED framework in capturing the economic complexities that contribute to illegal mining phenomena.

Finally, the prospect of interdisciplinary collaborations emerges as a compelling avenue for future research. By forging intellectual synergies with experts spanning diverse disciplines such as Geographic Information Systems, Economics, Geology, Criminology, Environmental Science, Computer Science, Remote Sensing and Aerospace Engineering future studies stand to construct more comprehensive and methodologically robust analytical frameworks. Such interdisciplinary engagements would not only augment the methodological rigor of the research but also expand its theoretical scaffolding. In doing so, these collaborative efforts would yield a more holistic and nuanced understanding of the complex phenomenon of illegal mining, thereby significantly enriching the scholarly discourse in the domain of environmental criminology.

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Appendix A Brazilian Federal Police Staff 2007-2022

Year	Career					Police Staff	Support Staff	Total Staff
	DPF	PCF	EPF	APF	PPF			
2007	1,585 (11.56%)	824 (6.01%)	1,684 (12.28%)	5,949 (43.39%)	474 (3.46%)	10,516 (76.65%)	3,201 (23.35%)	13,717
2008	1,764 (12.49%)	939 (6.64%)	1,690 (11.95%)	6,225 (44.03%)	469 (3.32%)	11,087 (78.43%)	3,053 (21.57%)	14,140
2009	1,852 (12.75%)	1,119 (7.70%)	1,627 (11.20%)	6,415 (44.14%)	463 (3.18%)	11,476 (78.97%)	3,054 (21.03%)	14,530
2010	1,820 (12.57%)	1,117 (7.71%)	1,926 (13.30%)	6,409 (44.25%)	454 (3.13%)	11,726 (80.96%)	2,755 (19.04%)	14,481
2011	1,774 (12.70%)	1,107 (7.92%)	1,880 (13.45%)	6,147 (43.98%)	439 (3.14%)	11,347 (81.19%)	2,627 (18.81%)	13,974
2012	1,744 (12.81%)	1,107 (8.13%)	1,843 (13.54%)	5,964 (43.81%)	423 (3.11%)	11,081 (81.40%)	2,532 (18.60%)	13,613
2013	1,708 (12.42%)	1,097 (7.98%)	1,798 (13.08%)	6,219 (45.24%)	514 (3.74%)	11,336 (82.46%)	2,413 (17.54%)	13,749

Year	Career					Police Staff	Support Staff	Total Staff
	DPF	PCF	EPF	APF	PPF			
2014	1,686 (12.43%)	1,089 (8.02%)	1,768 (13.04%)	6,178 (45.54%)	504 (3.71%)	11,225 (82.74%)	2,343 (17.26%)	13,568
2015	1,654 (12.13%)	1,117 (8.19%)	1,947 (14.28%)	5,707 (41.83%)	467 (3.42%)	10,892 (79.87%)	2,741 (20.13%)	13,633
2016	1,717 (11.91%)	1,152 (7.99%)	1,953 (13.56%)	6,348 (44.05%)	474 (3.29%)	11,644 (80.81%)	2,762 (19.19%)	14,406
2017	1,659 (11.94%)	1,128 (8.12%)	1,858 (13.37%)	6,066 (43.64%)	466 (3.35%)	11,177 (80.42%)	2,723 (19.58%)	13,900
2018	1,606 (11.89%)	1,105 (8.19%)	1,809 (13.40%)	5,890 (43.63%)	452 (3.35%)	10,862 (80.46%)	2,638 (19.54%)	13,500
2019	1,570 (11.89%)	1,091 (8.27%)	1,769 (13.41%)	5,797 (43.92%)	449 (3.40%)	10,676 (80.89%)	2,523 (19.11%)	13,199
2020	1,692 (12.73%)	1,136 (8.55%)	1,788 (13.45%)	5,838 (43.97%)	468 (3.52%)	10,922 (82.21%)	2,363 (17.79%)	13,285
2021	1,823 (13.49%)	1,195 (8.84%)	1,803 (13.34%)	5,918 (43.79%)	474 (3.51%)	11,213 (82.98%)	2,296 (17.02%)	13,509

Year	Career					Police Staff	Support Staff	Total Staff
	DPF	PCF	EPF	APF	PPF			
2022	1,799 (12.87%)	1,183 (8.46%)	1,897 (13.57%)	6,453 (46.16%)	484 (3.46%)	11,816 (84.52%)	2,160 (15.48%)	13,976

Note. Data from 2007 to 2016 (Brazil, 2017), 2018-2022 (Federal Police, 2022a). Police commissioners (DPF), experts (PCF), agents (APF), clerks (EPF), fingerprint analyst (PPF).

Appendix B Mining Proxy Composition

COLLECTION 7 CLASSES	NEW ID		COLLECTION 7 CLASSES	NEW ID	Transition ID
All transitions		TO	Mining	30	
Mining	30				3030
Savanna Formation	04				0430
Mosaic of Uses	21				2130
Pasture	15				1530
Other Temporary Crops	41				4130
Grassland	12				1230
Urban Area	24	TO	Mining		2430
Other non-Vegetated Areas	25				2530
River, Lake and Ocean	33				3330
Forest Formation	03				0330
Rocky Outcrop	29				2930
Other Perennial Crops	48				4830
AND					
Forest Formation	3				0329 0325
Savanna Formation	4				0429 0425
Mangrove	5				0525
Wooded Sandbank Vegetation	49		Rocky Outcrop &	29	4925
Wetland	11	TO	Other non-Vegetated Areas	&	
Grassland	12			25	1229 1225
Salt Flat	32				3225
Rocky Outcrop*	29				2925
Herbaceous Sandbank Vegetation	50				5025

Appendix C Main Features of Independent Variables

Variable name	Group	Hyp.	Routine Activity Triangle	Time span	Operational Definition	Variable explanation	Signal	Source	Type
nl_anm_mean_area	control	n/a	n/a	2010-2020	Mining tenements area in hectare	Since the dependent variable is the sum of transitions that happened inside mining tenements, controlling for their area is recommended.	+	ANM	control
nl_out_mean	control	n/a	n/a	2010-2020	Area of transitions to mining, non-vegetated areas and rocky outcrops outside mining tenements in hectare	Since the dependent variable is the sum of transitions that happened inside mining tenements, controlling for the area that transitioned outside mining tenements is necessary.	+	Mapbiomas	control
nl_anm_mean_myp	governance	1.1	offender	2010-2020	Average year of the start of mining processes	Hypothesis 1.1 states that the more a miner waits for a request to be approved, the more likely it is for him to start mining without permission. Hence, cells with older processes would be more susceptible to illegal mining.	-	ANM	independent
nl_mean_RDAI	governance	1	offender	2010-2020	Relative distance to average GDP	The distance to the average national GDP is a measure of how developed is the place,	-	IBGE	independent

Variable name	Group	Hyp.	Routine Activity Triangle	Time span	Operational Definition	Variable explanation	Signal	Source	Type
						which is related to legal income opportunities.			
nl_anm_mean_fines	governance	1	offender	2010-2020	Number of fines and administrative infractions applied by the National Mining Agency	Fines and infractions are a instrument of punishing miners for eventual illegal actions. Therefore, an instrument of deterrence.	-	ANM	independent
nl_ibama_interdict_mean_value	governance	1	offender	2010-2020	Sum of the values of the seizures applied alongside the interdiction of areas that were target of environmental infractions.	IBAMA has the power to interdict areas where environmental infractions were being committed. In the process, they apply a fine, giving a value to the interdiction. The deterrence tool is double in this case: a fine and na interdiction.	-	IBAMA	independent
nl_ibama_mean	governance	1	offender	2010-2020	Number of environmental fines	IBAMA environmental fines are a deterrence tool.	-	IBAMA	independent
nl_anm_mean_AAU	governance	1	offender	2010-2020	Number of mining administrative infractions	Administrative infractions are less serious events related to the breaking of mining norms.	-	ANM	independent
nl_anm_mean_AFS	governance	1	offender	2010-2020	Number of mining fines	Mining fines are more serious events related to	-	ANM	independent

Variable name	Group	Hyp.	Routine Activity Triangle	Time span	Operational Definition	Variable explanation	Signal	Source	Type
nl_pf_mean_mining_r	governance	1	offender	2010-2020	Number of mining-related federal police investigations	the breaking of mining norms. Federal Police investigations are related to the possibility of the miner be the object of the most heavy type of punishment available, which is prison.	-	Federal Police	independent
nl_mean_MRI	illegal income	2	target	2010-2020	A composite variable representing how suitable is the mineral as a target for crimes.	The MRI variable represents the suitability of the mineral as a target for illegal mining, representing its value, abundance, localization, use, exploration and disposability.	+	Author, based on multiple sources	independent
nl_leg_mean	place	3.1	place	2010-2020	Legal mining exploration area in hectare	The area of legal mining inside the cells is expected to be a driver for illegal mining, since it corresponds to the presence of a probable market for the illegally extracted minerals.	+	ANM/MapBio mas	independent
nl_roads_km	place	3	place	2023	Roads total length in km	The density of roads infrastructure is expected to contribute to illegal mining as it is essential for mineral transportation.	+	Open Street Maps	independent

Variable name	Group	Hyp.	Routine Activity Triangle	Time span	Operational Definition	Variable explanation	Signal	Source	Type
nl_cprm_poi_mean	place	3	place	2023	Brazilian Mineral Research Company Points of Interest	CPRM POIs represent mineral deposits and mines that can contribute to mining activities in the region.	+	CPRM	independent
nl_gas	place	3	place	2023	Number of Gas Stations	Gas stations are important to mining because they provide fuel for the machinery to work.	+	Open Street Maps	independent
nl_urban_mean	place	3	place	2010-2020	Urban area in hectare	Cities are expected to contribute to illegal mining because they would be the source of buyers, workers, equipment and inputs to illegal mining.	+	Mapbiomas	independent

Note. All variables are averaged over the period 2010-2020, except for 'Roads total length in km', 'Brazilian Mineral Research Company Points of Interest', and 'Number of Gas Stations'. These exceptions are based on static datasets corresponding to the year 2023. Additionally, all variables have undergone natural logarithm transformation to enhance the rigor of the subsequent statistical analyses.

Appendix D Mapbiomas Collection 7 Land Use Classes

COLLECTION 7 CLASSES	NEW ID
1. Forest	1
1.1. Forest Formation	3
1.2. Savanna Formation	4
1.3. Mangrove	5
1.4. Wooded Sandbank Vegetation	49
2. Non-Forest Natural Formation	10
2.1. Wetland	11
2.2. Grassland	12
2.3. Salt Flat	32
2.4. Rocky Outcrop	29
2.5. Herbaceous Sandbank Vegetation	50
2.5. Other non-Forest Formations	13
3. Farming	14
3.1. Pasture	15
3.2. Agriculture	18
3.2.1. Temporary Crop	19
3.2.1.1. Soybean	39
3.2.1.2. Sugar cane	20
3.2.1.3. Rice	40
3.2.1.4. Cotton (beta)	62
3.2.1.5. Other Temporary Crops	41
3.2.2. Perennial Crop	36
3.2.2.1. Coffee	46
3.2.2.2. Citrus	47
3.2.2.3. Other Perennial Crops	48
3.3. Forest Plantation	9
3.4. Mosaic of Uses	21
4. Non-vegetated area	22
4.1. Beach, Dune and Sand Spot	23
4.2. Urban Area	24
4.3. Mining	30
4.4. Other non-Vegetated Areas	25
5. Water	26
5.1. River, Lake and Ocean	33
5.2. Aquaculture	31
6. Non-Observed	27

Note. From Legend Codes, by Mapbiomas, 2022, (https://mapbiomas-br-site.s3.amazonaws.com/downloads/_EN__C%C3%B3digos_da_legenda_Cole%C3%A7%C3%A3o_7.pdf).

Appendix E Estimated transition area in Caatinga between 2010 and 2020 of values chosen to compose the mining proxy variable

Label	Value	Area (ha)
Mining to Mining	3030	85,512.34
Savanna Formation to Mining	430	1,017.34
Mosaic of Uses to Mining	2130	348.72
Pasture to Mining	1530	326.81
Other Temporary Crops to Mining	4130	139.03
Grassland to Mining	1230	63.23
Urban Area to Mining	2430	59.87
Other Non-Vegetated Areas to Mining	2530	50.38
River, Lake and Ocean to Mining	3330	31.72
Forest Formation to Mining	330	10.59
Rocky Outcrop to Mining	2930	2.81
Other Perennial Crops to Mining	4830	0.62
Savanna Formation to Rocky Outcrop	429	14,928.05
Grassland to Rocky Outcrop	1229	4,785.59
Mosaic of Uses to Rocky Outcrop	2129	1,629.50
River, Lake and Ocean to Rocky Outcrop	3329	393.06
Pasture to Rocky Outcrop	1529	353.89
Forest Formation to Rocky Outcrop	329	225.53
Pasture to Other Non-Vegetated Areas	1525	237,317.50
Mosaic of Uses to Other Non-Vegetated Areas	2125	94,486.12
River, Lake and Ocean to Other Non-Vegetated Areas	3325	17,341.51
Grassland to Other Non-Vegetated Areas	1225	15,937.86
Savanna Formation to Other Non-Vegetated Areas	425	15,635.01
Other Temporary Crops to Other Non-Vegetated Areas	4125	9,809.83
Forest Formation to Other Non-Vegetated Areas	325	4,941.63
Wooded Sandbank Vegetation to Other Non-Vegetated Areas	4925	1,006.12
Other Perennial Crops to Other Non-Vegetated Areas	4825	224.24
Herbaceous Sandbank Vegetation to Other Non-Vegetated Areas	5025	72.30
Mangrove to Other Non-Vegetated Areas	525	29.36
Salt Flat to Other Non-Vegetated Areas	3225	22.56
Total		506,703.15

Appendix F Correlation Matrix with VIF

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	VIF
1. nl_no_title_mean	1.00*	0.04*	0.05*	0.13*	0.08*	0.05*	0.01	0.02*	0.02*	0.56*	0.13*	0.01	0.22*	0.03*	0.07*	0.05*	NA
2. nl_anm_mean_AAU	0.04*	1.00*	0.07*	0	0.03*	0.05*	0.03*	0.02*	0.06*	0.07*	0.01	0.05*	0	0.01*	0.05*	0.05*	1.02
3. nl_anm_mean_AFS	0.05*	0.07*	1.00*	0.28*	0.21*	0.02*	-0.01*	0	0	0.06*	0.34*	0.01	-0.07*	0.04*	-0.03*	0.01	1.16
4. nl_anm_mean_area	0.13*	0	0.28*	1.00*	0.48*	0.03*	-0.04*	-0.01	-0.08*	0.11*	0.91*	-0.01*	-0.22*	0.01*	-0.12*	-0.08*	6.25
5. nl_anm_mean_myp	0.08*	0.03*	0.21*	0.48*	1.00*	0.05*	0	0	0	0.06*	0.43*	0.01*	-0.08*	-0.01	0	0.02*	1.32
6. nl_cprm_poi_mean	0.05*	0.05*	0.02*	0.03*	0.05*	1.00*	0.02*	0	0.04*	0.08*	0.05*	0.06*	0	0.04*	0.10*	0.06*	1.03
7. nl_gas	0.01	0.03*	-0.01*	-0.04*	0	0.02*	1.00*	0.04*	0.39*	0.01	-0.03*	0.04*	0.03*	0	0.20*	0.47*	1.35
8. nl_ibama_interdict_mean_value	0.02*	0.02*	0	-0.01	0	0	0.04*	1.00*	0.24*	0.02*	0	0.02*	0.03*	0	0.03*	0.07*	1.07
9. nl_ibama_mean	0.02*	0.06*	0	-0.08*	0	0.04*	0.39*	0.24*	1.00*	0.02*	-0.06*	0.12*	0.09*	0.05*	0.24*	0.47*	1.45
10. nl_leg_mean	0.56*	0.07*	0.06*	0.11*	0.06*	0.08*	0.01	0.02*	0.02*	1.00*	0.12*	0.03*	0.18*	0.04*	0.06*	0.04*	1.08
11. nl_mean_MRI	0.13*	0.01	0.34*	0.91*	0.43*	0.05*	-0.03*	0	-0.06*	0.12*	1.00*	0.01*	-0.22*	0.03*	-0.11*	-0.06*	6.18
12. nl_mean_RDAI	0.01	0.05*	0.01	-0.01*	0.01*	0.06*	0.04*	0.02*	0.12*	0.03*	0.01*	1.00*	0.03*	0.38*	0.11*	0.12*	1.2
13. nl_out_mean	0.22*	0	-0.07*	-0.22*	-0.08*	0	0.03*	0.03*	0.09*	0.18*	-0.22*	0.03*	1.00*	0.01	0.13*	0.12*	1.12
14. nl_pf_mean_mining_r	0.03*	0.01*	0.04*	0.01*	-0.01	0.04*	0	0	0.05*	0.04*	0.03*	0.38*	0.01	1.00*	-0.03*	0.06*	1.18
15. nl_roads_km	0.07*	0.05*	-0.03*	-0.12*	0	0.10*	0.20*	0.03*	0.24*	0.06*	-0.11*	0.11*	0.13*	-0.03*	1.00*	0.42*	1.26
16. nl_urban_mean	0.05*	0.05*	0.01	-0.08*	0.02*	0.06*	0.47*	0.07*	0.47*	0.04*	-0.06*	0.12*	0.12*	0.06*	0.42*	1.00*	1.67

Note. The dataset emanates from the scholarly research conducted for the fulfillment of this doctoral dissertation.

* p-value<0.5.

Appendix G Summary Statistics of Generalized Linear Regression Models

Table G 1

Generalized Linear Regression Models Results

Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
1	nl_anm_mean_area	0.009	0.00000	sl_knearest8	0.00	5.97	control	na
1	nl_out_mean	0.028	0.00000	sl_knearest8	0.00	8.66	control	na
1	nl_anm_mean_AAU	0.04	0.546774	sl_knearest8	0.06	0.60	governance	1
1	nl_anm_mean_AFS	-0.01	0.190679	sl_knearest8	0.01	-1.31	governance	1
1	nl_anm_mean_myp	-0.007	0.00352	sl_knearest8	0.00	-2.92	governance	1.1
1	nl_ibama_mean	0.01	0.25891	sl_knearest8	0.01	1.13	governance	1
1	nl_mean_RDAI	-0.007	0.01735	sl_knearest8	0.00	-2.38	governance	1
1	nl_pf_mean_mining_r	0.00	0.88742	sl_knearest8	0.01	0.14	governance	1
1	nl_mean_MRI	0.009	0.00424	sl_knearest8	0.00	2.86	illegal income	2
1	nl_cprm_poi_mean	0.00	0.77662	sl_knearest8	0.00	-0.28	place	3
1	nl_gas	-0.01	0.47487	sl_knearest8	0.01	-0.71	place	3
1	nl_leg_mean	0.326	0.00000	sl_knearest8	0.00	81.08	place	3.1
1	nl_roads_km	0.008	0.00000	sl_knearest8	0.00	8.64	place	3
1	nl_urban_mean	0.00	0.13918	sl_knearest8	0.00	1.48	place	3
1	sl_knearest8	0.16	0	sl_knearest8	0.00	95.26	spatial lag	na
2	nl_anm_mean_area	0.009	0.00000	sl_knearest16	0.00	6.25	control	na
2	nl_out_mean	0.035	0.00000	sl_knearest16	0.00	10.42	control	na
2	nl_anm_mean_AAU	0.07	0.29310	sl_knearest16	0.06	1.05	governance	1
2	nl_anm_mean_AFS	-0.01	0.30834	sl_knearest16	0.01	-1.02	governance	1
2	nl_anm_mean_myp	-0.005	0.036618	sl_knearest16	0.00	-2.09	governance	1.1
2	nl_ibama_mean	0.02	0.19695	sl_knearest16	0.01	1.29	governance	1
2	nl_mean_RDAI	-0.009	0.00545	sl_knearest16	0.00	-2.78	governance	1
2	nl_pf_mean_mining_r	0.00	0.94176	sl_knearest16	0.01	-0.07	governance	1
2	nl_mean_MRI	0.009	0.00860	sl_knearest16	0.00	2.63	illegal income	2
2	nl_cprm_poi_mean	0.00	0.87729	sl_knearest16	0.00	-0.15	place	3
2	nl_gas	-0.01	0.287205	sl_knearest16	0.01	-1.06	place	3
2	nl_leg_mean	0.360	0.00000	sl_knearest16	0.00	87.90	place	3.1
2	nl_roads_km	0.009	0.00000	sl_knearest16	0.00	8.69	place	3
2	nl_urban_mean	0.00	0.05763	sl_knearest16	0.00	1.90	place	3
2	sl_knearest16	0.16	0.00000	sl_knearest16	0.00	79.62	spatial lag	na
3	nl_anm_mean_area	0.009	0.00000	sl_knearest50	0.00	5.75	control	na
3	nl_out_mean	0.053	0.00000	sl_knearest50	0.00	15.15	control	na
3	nl_anm_mean_AAU	0.06	0.31923	sl_knearest50	0.06	1.00	governance	1
3	nl_anm_mean_AFS	-0.01	0.12852	sl_knearest50	0.01	-1.52	governance	1
3	nl_anm_mean_myp	0.00	0.64424	sl_knearest50	0.00	-0.46	governance	1.1
3	nl_ibama_mean	0.02	0.24681	sl_knearest50	0.01	1.16	governance	1
3	nl_mean_RDAI	-0.011	0.000738	sl_knearest50	0.00	-3.38	governance	1
3	nl_pf_mean_mining_r	0.00	0.94403	sl_knearest50	0.01	-0.07	governance	1
3	nl_mean_MRI	0.012	0.00054	sl_knearest50	0.00	3.46	illegal income	2
3	nl_cprm_poi_mean	0.00	0.70751	sl_knearest50	0.00	-0.38	place	3

Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
3	nl_gas	-0.01	0.222503	sl_knearest50	0.01	-1.22	place	3
3	nl_leg_mean	0.404	0.00000	sl_knearest50	0.00	96.83	place	3.1
3	nl_roads_km	0.009	0.00000	sl_knearest50	0.00	9.10	place	3
3	nl_urban_mean	0.00	0.14877	sl_knearest50	0.00	1.44	place	3
3	sl_knearest50	0.15	0.00000	sl_knearest50	0.00	57.65	spatial lag	na
4	nl_anm_mean_area	0.009	0.00000	sl_knearest250	0.00	5.84	control	na
4	nl_anm_mean_area	0.008	0.00000	sl_knearest250	0.00	5.21	control	na
4	nl_out_mean	0.082	0.00000	sl_knearest250	0.00	23.15	control	na
4	nl_anm_mean_AAU	0.04	0.59808	sl_knearest250	0.07	0.53	governance	1
4	nl_anm_mean_AFS	-0.01	0.36922	sl_knearest250	0.01	-0.90	governance	1
4	nl_anm_mean_myp	0.00	0.12521	sl_knearest250	0.00	1.53	governance	1.1
4	nl_ibama_mean	0.01	0.29908	sl_knearest250	0.01	1.04	governance	1
4	nl_mean_RDAI	-0.012	0.000346	sl_knearest250	0.00	-3.58	governance	1
4	nl_pf_mean_mining_r	0.00	0.61927	sl_knearest250	0.01	0.50	governance	1
4	nl_mean_MRI	0.016	0.00001	sl_knearest250	0.00	4.44	illegal income	2
4	nl_cprm_poi_mean	0.00	0.49636	sl_knearest250	0.00	-0.68	place	3
4	nl_gas	-0.01	0.29096	sl_knearest250	0.01	-1.06	place	3
4	nl_leg_mean	0.444	0	sl_knearest250	0.00	105.44	place	3.1
4	nl_roads_km	0.010	0.00000	sl_knearest250	0.00	9.51	place	3
4	nl_urban_mean	0.00	0.364246	sl_knearest250	0.00	0.91	place	3
4	sl_knearest250	0.14	0.00000	sl_knearest250	0.00	32.51	spatial lag	na
5	nl_anm_mean_area	0.009	0	sl_fixdis25	0.00	5.58	control	na
5	nl_out_mean	0.065	0.00000	sl_fixdis25	0.00	18.24	control	na
5	nl_anm_mean_AAU	0.05	0.49264	sl_fixdis25	0.07	0.69	governance	1
5	nl_anm_mean_AFS	-0.01	0.12417	sl_fixdis25	0.01	-1.54	governance	1
5	nl_anm_mean_myp	0.00	0.66004	sl_fixdis25	0.00	0.44	governance	1.1
5	nl_ibama_mean	0.02	0.25368	sl_fixdis25	0.01	1.14	governance	1
5	nl_mean_RDAI	-0.012	0.00043	sl_fixdis25	0.00	-3.52	governance	1
5	nl_pf_mean_mining_r	0.00	0.978746	sl_fixdis25	0.01	-0.03	governance	1
5	nl_mean_MRI	0.014	0.00017	sl_fixdis25	0.00	3.76	illegal income	2
5	nl_cprm_poi_mean	0.00	0.70067	sl_fixdis25	0.00	-0.38	place	3
5	nl_gas	-0.01	0.246031	sl_fixdis25	0.01	-1.16	place	3
5	nl_leg_mean	0.429	0.00000	sl_fixdis25	0.00	102.69	place	3.1
5	nl_roads_km	0.010	0.00000	sl_fixdis25	0.00	9.57	place	3
5	nl_urban_mean	0.00	0.23041	sl_fixdis25	0.00	1.20	place	3
5	sl_fixdis25	0.15	0.00000	sl_fixdis25	0.00	44.98	spatial lag	na
6	nl_anm_mean_area	0.008	0.00000	sl_fixdis50	0.00	5.01	control	na
6	nl_out_mean	0.088	0.00000	sl_fixdis50	0.00	24.59	control	na
6	nl_anm_mean_AAU	0.04	0.59348	sl_fixdis50	0.07	0.53	governance	1
6	nl_anm_mean_AFS	-0.01	0.33963	sl_fixdis50	0.01	-0.95	governance	1
6	nl_anm_mean_myp	0.005	0.084854	sl_fixdis50	0.00	1.72	governance	1.1
6	nl_ibama_mean	0.01	0.32473	sl_fixdis50	0.01	0.98	governance	1
6	nl_mean_RDAI	-0.012	0.00021	sl_fixdis50	0.00	-3.71	governance	1
6	nl_pf_mean_mining_r	0.01	0.10574	sl_fixdis50	0.01	1.62	governance	1

Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
6	nl_mean_MRI	0.017	0.00000	sl_fixdis50	0.00	4.61	illegal income	2
6	nl_cprm_poi_mean	0.00	0.45707	sl_fixdis50	0.00	-0.74	place	3
6	nl_gas	-0.01	0.33175	sl_fixdis50	0.01	-0.97	place	3
6	nl_leg_mean	0.452	0.00000	sl_fixdis50	0.00	107.23	place	3.1
6	nl_roads_km	0.010	0.00000	sl_fixdis50	0.00	9.37	place	3
6	nl_urban_mean	0.00	0.39910	sl_fixdis50	0.00	0.84	place	3
6	sl_fixdis50	0.13	0.00000	sl_fixdis50	0.00	26.54	spatial lag	na
7	nl_anm_mean_area	0.009	0.00000	sl_inversedis25	0.00	5.66	control	na
7	nl_out_mean	0.083	0.00000	sl_knearest250	0.00	23.36	control	na
7	nl_out_mean	0.036	0.00000	sl_inversedis25	0.00	10.32	control	na
7	nl_anm_mean_AAU	0.06	0.35224	sl_inversedis25	0.06	0.93	governance	1
7	nl_anm_mean_AFS	-0.02	0.08750	sl_inversedis25	0.01	-1.71	governance	1
7	nl_anm_mean_myp	0.00	0.26380	sl_inversedis25	0.00	-1.12	governance	1.1
7	nl_gov	0.00	0.37416	sl_knearest250	0.00	0.89	governance	1
7	nl_ibama_mean	0.02	0.08245	sl_inversedis25	0.01	1.74	governance	1
7	nl_mean_RDAI	-0.011	0.00032	sl_knearest250	0.00	-3.60	governance	1
7	nl_mean_RDAI	-0.008	0.00913	sl_inversedis25	0.00	-2.61	governance	1
7	nl_pf_mean_mining_r	-0.01	0.13029	sl_inversedis25	0.01	-1.51	governance	1
7	nl_mean_MRI	0.015	0.00002	sl_knearest250	0.00	4.29	illegal income	2
7	nl_mean_MRI	0.011	0.00138	sl_inversedis25	0.00	3.20	illegal income	2
7	nl_cprm_poi_mean	0.00	0.95091	sl_inversedis25	0.00	-0.06	place	3
7	nl_gas	-0.02	0.16595	sl_inversedis25	0.01	-1.39	place	3
7	nl_leg_mean	0.444	0.00000	sl_knearest250	0.00	105.92	place	3.1
7	nl_leg_mean	0.386	0.00000	sl_inversedis25	0.00	93.82	place	3.1
7	nl_roads_km	0.010	0.00000	sl_knearest250	0.00	10.54	place	3
7	nl_roads_km	0.010	0.00000	sl_inversedis25	0.00	9.62	place	3
7	nl_urban_mean	0.00	0.10460	sl_inversedis25	0.00	1.62	place	3
7	sl_inversedis25	0.20	0.00000	sl_inversedis25	0.00	69.09	spatial lag	na
7	sl_knearest250	0.14	0.00000	sl_knearest250	0.00	32.72	spatial lag	na
8	nl_anm_mean_area	0.008	0.00000	sl_inversedis50	0.00	5.02	control	na
8	nl_out_mean	0.050	0.00000	sl_inversedis50	0.00	14.17	control	na
8	nl_anm_mean_AAU	0.05	0.43532	sl_inversedis50	0.06	0.78	governance	1
8	nl_anm_mean_AFS	-0.01	0.12802	sl_inversedis50	0.01	-1.52	governance	1
8	nl_anm_mean_myp	0.00	0.70434	sl_inversedis50	0.00	0.38	governance	1.1
8	nl_ibama_mean	0.03	0.03374	sl_inversedis50	0.01	2.12	governance	1
8	nl_mean_RDAI	-0.009	0.00603	sl_inversedis50	0.00	-2.75	governance	1
8	nl_pf_mean_mining_r	-0.01	0.32777	sl_inversedis50	0.01	-0.98	governance	1
8	nl_mean_MRI	0.014	0.00007	sl_inversedis50	0.00	3.97	illegal income	2
8	nl_cprm_poi_mean	0.00	0.72941	sl_inversedis50	0.00	-0.35	place	3
8	nl_gas	-0.01	0.19606	sl_inversedis50	0.01	-1.29	place	3
8	nl_leg_mean	0.407	0.00000	sl_inversedis50	0.00	97.74	place	3.1
8	nl_roads_km	0.010	0.00000	sl_inversedis50	0.00	9.95	place	3
8	nl_urban_mean	0.00	0.23564	sl_inversedis50	0.00	1.19	place	3
8	sl_inversedis50	0.23	0.00000	sl_inversedis50	0.00	56.53	spatial lag	na

Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
9	nl_out_mean	0.028	0.00000	sl_knearest8	0.00	8.63	control	na
9	nl_anm_mean_fines	-0.01	0.09747	sl_knearest8	0.01	-1.66	governance	1
9	nl_anm_mean_myp	0.00	0.22034	sl_knearest8	0.00	-1.23	governance	1.1
9	nl_ibama_mean_value	0.00	0.13682	sl_knearest8	0.00	1.49	governance	1
9	nl_mean_gdp	0.00	0.00007	sl_knearest8	0.00	-3.97	governance	1
9	nl_pf_sum	0.00	0.23739	sl_knearest8	0.00	1.18	governance	1
9	nl_mean_MRI	0.026	0.00000	sl_knearest8	0.00	16.20	illegal income	2
9	nl_cprm_dist	0.00	0.08617	sl_knearest8	0.00	1.72	place	3
9	nl_gas_dist	0.00	0.40612	sl_knearest8	0.00	0.83	place	3
9	nl_leg_mean	0.327	0.00000	sl_knearest8	0.00	81.44	place	3.1
9	nl_roads_km	0.010	0.00000	sl_knearest8	0.00	9.49	place	3
9	nl_urban_dist	0.00	0.06338	sl_knearest8	0.00	1.86	place	3
9	sl_knearest8	0.16	0.00000	sl_knearest8	0.00	95.29	spatial lag	na
10	nl_out_mean	0.028	0.00000	sl_knearest8	0.00	8.60	control	na
10	nl_anm_mean_fines	-0.02	0.05628	sl_knearest8	0.01	-1.91	governance	1
10	nl_ibama_interdict_mean_value	0.01	0.00059	sl_knearest8	0.00	3.43	governance	1
10	nl_mean_RDAI	-0.007	0.01598	sl_knearest8	0.00	-2.41	governance	1
10	nl_pf_sum_value_ca	0.00	0.49861	sl_knearest8	0.00	-0.68	governance	1
10	nl_mean_MRI	0.026	0.00000	sl_knearest8	0.00	17.35	illegal income	2
10	nl_leg_mean	0.327	0.00000	sl_knearest8	0.00	81.52	place	3.1
10	nl_roads_km	0.009	0.00000	sl_knearest8	0.00	9.88	place	3
10	sl_knearest8	0.16	0.00000	sl_knearest8	0.00	95.35	spatial lag	na
11	nl_anm_mean_area	0.009	0.00000	sl_knearest8	0.00	5.92	control	na
11	nl_out_mean	0.028	0.00000	sl_knearest8	0.00	8.71	control	na
11	nl_anm_mean_fines	-0.01	0.25679	sl_knearest8	0.01	-1.13	governance	1
11	nl_anm_mean_myp	-0.007	0.00420	sl_knearest8	0.00	-2.86	governance	1.1
11	nl_ibama_interdict_mean_value	0.01	0.00179	sl_knearest8	0.00	3.12	governance	1
11	nl_ibama_mean	0.01	0.34368	sl_knearest8	0.01	0.95	governance	1
11	nl_mean_RDAI	-0.007	0.01640	sl_knearest8	0.00	-2.40	governance	1
11	nl_mean_MRI	0.009	0.00433	sl_knearest8	0.00	2.85	illegal income	2
11	nl_leg_mean	0.327	0.00000	sl_knearest8	0.00	81.46	place	3.1
11	nl_roads_km	0.009	0.00000	sl_knearest8	0.00	9.80	place	3
11	sl_knearest8	0.16	0.00000	sl_knearest8	0.00	95.38	spatial lag	na
12	nl_anm_mean_area	0.008	0.00000	sl_knearest8	0.00	5.56	control	na
12	nl_out_mean	0.028	0.00000	sl_knearest8	0.00	8.81	control	na
12	nl_gov	0.00	0.30351	sl_knearest8	0.00	1.03	governance	1
12	nl_mean_RDAI	-0.007	0.01238	sl_knearest8	0.00	-2.50	governance	1
12	nl_mean_MRI	0.009	0.00813	sl_knearest8	0.00	2.65	illegal income	2
12	nl_leg_mean	0.327	0.00000	sl_knearest8	0.00	81.49	place	3.1
12	nl_roads_km	0.009	0.00000	sl_knearest8	0.00	9.78	place	3
12	sl_knearest8	0.16	0.00000	sl_knearest8	0.00	95.30	spatial lag	na
13	nl_anm_mean_area	0.008	0.00000	sl_inversedis50	0.00	5.44	control	na
13	nl_out_mean	0.051	0.00000	sl_inversedis50	0.00	14.43	control	na
13	nl_gov	0.00	0.11941	sl_inversedis50	0.00	1.56	governance	1

Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
13	nl_mean_RDAI	-0.010	0.00085	sl_inversedis50	0.00	-3.34	governance	1
13	nl_mean_MRI	0.013	0.00029	sl_inversedis50	0.00	3.63	illegal income	2
13	nl_leg_mean	0.407	0.00000	sl_inversedis50	0.00	98.19	place	3.1
13	nl_roads_km	0.011	0.00000	sl_inversedis50	0.00	11.32	place	3
13	sl_inversedis50	0.23	0.00000	sl_inversedis50	0.00	56.63	spatial lag	na
14	nl_anm_mean_area	0.008	0.00000	sl_inversedis25	0.00	5.71	control	na
14	nl_out_mean	0.036	0.00000	sl_inversedis25	0.00	10.59	control	na
14	nl_gov	0.00	0.37279	sl_inversedis25	0.00	0.89	governance	1
14	nl_mean_RDAI	-0.010	0.00113	sl_inversedis25	0.00	-3.26	governance	1
14	nl_mean_MRI	0.010	0.00404	sl_inversedis25	0.00	2.88	illegal income	2
14	nl_leg_mean	0.387	0.00000	sl_inversedis25	0.00	94.32	place	3.1
14	nl_roads_km	0.010	0.00000	sl_inversedis25	0.00	11.19	place	3
14	sl_inversedis25	0.20	0.00000	sl_inversedis25	0.00	69.14	spatial lag	na
15	nl_anm_mean_area	0.009	0.00000	sl_fixdis25	0.00	6.00	control	na
15	nl_out_mean	0.065	0.00000	sl_fixdis25	0.00	18.46	control	na
15	nl_gov	0.00	0.46990	sl_fixdis25	0.00	0.72	governance	1
15	nl_mean_RDAI	-0.011	0.00024	sl_fixdis25	0.00	-3.68	governance	1
15	nl_mean_MRI	0.012	0.00050	sl_fixdis25	0.00	3.48	illegal income	2
15	nl_leg_mean	0.429	0.00000	sl_fixdis25	0.00	103.19	place	3.1
15	nl_roads_km	0.011	0.00000	sl_fixdis25	0.00	10.80	place	3
15	sl_fixdis25	0.15	0.00000	sl_fixdis25	0.00	45.14	spatial lag	na
16	nl_anm_mean_area	0.009	0.00000	sl_fixdis50	0.00	5.69	control	na
16	nl_out_mean	0.088	0.00000	sl_fixdis50	0.00	24.77	control	na
16	nl_gov	0.00	0.18893	sl_fixdis50	0.00	1.31	governance	1
16	nl_mean_RDAI	-0.011	0.00067	sl_fixdis50	0.00	-3.40	governance	1
16	nl_mean_MRI	0.016	0.00001	sl_fixdis50	0.00	4.43	illegal income	2
16	nl_leg_mean	0.452	0.00000	sl_fixdis50	0.00	107.72	place	3.1
16	nl_roads_km	0.010	0.00000	sl_fixdis50	0.00	10.21	place	3
16	sl_fixdis50	0.13	0.00000	sl_fixdis50	0.00	26.76	spatial lag	na
17	nl_anm_mean_area	0.009	0.00000	sl_knearest16	0.00	6.02	control	na
17	nl_out_mean	0.035	0.00000	sl_knearest16	0.00	10.61	control	na
17	nl_gov	0.00	0.18130	sl_knearest16	0.00	1.34	governance	1
17	nl_mean_RDAI	-0.009	0.00275	sl_knearest16	0.00	-2.99	governance	1
17	nl_mean_MRI	0.008	0.01387	sl_knearest16	0.00	2.46	illegal income	2
17	nl_leg_mean	0.361	0.00000	sl_knearest16	0.00	88.39	place	3.1
17	nl_roads_km	0.009	0.00000	sl_knearest16	0.00	10.04	place	3
17	sl_knearest16	0.16	0.00000	sl_knearest16	0.00	79.68	spatial lag	na
18	nl_anm_mean_area	0.009	0.00000	sl_knearest50	0.00	5.94	control	na
18	nl_out_mean	0.053	0.00000	sl_knearest50	0.00	15.36	control	na
18	nl_gov	0.00	0.41040	sl_knearest50	0.00	0.82	governance	1
18	nl_mean_RDAI	-0.011	0.00039	sl_knearest50	0.00	-3.54	governance	1
18	nl_mean_MRI	0.011	0.00142	sl_knearest50	0.00	3.19	illegal income	2
18	nl_leg_mean	0.404	0.00000	sl_knearest50	0.00	97.33	place	3.1
18	nl_roads_km	0.010	0.00000	sl_knearest50	0.00	10.36	place	3

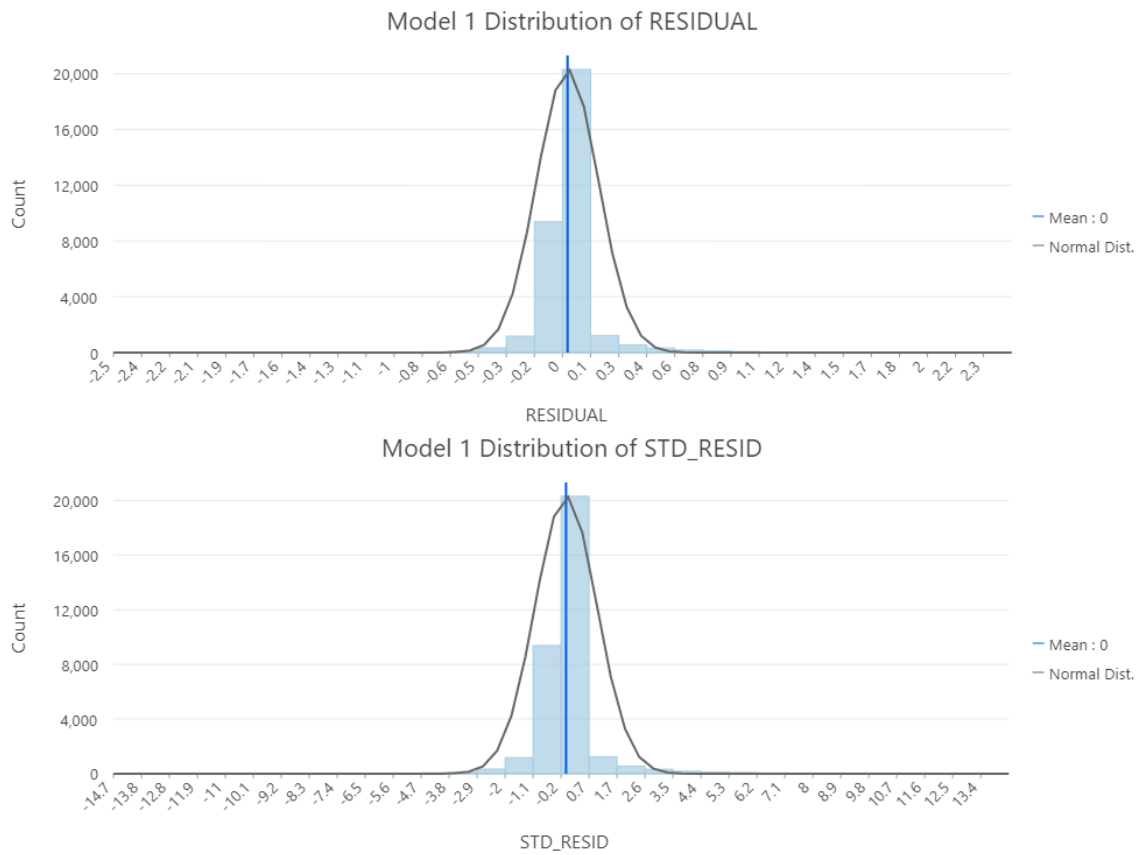
Model	Variable	Coef	P-value	Spatial lag	S.E.	t stat	Group	Hyp.
18	sl_knearest50	0.15	0.00000	sl_knearest50	0.00	57.76	spatial lag	na
20	nl_anm_mean_area	0.009	0.00000	sl_knearest8	0.00	6.05	control	na
20	nl_out_mean	0.029	0.00000	sl_knearest8	0.00	8.87	control	na
20	nl_anm_mean_myp	-0.007	0.00298	sl_knearest8	0.00	-2.97	governance	1.1
20	nl_mean_RDAI	-0.006	0.02324	sl_knearest8	0.00	-2.27	governance	1
20	nl_mean_MRI	0.009	0.00700	sl_knearest8	0.00	2.70	illegal income	2
20	nl_leg_mean	0.327	0.00000	sl_knearest8	0.00	81.48	place	3.1
20	nl_roads_km	0.009	0.00000	sl_knearest8	0.00	10.34	place	3
20	sl_knearest8	0.159	0.00000	sl_knearest8	0.00	95.34	spatial lag	na
21	nl_anm_mean_myp	0.008	0.00119	none	0.00	3.24	governance	1.1
21	nl_mean_RDAI	-0.009	0.00328	none	0.00	-2.94	governance	1
21	nl_mean_MRI	0.022	0.00000	none	0.00	13.15	illegal income	2
21	nl_leg_mean	0.499	0.00000	none	0.00	120.12	place	3.1
21	nl_roads_km	0.012	0.00000	none	0.00	11.61	place	3
22	nl_anm_mean_myp	-0.004	0.10825	sl_knearest8	0.00	-1.61	governance	1.1
22	nl_mean_RDAI	-0.007	0.01597	sl_knearest8	0.00	-2.41	governance	1
22	nl_mean_MRI	0.023	0.00000	sl_knearest8	0.00	15.18	illegal income	2
22	nl_leg_mean	0.330	0.00000	sl_knearest8	0.00	82.37	place	3.1
22	nl_roads_km	0.009	0.00000	sl_knearest8	0.00	10.79	place	3
22	sl_knearest8	0.163	0.00000	sl_knearest8	0.00	101.29	spatial lag	na

Note. Models 1, 11, 20, 21, and 22 were chosen to summarize GLR as models 5,4,3,1 and 2 respectively.

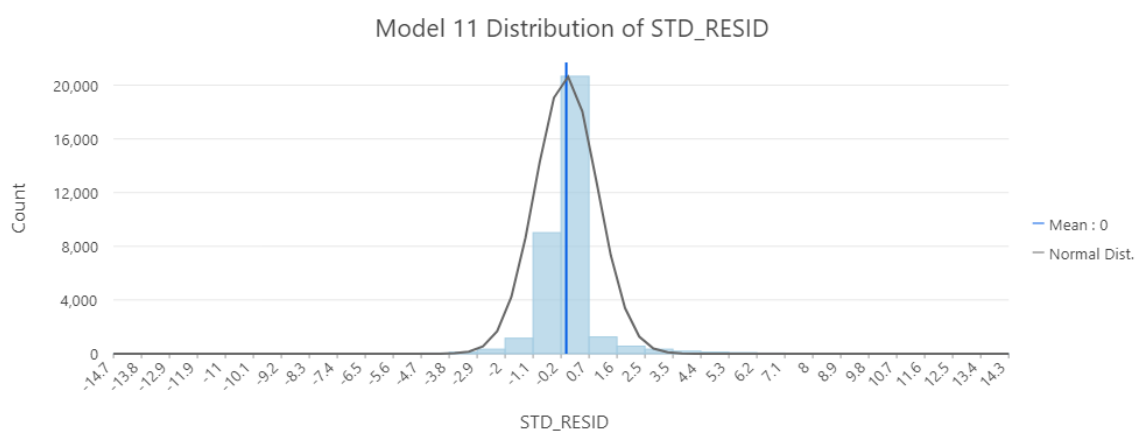
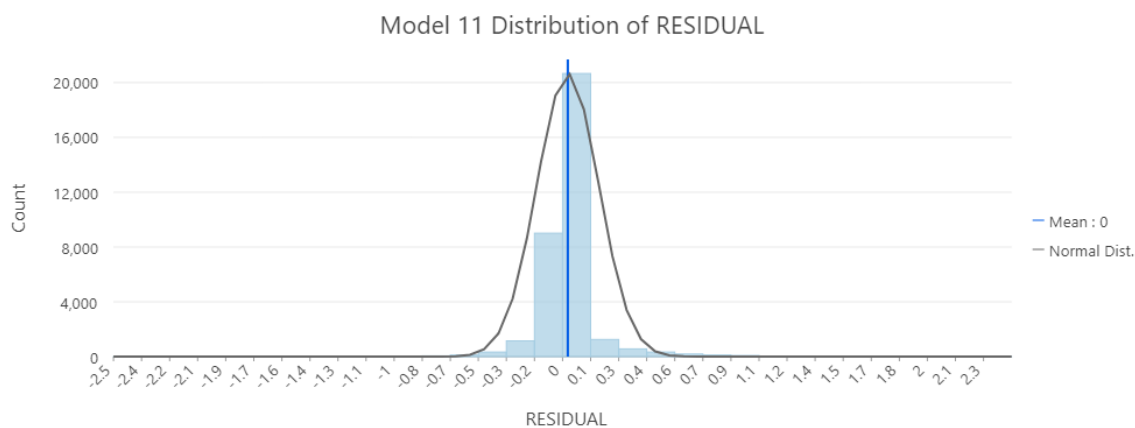
Table G 2

Generalized Linear Regression Model 1 Residuals

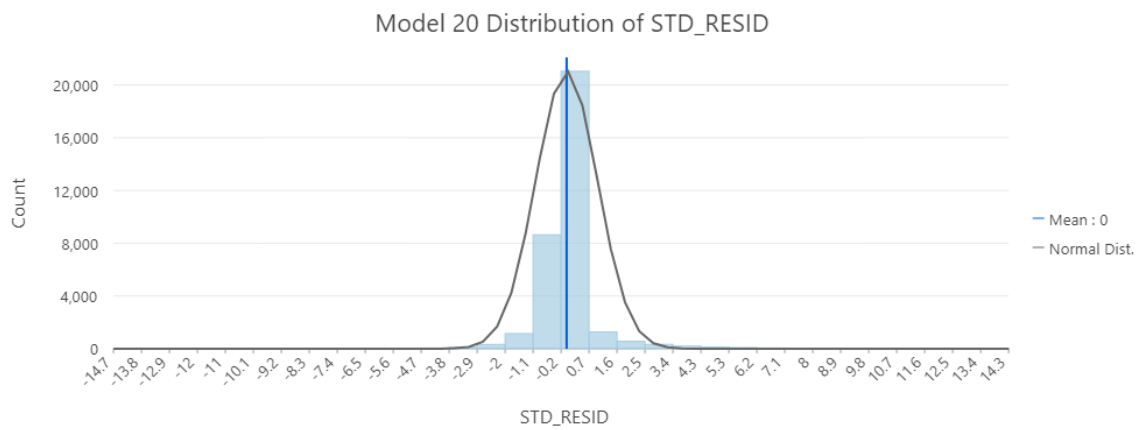
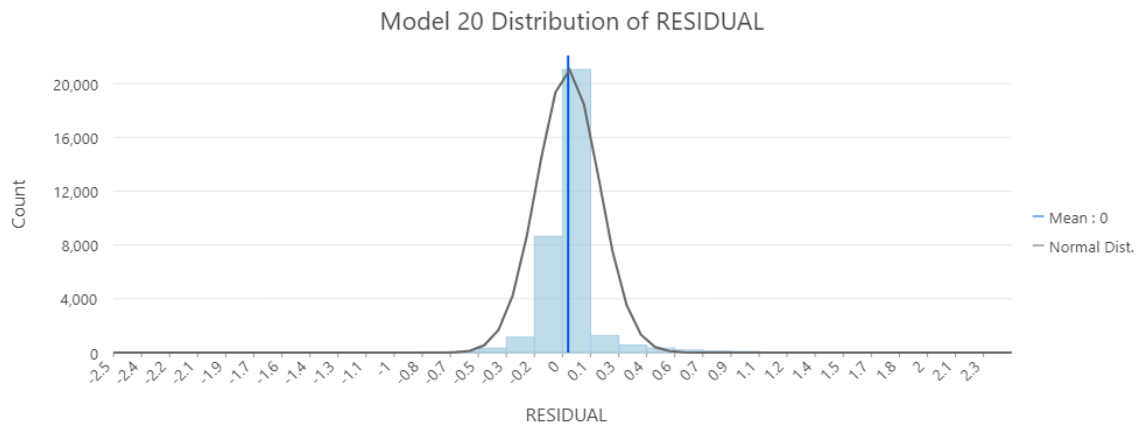
Field Name	PREDICTED	RESIDUAL	STD_RESID
Minimum	-0.07321	-2.51703	-14.6586
Maximum	3.286829	2.461729	14.33658
Mean	0.079858	3.64E-19	-1.8E-17
Standard Deviation	0.163738	0.171672	0.999779
Median	0.026346	-0.00961	-0.05598
Number of Unique Values	33988	33988	33988
Outliers	3662	5727	5727
Sum	2714.383	1.24E-14	-6.2E-13
Range	3.360038	4.978756	28.9952
Coefficient of Variation	2.050351	4.72E+17	-5.5E+16
Skewness	4.829756	2.592529	2.592529
Kurtosis	44.28291	31.59759	31.59759

**Table G 3***Generalized Linear Regression Model 11 Residuals*

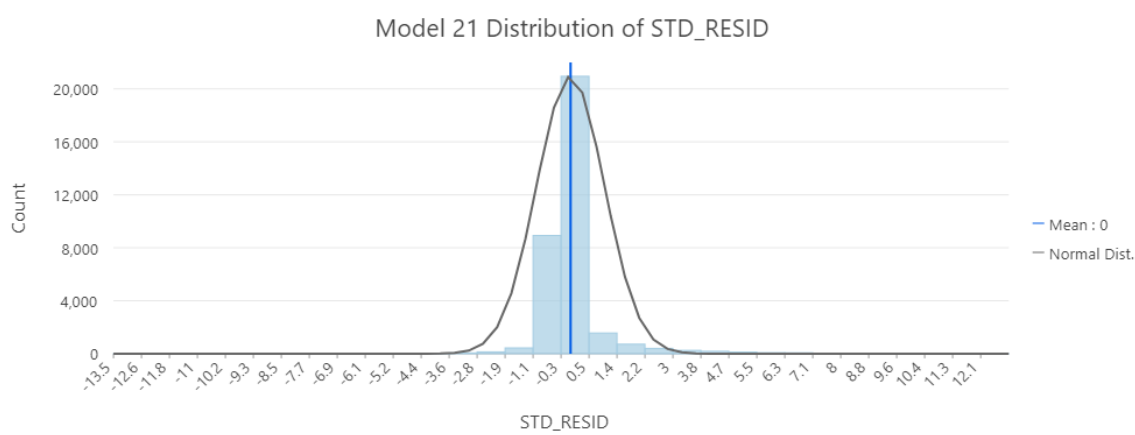
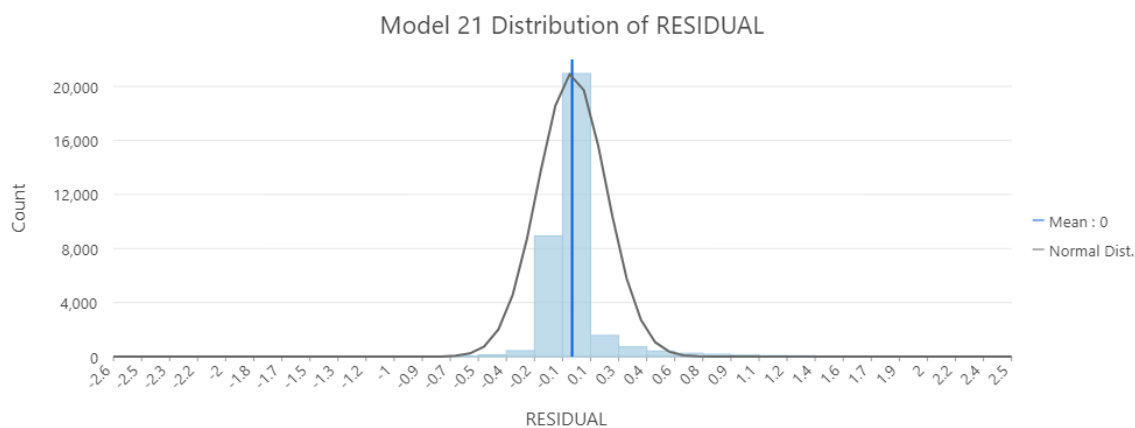
Field Name	PREDICTED	RESIDUAL	STD_RESID
Minimum	-0.07304	-2.51816	-14.6676
Maximum	3.281136	2.459589	14.3264
Mean	0.079858	3.34E-17	1.81E-16
Standard Deviation	0.163756	0.171655	0.999838
Median	0.026377	-0.00973	-0.05665
Number of Unique Values	33986	33986	33986
Outliers	3648	5738	5738
Sum	2714.383	1.14E-12	6.16E-12
Range	3.354181	4.977753	28.99397
Coefficient of Variation	2.050577	5.14E+15	5.52E+15
Skewness	4.829052	2.589706	2.589706
Kurtosis	44.24776	31.57175	31.57175

**Table G 4***Generalized Linear Regression Model 20 Residuals*

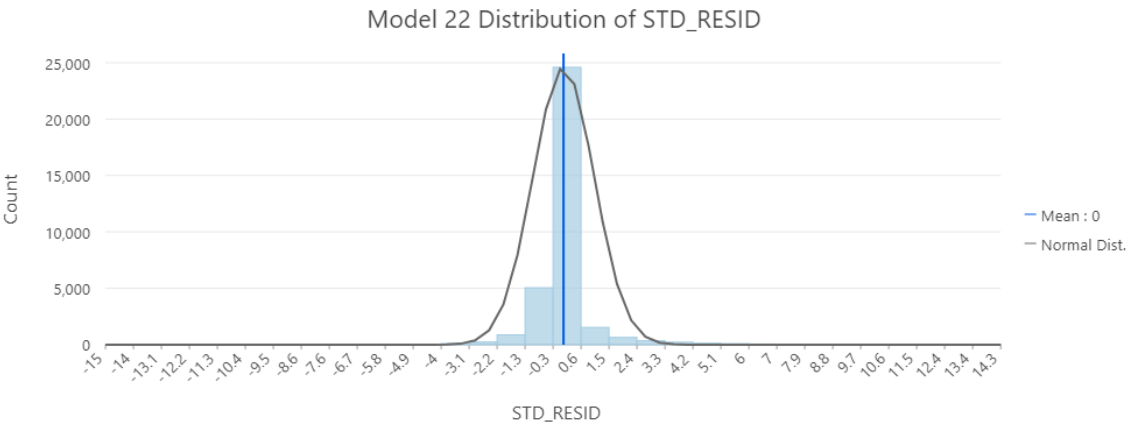
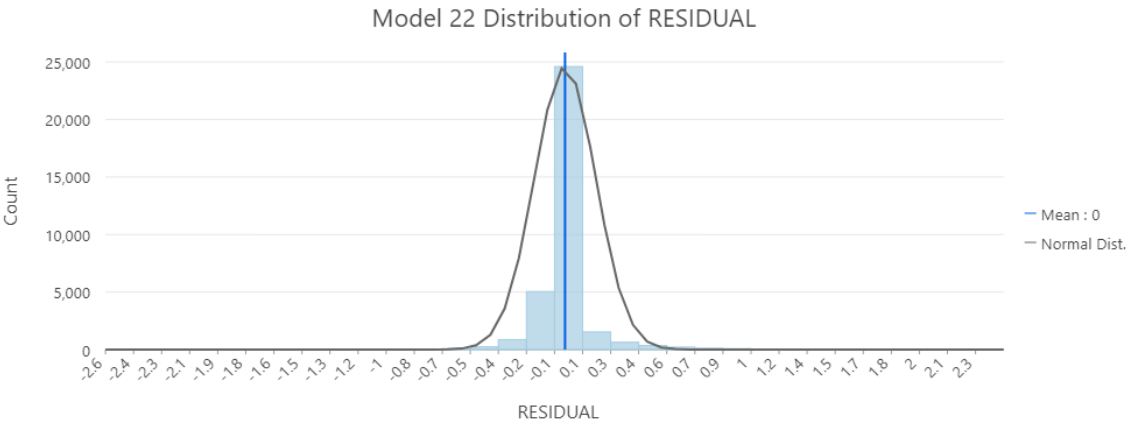
Field Name	PREDICTED	RESIDUAL	STD_RESID
Minimum	-0.07337	-2.51922	-14.6714
Maximum	3.285843	2.457466	14.31171
Mean	0.079858	6.02E-18	4.86E-17
Standard Deviation	0.163719	0.17169	0.999882
Median	0.026408	-0.00975	-0.05678
Number of Unique Values	33986	33986	33986
Outliers	3669	5734	5734
Sum	2714.383	2.05E-13	1.65E-12
Range	3.359211	4.976687	28.98308
Coefficient of Variation	2.050113	2.85E+16	2.06E+16
Skewness	4.8367	2.590994	2.590994
Kurtosis	44.38455	31.60612	31.60612

**Table G 5***Generalized Linear Regression Model 21 Residuals*

Field Name	PREDICTED	RESIDUAL	STD_RESID
Minimum	-0.02152	-2.64342	-13.4706
Maximum	3.093548	2.533517	12.91057
Mean	0.079858	1.61E-17	4.45E-17
Standard Deviation	0.133335	0.196221	0.999926
Median	0.050782	-0.03738	-0.1905
Number of Unique Values	33972	33974	33974
Outliers	3620	5809	5809
Sum	2714.383	5.48E-13	1.51E-12
Range	3.115065	5.176936	26.38118
Coefficient of Variation	1.669649	1.22E+16	2.24E+16
Skewness	8.275453	3.300776	3.300776
Kurtosis	110.6491	33.78028	33.78028

**Table G 6***Generalized Linear Regression Model 22 Residuals*

Field Name	PREDICTED	RESIDUAL	STD_RESID
Minimum	-0.04706	-2.57125	-14.9501
Maximum	3.333898	2.453436	14.26511
Mean	0.079858	4.58E-17	2.24E-16
Standard Deviation	0.163421	0.171973	0.999912
Median	0.025928	-0.00877	-0.05101
Number of Unique Values	33978	33978	33978
Outliers	3660	6010	6010
Sum	2714.383	1.56E-12	7.61E-12
Range	3.380955	5.024684	29.21521
Coefficient of Variation	2.046383	3.76E+15	4.47E+15
Skewness	4.970202	2.613598	2.613598
Kurtosis	46.61824	31.90331	31.90331



Appendix H Data Assembling Workflow

ANM

* Encoding: UTF-8.

* Get data from mining process events registered in ANM.

PRESERVE.

SET DECIMAL COMMA.

GET DATA /TYPE=TXT

/FILE="E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessoEvento.txt"

/ENCODING='LOCALE'

/DELCASE=LINE

/DELIMITERS=";"

/ARRANGEMENT=DELIMITED

/FIRSTCASE=2

/LEADINGSPACES IGNORE=YES

/DATATYPEMIN PERCENTAGE=95.0

/VARIABLES=

DSPprocesso AUTO

IDEvento AUTO

DTEvento AUTO

/MAP.

RESTORE.

CACHE.

EXECUTE.

DATASET NAME ProcessoEvento WINDOW=FRONT.

*Add metadata to the variables.

VARIABLE LABELS

DSPProcesso "ANM process number"

/DTEvento "Event date"

/IDEvento "Event type".

VALUE LABELS IDEvento

```
1 'PROCESSO LOCALIZADO EM FAIXA DE FRONTEIRA'
2 'DOCUMENTO DIVERSO PROTOCOLIZADO'
3 'EXIGÊNCIA PUBLICADA'
4 'CUMPRIMENTO EXIGÊNCIA PROTOCOLIZADA'
5 'DÉBITO INSCRITO NA DÍVIDA ATIVA'
6 'RECONSTITUIÇÃO DE PROCESSO AUTORIZADA'
7 'PROCESSO COM PRAZO SUSPENSO'
10 'RECONH GEOL/REQUERIMENTO PROTOCOLIZADO'
15 'RECONH GEOL/INDEFERIMENTO DE PLANO PUBL'
16 'RECONH GEOL/INDEFERIMENTO ÁREA LIVRE PUB'
20 'RECONH GEOL/ASSENTIMENTO EMFA'
21 'AUTO DE INFRAÇÃO MULTA-RAL'
22 'TORNA S/EFEITO AUTO INFRAÇÃO-RAL'
23 'ARQUIVAMENTO AUTO INFRAÇÃO-RAL'
24 'MULTA APLICADA-RAL'
25 'PAGAMENTO DA MULTA EFETUADO-RAL'
26 'TORNA S/EFEITO MULTA APLICADA-RAL'
27 'EXIGÊNCIA PARA APRESENTAÇÃO DE RAL PUBLICADA'
30 'RECONH GEOL/PERMISSÃO PUBLICADA'
50 'RECONH GEOL/RELATÓRIO RG PROTOCOLIZADO'
99 'DISPONIBILIDADE S/PRETEN PROC ARQ ÁREA LIVRE'
100 'REQ PESQ/REQUERIMENTO PESQUISA PROTOCOLIZADO'
101 'REQ PESQ/INDEFERIMENTO DE PLANO CAPUT ART 17 PUB'
102 'REQ PESQ/INDEFERIMENTO "DE PLANO" PUBLIC'
103 'AUT PESQ/TRANSF DIREITOS -CESSÃO TOTAL ANULADA'
104 'REQ PESQ/REQ PESQUISA INCOMPLETO PROTOCO'
105 'REQ PESQ/COMPLEMENTAÇÃO REQ PESQ PROTOCO'
106 'AUT PESQ/TORNA S/EFEITO MULTA APLICADA'
107 'REQ PESQ/ACORDO C/INTERFICÁRIO PROTOCOL'
108 'REQ PESQ/PEDIDO INCORPORAÇÃO/CESSÃO PROT'
109 'AUT PESQ/TORNA S/EFEITO AUTO INFRAÇÃO PU'
110 'REQ PESQ/ASSENTIMENTO CDN SOLICITADO'
111 'REQ PESQ/CONSULTA FUNAL ENCAMINHADA'
112 'REQ PESQ/CONSULTA M MARINHA ENCAMINHADA'
113 'REQ PESQ/CONSULTA ORGÃOS DIVERS ENCAMINH'
114 'AUT PESQ/HOMOLOGA DESISTÊNCIA PRORROGAÇÃO PRAZO ALV'
115 'REQ PESQ/DENÚNCIA C/REQUERENTE PROTOCOL'
116 'REQ PESQ/DENÚNCIA C/REQUERENTE IMPROCEDE'
117 'REQ PESQ/DENÚNCIA C/REQUERENTE PROCEDENTE'
118 'REQ PESQ/AVERB INCORPORAÇÃO APROV PUBL'
119 'REQ PESQ/AVERB INCORPORAÇÃO EFETIVADA'
120 'REQ PESQ/INDEFERIMENTO INTERFER.ÁREA GARIMPO PUB'
121 'REQ PESQ/INDEFERIMENTO ART 18 PAR 1 PUBLICADO'
122 'REQ PESQ/INDEFERIMENTO P/ NAO CUMPRIMENTO EXIGÊNCIA'
123 'REQ PESQ/INDEF ART 25 E 18 II B PUBLICADO'
124 'REQ PESQ/INDEF ART 20 PAR 5 PUBLICADO'
125 'REQ PESQ/INDEFERIMENTO ART 21 PAR 3 RCM PUB'
126 'REQ PESQ/INDEFERIMENTO ART 20 PAR 5 RCM-MAX PUB'
128 'REQ PESQ/INDEF ART 20 VII RCM PUBLICADO'
129 'REQ PESQ/INDEF ART 26 E 18 IIB PUBLICADO'
130 'REQ PESQ/REQUERIMENTO RETIFICAÇÃO ÁREA PROT'
131 'REQ PESQ/EXIGÊNCIA PUBLICADA'
132 'REQ PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
133 'REQ PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
134 'REQ PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADA'
135 'REQ PESQ/CUMPRIMENTO EXIGÊNCIA PROTOCOL'
136 'REQ PESQ/DOCUMENTO DIVERSO PROTOCOLIZADO'
137 'REQ PESQ/TORNA S/EFEITO EXIGÊNCIA PUBLIC'
138 'REQ PESQ/CONVITE PAGAM TAXA ALVARÁ PUBL'
139 'REQ PESQ/TORNA S/EFEITO DESPACHO INDEFERIMENTO'
140 'REQ PESQ/COMPROV PAGAM TAXA ALVARÁ PROT'
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141 'REQ PESQ/ASSENTIMENTO FUNAI AUTORIZADO'
 142 'REQ PESQ/ASSENTIMENTO M MARINHA AUTORIZA'
 143 'REQ PESQ/ASSENTIMENTO CDN AUTORIZADO'
 144 'REQ PESQ/ASSENTI ORGAOS DIVERSOS AUTORIZ'
 145 'REQ PESQ/ASSENTIMENTO FUNAI NÃO AUTORIZA'
 146 'REQ PESQ/ASSENTIM M MARINHA NÃO AUTORIZD'
 147 'REQ PESQ/ASSENTIMENTO CDN NÃO AUTORIZADO'
 148 'REQ PESQ/ASSENT ORGAOS DIVERS NÃO AUTORIZ'
 149 'REQ PESQ/NEGA ANUÊNCIA CESSAO TOT DIR PU'
 150 'REQ PESQ/DESISTENCIA REQ PESQ PROTOCOLIZADA'
 151 'REQ PESQ/PEDIDO DE DESCONSID DESIST PROT'
 152 'REQ PESQ/NEGA ANUÊNCIA CESSAO PARC DIR PU'
 153 'REQ PESQ/TORNA SEM EFEITO ANUÊNCIA CESSAO'
 154 'TORNA S/EFEITO NOTIF ADM I PGTO DEB TAH'
 155 'REQ PESQ/ARQUIVAMENTO PROCESSO PUBLICADO'
 156 'REQ PESQ/DESPACHO DIVERSO PUBLICADO'
 157 'REQ PESQ/DESISTÊNCIA REQ PESQ HOMOLOGADA PUB'
 158 'REQ PESQ/ÁREA LIVRE A PARTIR DE:'
 159 'REQ PESQ/ÁREA LIVRE 30 DIAS APÓS A PUBLICAÇÃO'
 160 'REQ PESQ/ÁREA NÃO ONERAD PUBLICADO'
 161 'REQ PESQ/TORNA S/EFEITO HOMOL DESIST PUB'
 162 'REQ PESQ/OPÇÃO REGIME LICENCIAMENTO PROTOCOLIZADO'
 163 'REQ PESQ/TORNA S/EFEITO DESPACHO ARQUIVAMENTO PROCESSO'
 164 'REQ PESQ/PED RECON IND PROR EXIG NEGADO'
 165 'REQ PESQ/OPÇÃO REGIME LICENCIAMENTO NEGADO'
 166 'REQ PESQ/INDEFERIMENTO ART 20 PAR 6 RCM PUB'
 167 'REQ LAV/CESSÃO-INCORP REQUERIMENTO LAV PU'
 168 'REQ PESQ/INDEFERIMENTO INCISO 7º PORT 50/998 PUB'
 169 'AUT PESQ/ÁREA BLOQUEADA ART 42 CM PUB'
 170 'REQ PESQ/INDEFERIMENTO MOTIVO DIVERSO PUBLICADO'
 171 'REQ PESQ/ÁREA BLOQUEADA ART 42 CM PUBLIC'
 172 'REQ PESQ/ÁREA BLOQUEADA-INUNDACAO PUB'
 173 'REQ PESQ/INDEFERIMENTO ÁREA EM PARQUE NAC EST MUN'
 174 'REQ PESQ/IND ART 1 LEI 6567/78 PUBLICADO'
 175 'AUT PESQ/TRANSF DIREITOS -CESSAO PARCIAL APROVADA'
 176 'AUT PESQ/ALVARÁ DE PESQUISA DE CESSÃO PUB'
 177 'AUT PESQ/TORNA S/EFEITO DESP ARQ REL PUB'
 178 'AUT PESQ/NOTIFICAÇÃO ADM L PGTO DÉBITO TAH'
 179 'NOTIFICAÇÃO DÉBITO CFEM (NFLDPY'
 180 'REQ PESQ/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 181 'REQ PESQ/PEDIDO RECONSIDERAÇÃO NEGADA'
 182 'REQ PESQ/PEDIDO RECONSIDERAÇÃO PROVIDA'
 183 'REQ PESQ/TORNA S/EFEITO RECONSIDERAÇÃO INDEFERIMENTO'
 184 'REQ PESQ/TORNA S/EFEITO DESPACHO NEGA RECONSIDERAÇÃO'
 185 'REQ PESQ/RECURSO AO MINISTRO PROTOCOLIZADO'
 186 'AUT PESQ/OPÇÃO REGIME LICENC INDEFERIDO PUB'
 187 'REQ PESQ/RECURSO NEGADO PUBLICADO'
 188 'REQ PESQ/RECURSO PROVIDO PUBLICADO'
 189 'REQ LAV/TORNA S/EFEITO DESPACHO DIR REQ LA'
 190 'AUT PESQ/TORNA S/EFEITO PROC ADM CAD/NUL'
 191 'AUT PESQ/TORNA S/EFEITO DESP NÃO APROV REL'
 192 'AUT PESQ/TORNA S/EFEITO DESPACHO PUBLICADO'
 193 'AUT PESQ/TRANSF DIREITOS -CESSAO TOTAL NEGADA'
 194 'AUT PESQ/TRANSF DIREITOS -CESSAO PARCIAL NEGADA'
 195 'AUT PESQ/TORNA S/EFEITO DESP PRORR ALV PU'
 196 'AUT PESQ/TORNA S/EFEITO DESP APROV REL PUB'
 197 'AUT PESQ/INDEFERIMENTO PRORROGAÇÃO PRAZO ALVARA'
 198 'AUT PESQ/OPÇÃO REGIME LICENCIAMENTO PROT'
 199 'AUT PESQ/TORNA S/EFEITO EXIGÊNCIA PUB'
 200 'AUT PESQ/REDUÇÃO DE ÁREA ART 26 PUBL'
 201 'AUT PESQ/ALVARÁ DE PESQUISA PUBLICADO'
 202 'AUT PESQ/OFÍCIO C COPIA AUTO INFRACÇÃO'
 203 'AUT PESQ/ÁREA LIVRE 30 DIAS APÓS PUBLICA'
 204 'AUT PESQ/ACORDO C/SUPERFICIÁRIO PROTOCOL'
 205 'AUT PESQ/OFÍCIO C COPIA IMPOS ADV MULTA'
 206 'AUT PESQ/EMOLUMENTOS PRENOV ALVARA PAGO'
 207 'AUT PESQ/OFÍCIO AO JUIZ ENVIADO'
 208 'AUT PESQ/INGRESSO JUDICIAL NA ÁREA'
 209 'AUT PESQ/INÍCIO DE PESQUISA COMUNICADO'
 210 'AUT PESQ/PLANO ÚNICO PESQUISA APRESENTADO'
 211 'AUT PESQ/PLANO ÚNICO PESQUISA APROVADO PUBL'
 212 'AUT PESQ/PLANO ÚNICO PESQUISA NÃO APROVADO PUBL'
 213 'AUT PESQ/SUSPENSÃO TRAB PESQ SOLICITADO'
 214 'AUT PESQ/COMUNICAÇÃO OCORR OUTRA SUBSTANTCT'
 215 'AUT PESQ/VISTORIA REALIZADA -REEMBOLSO PROTOCOLIZADO'
 216 'AUT PESQ/VERIFICAÇÃO IN LOCO PESQ NORMAL'
 217 'AUT PESQ/VERIFICAÇÃO IN LOCO PESQ NÃO INICIADA'
 218 'AUT PESQ/VERIFICAÇÃO IN LOCO PESQ IRREGULAR'
 219 'AUT PESQ/SUSPENSÃO TRAB PESQ AUTORIZ PUB'
 220 'AUT PESQ/INTERDIÇÃO TRABALHO PESQ PUBLIC'
 221 'AUT PESQ/AUTO INFRAÇÃO ADVERTENCIA PUBL'
 222 'AUT PESQ/ADVERTENCIA PUBLICADA'
 223 'AUT PESQ/CONVITE PAG TAXA RENOV ALV PUBL'
 224 'AUT PESQ/AUTO INFRAÇÃO MULTA PUBLICADA'
 225 'AUT PESQ/MULTA APLICADA PUBLICADA'
 226 'AUT PESQ/SEGUNDA IMPOSIÇÃO DE MULTA PUBL'
 227 'AUT PESQ/PAGAMENTO MULTA EFETUADO'
 228 'AUT PESQ/SOLICITA ANULAÇÃO AUTO INFRAÇÃO'
 229 'AUT PESQ/COBRANÇA JUDICIAL DE MULTA'
 230 'AUT PESQ/ARQUIVAMENTO AUTO INFRAÇÃO PUBL'
 231 'AUT PESQ/DENÚNCIA CONTRA TITULAR DE PESQ'
 232 'AUT PESQ/DENÚNCIA IMPROCEDENTE PUBLICADA'
 233 'AUT PESQ/DENÚNCIA PROCEDENTE PUBLICADA'
 234 'AUT PESQ/SUSPENSÃO TRAB PESQ NEGADA PUBL'
 235 'AUT PESQ/PAGAMENTO TAXA ALVARA RENOV PROT'
 236 'AUT PESQ/DOCUMENTO DIVERSO PROTOCOLIZADO'
 237 'AUT PESQ/INSTAURA PROC ADM CAD/NULID ALVARÁ PUBL'
 238 'AUT PESQ/ARQUIVAMENTO PROC ADM CAD/NUL ALV PUBL'
 239 'AUT PESQ/DENÚNCIA DE INVASÃO DA ÁREA'
 240 'AUT PESQ/DEFESA APRESENTADA'
 241 'AUT PESQ/DEFESA ACEITA PUBLICADA'
 242 'AUT PESQ/DEFESA NÃO ACEITA PUBLICADA'
 243 'AUT PESQ/RECURSO PROTOCOLIZADO'
 244 'AUT PESQ/RECURSO NEGADO PUBLICADO'
 245 'AUT PESQ/RECURSO PROVIDO PUBLICADO'
 246 'AUT PESQ/ÁREA SERVIDÃO SOLICITADA'
 247 'AUT PESQ/ÁREA SERVIDÃO NÃO CONCEDIDA PUB'
 248 'AUT PESQ/ÁREA SERVIDÃO CONCEDIDA PUBLICA'
 249 'AUT PESQ/TRANSF DIREITOS -CESSAO TOTAL PROTOCOLIZADA'
 250 'AUT PESQ/EXIGÊNCIA PUBLICADA'
 251 'AUT PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 252 'AUT PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
 253 'AUT PESQ/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
 254 'AUT PESQ/ÁREA LIVRE A PARTIR DE:'
 255 'AUT PESQ/CUMPRIMENTO EXIGÊNCIA PROTOCOLI'
 256 'AUT PESQ/DESPACHO PUBLICADO'
 257 'AUT PESQ/REL ART 43 CONSTIT PROTOC'
 258 'AUT PESQ/REL ART 43 CONSTIT ACEITO PUB'
 259 'AUT PESQ/REL ART 43 CONST NÃO ACEITO PUB'
 260 'AUT PESQ/TORNA S/EFEITO ALVARA DE PESQUISA ART 43 CONST'
 261 'AUT PESQ/PEDIDO RECONSIDERAÇÃO PROTOCOL'
 262 'AUT PESQ/PEDIDO RECONSIDERAÇÃO ACEITA PUBLIC'
 263 'AUT PESQ/PEDIDO RECONSIDERAÇÃO NEGADA PUBL'
 264 'AUT PESQ/PAGAMENTO TAH EFETUADO'
 265 'AUT PESQ/PRORROGAÇÃO PRAZO ALVARA SOLICITADO'
 266 'AUT PESQ/OFÍCIO ÍNTIMA P DEFESA CAD/NULID'
 267 'AUT PESQ/INDEFERIMENTO RENOVAÇÃO ALVARÁ PUBLICADO'
 268 'AUT PESQ/ALVARÁ DE RETIFICAÇÃO SOLICITADO'
 269 'AUT PESQ/ALVARA DE RETIFICAÇÃO INDEFERIDO PUBL'
 270 'AUT PESQ/NÃO CONHECE REQUERIMENTO PUBLICADO'
 271 'AUT PESQ/ALVARA RENOVAÇÃO 1 ANO PUBLICAD'
 272 'AUT PESQ/ALVARA RENOVAÇÃO 2 ANOS PUBLICA'
 273 'AUT PESQ/TÍTULO DECLARADO NULO PUBLICADO'
 274 'AUT PESQ/DESP DECL CAD/S/REV ALV PUBL'
 275 'AUT PESQ/ALVARÁ RENOVAÇÃO PUBLICADO'
 276 'AUT PESQ/ALVARÁ DE RETIFICAÇÃO PUBLICADO'
 277 'AUT PESQ/ALVARÁ RENOVAÇÃO 3 ANOS PUBLICA'
 278 'AUT PESQ/RENÚNCIA AUT PESQ PROTOCOLIZADA'
 279 'AUT PESQ/ARQUIVAMENTO PROCESSO PUBLICADO'
 280 'AUT PESQ/BAIXA TRANSCRIÇÃO ALVARÁ'
 281 'AUT PESQ/TRANSF DIREITOS -CESSAO TOTAL APROVADA'
 282 'AUT PESQ/TRANSF DIREITOS -CESSAO TOTAL EFETIVADA'
 283 'AUT PESQ/GUIA UTILIZAÇÃO REQUERIMENTO PROTOC'
 284 'AUT PESQ/GUIA UTILIZAÇÃO INDEFERIDA PUBLICADA'
 285 'AUT PESQ/GUIA UTILIZAÇÃO AUTORIZADA PUBLICADA'
 286 'AUT PESQ/TORNA S/EFEITO BAIXA TRANSCRIC'
 287 'AUT PESQ/SOLICITA DESCONS RENÚNCIA ALVARA'
 288 'AUT PESQ/INCUR ART 23 CM NESTA DATA'
 289 'AUT PESQ/INCUR ART 23 CM SAIDA RELAT FORA PRAZ'
 290 'AUT PESQ/RELATÓRIO PESQ FINAL APRESENTADO'
 291 'DIR REQ LAV/RELATÓRIO PESQ APROV CREDUC ÁREA PUB'
 292 'AUT PESQ/INCUR ART 23 CM FINAL PRAZO ALV'

293 'AUT PESQ/RELATORIO PESQ PARCIAL APRESENTADO'
 294 'AUT PESQ/RENÚNCIA AUT PESQ HOMOLOGADA PUB'
 295 'AUT PESQ/ÁREA INDISPONÍVEL PUBLICADO'
 296 'AUT PESQ/TÍTULO CANCELADO PUBLICADO'
 297 'AUT PESQ/REL PESQ ARO ART 30C CM PUBL'
 298 'AUT PESQ/REL PESQ NÃO APV ART 30B CM PUB'
 299 'AUT PESQ/REL PESQ APROV ART 30A CM PUBL'
 300 'AUT PESQ/TORNA S/EFEITO HOMOL RENUNC PUB'
 301 'DISPONIB/VISTORIA PARA DISPONIBIL. REALIZADA'
 302 'DISPONIB/HABILIT EDITAL DISPONIB ART 26 CM'
 303 'DISPONIB/CONSID PRIORITARIO- EDITAL PESQUISA PUB'
 304 'DISPONIB/EDITAL DISPONIB SEM PRETENDENTE PUBL'
 305 'DISPONIB/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 306 'DISPONIB/EDITAL DISPON LAV S/EFEITO PUBL'
 307 'DISPONIB/HABILIT EDITAL DISPONIB LAVRA'
 308 'DISPONIB/INDEF HABILIT EDIT DISPONIB LAV PUBL'
 309 'DISPONIB/CONSID PRIORITARIO- EDITAL LAVRA PUBL'
 310 'DISPONIB/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 311 'DISPONIB/EDITAL DISPON PESQ S/EFEITO PUB'
 312 'DISPONIB/HABILIT EDITAL DISPONIB P/PESQ'
 313 'DISPONIB/INDEF HABILIT EDIT DISPONIB PESQ PUBL'
 314 'DISPONIB/CONSID PRIOR EDIT DISP PESQ PUB'
 315 'DISPONIB/DOCUMENTO DIVERSO PROTOCOLIZADO'
 316 'DISPONIB/DESPACHO PUBLICADO'
 317 'DIR REQ LAVRA/RELATORIO PESQ APROV ART 30 I CM PUBL'
 318 'AUT PESQ/RELATORIO PESQ NÃO APV ART 30 II CM PUB'
 319 'AUT PESQ/RELATORIO PESQ ARO ART 30 III CM PUBL'
 320 'AUT PESQ/RELATORIO PESQ SOBRE ART 30 IV CM PUBL'
 321 'AUT PESQ/ALVARÁ DE PESQUISA 01 ANO PUBL'
 322 'AUT PESQ/ALVARÁ DE PESQUISA 02 ANOS PUBL'
 323 'AUT PESQ/ALVARÁ DE PESQUISA 03 ANOS PUBL'
 324 'AUT PESQ/PRORROGAÇÃO PRAZO 01 ANO PUBL'
 325 'AUT PESQ/PRORROGAÇÃO PRAZO 02 ANOS PUB'
 326 'AUT PESQ/PRORROGAÇÃO PRAZO 03 ANOS PUB'
 327 'AUT PESQ/DESPACHO RETIFICAÇÃO ALVARÁ PUB'
 328 'DISPONIB/ÁREA DISPONÍVEL ART 26 CM PUBL'
 329 'DISPONIB/ÁREA DISP LAVRA ART 26 CM PUBL'
 330 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL DIREITO REQ LAV PROT'
 331 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL DIREITO REQ LAV APROV'
 332 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL DIREITO REQ LAV EFETIV'
 333 'REQ PLG/REQUERIMENTO LAVRA GARMPEIRA PROTOCOLIZADO'
 334 'REQ PLG/INDEFERIMENTO DE PLANO PUBLICADO'
 335 'REQ PLG/INDEFERIMENTO PUBLICADO'
 336 'REQ LAV/DOCUMENTO DIVERSO PROTOCOLIZADO'
 337 'REQ PLG/IND ART 1 LEI 6507/78 PUBLICADO'
 338 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL DIREITO REQ LAV NEGADA'
 339 'PLG/INCORPORAÇÃO/CESSÃO EFETIVADA'
 340 'REQ LAV/INTERDIÇÃO LAVRA ILLEGAL'
 341 'REQ PLG/MEMORIAL DESCRITIVO ÁREA PLG PUB'
 342 'REQ PLG/CONTESTAÇÃO COOPERATIVA PROTOC'
 343 'MANIFESTO DE JAZIDA'
 344 'REQ PLG/EXIGÊNCIA PUBLICADA'
 345 'REQ PLG/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 346 'REQ PLG/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDA'
 347 'REQ PLG/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADA'
 348 'REQ PLG/CUMPRIMENTO EXIGÊNCIA PROTOCOL'
 349 'AUT PESQ/PRORROGAÇÃO PRAZO REQ LAVRA-01 ANO PUB'
 350 'REQ LAV/REQUERIMENTO LAVRA PROTOCOLIZADO'
 351 'REQ LAV/DESISTENCIA REQ LAVRA PROTOCOLIZ'
 352 'REQ LAV/DESISTENCIA REQ LAVRA HOMOLOGADA PUB'
 353 'REQ PLG/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 354 'REQ PLG/PEDIDO RECONSIDERAÇÃO PROVIDO'
 355 'REQ LAV/INDENIZAÇÃO AO PESQUISADOR NEGADA'
 356 'REQ LAV/DESPACHO PUBLICADO'
 357 'DISPONIB/TORNA S/EFEITO DISPO ART 26 CM PU'
 358 'DISPONIB/EDITAL DISPONIB ART 26 CM SEM PRETENDENTE PUB'
 359 'DISPONIB/INDEF HABILIT EDIT DISPONIB ART 26 CM PUB'
 360 'DISPONIB/RECURSO PROTOCOLIZADO'
 361 'REQ LAV/EXIGÊNCIA PUBLICADA'
 362 'REQ LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 363 'REQ LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
 364 'REQ LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
 365 'REQ LAV/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZ'
 366 'REQ LAV/EXIGÊNCIA REITERAÇÃO PUBLICADA'
 367 'REQ PLG/PEDIDO RECONSIDERAÇÃO NEGADO'
 368 'REQ PLG/TORNA S/EFEITO RECONSIDERAÇÃO INDEFERIMENTO'
 369 'DISPONIB/RECURSO- SUPERINTENDENTE NEGADO PUBL'
 370 'REQ LAV/DENUNCIA CONTRA REQ LAVRA PROTOC'
 371 'REQ LAV/DENUNC CONTRA REQ LAVRA PROCEEDEN'
 372 'REQ LAV/DENUNC CONTRA REQ LAVRA IMPROCEED'
 373 'REQ LAV/ASSENTIMENTO CDN SOLICITADO'
 374 'REQ LAV/ASSENTIMENTO FUNAI SOLICITADO'
 375 'REQ LAV/ASSENTIMENTO ORGÃOS DIVERSOS SOLICITADO'
 376 'REQ LAV/ASSENTIMENTO MARINHA SOLICITADO'
 377 'REQ LAV/ASSENTIMENTO CDN AUTORIZADO'
 378 'REQ LAV/ASSENTIMENTO FUNAI AUTORIZADO'
 379 'REQ LAV/ASSENTIMENTO MARINHA AUTORIZAD'
 380 'REQ LAV/ASSENTIMENTO ORGÃOS DIVERSOS AUTORIZ'
 381 'REQ LAV/ASSENTIMENTO CDN NÃO AUTORIZADO'
 382 'REQ LAV/ASSENTIMENTO FUNAI NÃO AUTORIZAD'
 383 'REQ LAV/ASSENTIMENTO MARINHA NÃO AUTORIZ'
 384 'REQ LAV/ASSENTIMENTO ORGÃOS DIVERSOS NÃO AUTORIZ'
 385 'REQ LAV/ÁREA BLOQUEADA ART 42 CM PUBLIC'
 386 'DISPONIB/RECURSO- SUPERINTENDENTE PROVIDO PUBL'
 387 'REQ PLG/ANULÊNCIA CESSÃO APROVADA PUB'
 388 'REQ PLG/INDEF PLANO ART 9º IN 5/2000 PUB'
 389 'REQ LAV/TORNA S/EFEITO CADUCIDADE DIR REQ LAVRA'
 390 'REQ LAV/INDEFERIMENTO REQ LAVRA PUBLICAD'
 391 'REQ LAV/PEDIDO RECONSIDERAÇÃO PROTOCOLIZ'
 392 'REQ LAV/PEDIDO RECONSIDERAC PROVIDA PUBL'
 393 'REQ LAV/PEDIDO RECONSIDERAÇÃO NEGADO PUB'
 394 'REQ LAV/RECURSO AO MINISTRO PROTOCOLIZAD'
 395 'REQ LAV/RECURSO AO MINISTRO NEGADO PUBLIT'
 396 'REQ LAV/RECURSO AO MINISTRO PROVIDO PUBL'
 397 'REQ LAV/CONVITE PAG TAXA PORT LAVRA PUBL'
 398 'REQ LAV/COMPROV PAG TAXA PORT LAVRA PROT'
 399 'REQ LAV/DECLARA CADUC DREIT REQ LAV PUB'
 400 'CONC LAV/PORTARIA CONCESSÃO DE LAVRA PUBLICADA'
 401 'CONC LAV/PRORROGAÇÃO INICIO LAVRA SOLICITADO'
 402 'CONC LAV/PRORROGAÇÃO INICIO LAVRA AUTORIZADO'
 403 'CONC LAV/MISSÃO DE POSSE REQUERIDA'
 404 'CONC LAV/PRORROGAÇÃO INICIO LAVRA NAO AUTORIZADO'
 405 'CONC LAV/INICIO DE LAVRA COMUNICADO'
 406 'CONC LAV/EDITAL IMISSÃO POSSE PUBLICADA'
 407 'CONC LAV/MISSÃO DE POSSE REALIZADA'
 408 'CONC LAV/MISSÃO DE POSSE NÃO REALIZADA'
 409 'CONC LAV/MISSÃO DE POSSE ANULADA'
 410 'CONC LAV/ARQUIVAMENTO PROCESSO PUBLICADO'
 411 'CONC LAV/SUSPENSÃO TRABALHOS LAVRA PROTOCOLIZADO'
 412 'CONC LAV/VISTORIA LAVRA IRREGULAR'
 413 'CONC LAV/VISTORIA LAVRA ÁREA ABANDONADA'
 414 'CONC LAV/RELATÓRIO PESQ COMPLEMENTAR APRESENTADO'
 415 'CONC LAV/MODIFICAÇÃO DE PAE APRESENTADO'
 416 'CONC LAV/MODIFICAÇÃO DE PAE APROV PUBLICADO'
 417 'CONC LAV/MODIFICAÇÃO DE PAE NÃO APROV PUBL'
 418 'CONC LAV/RAL ANO BASE APRESENTADO'
 419 'CONC LAV/RAL NÃO ACEITO PUBLICADO'
 420 'CONC LAV/RAL ANOS ANTERIORES APRESENTADO'
 421 'CONC LAV/RETIFICAÇÃO ÁREA LAVRA PROTOCOLIZADO'
 422 'CONC LAV/TRANSF DIREITOS -CESSÃO TOTAL NEGADA'
 423 'CONC LAV/RETIFICAÇÃO ÁREA LAVRA NEGADO'
 424 'CONC LAV/RELATÓRIO REAVALIAÇÃO RESERVA APRESENTADO'
 425 'CONC LAV/RELATÓRIO REAVALIAÇÃO RESERVA APROVADO'
 426 'CONC LAV/ADITAMENTO NOVA SUBSTÂNCIA SOLICITADA'
 427 'CONC LAV/ADITAMENTO NOVA SUBST AUTORIZADO PUB'
 428 'CONC LAV/ADITAMENTO NOVA SUBST NÃO AUTORIZADO PUB'
 429 'CONC LAV/RELATÓRIO REAVALIAÇÃO RESERVA NÃO APROVADO'
 430 'CONC LAV/RENÚNCIA CONCESSÃO LAVRA PROTOC'
 431 'CONC LAV/BAIXA TRANSCRIÇÃO TITL LAV PUBL'
 432 'CONC LAV/ÁREA DE SERVIÇÃO SOLICITADA'
 433 'CONC LAV/ÁREA PROTEÇÃO DE FONTE SOLICITADA'
 434 'CONC LAV/ÁREA DE SERVIÇÃO NEGADA'
 435 'CONC LAV/ÁREA DE SERVIÇÃO CONCEDIDA PUBL'
 436 'CONC LAV/DOCUMENTO DIVERSO PROTOCOLIZADO'
 437 'CONC LAV/SUSPENSÃO TRABALHOS LAVRA AUTORIZADO'
 438 'CONC LAV/SUSPENSÃO TRABALHOS LAVRA NEGADA'
 439 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA 6 MESES PUBL'
 440 'CONC LAV/ROTULO ÁGUA MINERAL APROVADO PUB'
 441 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA 1 ANO PUBL'
 442 'CONC LAV/INTERDIÇÃO DA LAVRA PUBLICADA'
 443 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA 2 ANOS PUBL'
 444 'CONC LAV/DESINTERDIÇÃO LAVRA AUTORIZ PUB'

445 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA 3 ANOS PUBL'
 446 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA 4 ANOS PUBL'
 447 'CONC LAV/SUSPENSÃO LAVRA AUTORIZADA MAIS 4 ANOS PUBL'
 448 'CONC LAV/ROTULO ÁGUA MINERAL PROTOCOLIZADO'
 449 'CONC LAV/ARRENDAMENTO TOTAL AVERBAÇÃO APROVADA'
 450 'CONC LAV/ARRENDAMENTO TOTAL AVERBAÇÃO EFETIVADA'
 451 'CONC LAV/TRANSF DIREITOS -CESSÃO TOTAL APROVADA'
 452 'CONC LAV/TRANSF DIREITOS -CESSÃO TOTAL EFETIVADA'
 453 'CONC LAV/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
 454 'CONC LAV/PEDIDO AVERBAÇÃO NEGADO PUBLIC'
 455 'CONC LAV/ONERACAO DIREITOS LAVRA APROVADA'
 456 'CONC LAV/ONERACAO DIREITOS LAVRA AVERBADA'
 457 'CONC LAV/ADVERTENCIA PUBLICADA'
 458 'CONC LAV/PORTARIA ÁREA PROTEÇÃO PUBLICAD'
 459 'CONC LAV/AUTO INFRACAO MULTA PUBLICADA'
 460 'CONC LAV/MULTA APLICADA PUBLICADA'
 461 'CONC LAV/PAGAMENTO MULTA EFETUADO'
 462 'CONC LAV/ARQUIVAMENTO AUTO INFRACAO PUBLICADO'
 463 'CONC LAV/SOLICITA ANULACAO AUTO INFRACAO'
 464 'CONC LAV/ÁREA PROTEÇÃO DE FONTE NÃO AUTORIZADA'
 465 'CONC LAV/TRANSF DIREITOS -CESSÃO TOTAL PROTOCOL'
 466 'CONC LAV/DENÚNCIA CONTRA TITULAR LAVRA'
 467 'CONC LAV/DENUN CONTRA TITULAR LAV IMPROC'
 468 'CONC LAV/DENUN CONTRA TITULAR LAV PROCED'
 469 'CONC LAV/TRANSF DIREITOS -CESSÃO PARCIAL NEGADA'
 470 'CONC LAV/EXIGENCIA PUBLICADA'
 471 'CONC LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
 472 'CONC LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 473 'CONC LAV/CUMPRIMENTO EXIGÊNCIA PROTOCOLI'
 474 'CONC LAV/DEFESA PROTOCOLIZADA'
 475 'CONC LAV/DEFESA ACEITA PUBLICADA'
 476 'CONC LAV/DEFESA NÃO ACEITA PUBLICADA'
 477 'CONC LAV/RECURSO PROTOCOLIZADO'
 478 'CONC LAV/RECURSO PROVIDO PUBLICADO'
 479 'CONC LAV/RECURSO NEGADO PUBLICADO'
 480 'CONC LAV/ROTULO ÁGUA MINERAL NÃO APROVADO PUB'
 481 'CONC LAV/GRUPAMENTO MINEIRO REQUERIDO'
 482 'CONC LAV/GRUPAMENTO MINEIRO AUTORIZ PUBL'
 483 'CONC LAV/GRUPAMENTO MINEIRO NÃO AUTORIZADO PUBL'
 484 'CONC LAV/GRUPAMENTO MINEIRO INCLUSÃO ÁREA REQ'
 485 'CONC LAV/GRUPAMENTO MINEIRO INCLUSÃO ÁREA PUBL'
 486 'CONC LAV/GRUPAMENTO MINEIRO EXCLUSÃO ÁREA REQ'
 487 'CONC LAV/GRUPAMENTO MINEIRO EXCLUSÃO ÁREA PUBLI'
 488 'CONC LAV/PORTARIA ENLOBANDO OUTRO TITI PUBL'
 489 'CONC LAV/PORTARIA ENLOBADA POUTRA PORTARIA PUB'
 490 'CONC LAV/INSTAURADO PROC ADM CAD/NUL PUBLICADO'
 491 'CONC LAV/ARQUIVAMENTO PROC ADM CAD/NUL PUBLICADO'
 492 'CONC LAV/ÁREA NÃO DISPON P PESQ OU LAVRA'
 493 'CONC LAV/EDITAL DISPON P LAVRA PUBLICADO'
 494 'CONC LAV/ARQUIVAMENTO DO PROCESSO ÁREA LIVRE PUBL'
 495 'CONC LAV/PORTARIA RETIFIC CONCESSÃO PUBL'
 496 'CONC LAV/PORTARIA NULIDADE DE CONCE PUBL'
 497 'CONC LAV/MANIFESTO MINA CANCELADO PUBLIC'
 498 'CONC LAV/PORTARIA REVOGACAO LAVRA PUBLIC'
 499 'CONC LAV/PORTARIA CADUCADA S/EFEITO CONCES PUBL'
 500 'CONC LAV/GRUPAMENTO MINEIRO INCLUSÃO ÁREA NEGADA'
 501 'CONC LAV/ARRENDAMENTO RECISAO PROTOCOLIZADA'
 502 'CONC LAV/ARRENDAMENTO RECISÃO AVERBAÇÃO APROVADA'
 503 'CONC LAV/ARRENDAMENTO RECISÃO AVERBAÇÃO EFETIVADA'
 504 'CONC LAV/ONERACAO DIREITOS -CANCELADO'
 505 'CONC LAV/ONERACAO DIREITOS -CANCELAMENTO AVERBADO'
 506 'CONC LAV/PORTARIA DESMEMBRADA EM OUTRAS PUBLICADA'
 507 'CONC LAV/PORTARIA DESMEMBRADA DE OUTRA PUBLICADA'
 508 'CONC LAV/DESPACHO PUBLICADO'
 509 'CONC LAV/CONSORCIO MINERACAO REQUERIDO'
 510 'CONC LAV/CONSORCIO MINERACAO INDEFER PUB'
 511 'CONC LAV/CONSORCIO MINERACAO AUTORIZADO'
 512 'CONC LAV/CONCESSÃO INTEGRANTE DE G.M.'
 513 'PLG/PERMISSÃO LAVRA GARIMPEIRA PUBL'
 514 'CONC LAV/CONSORCIO MINERACAO INCLUSAO ÁREA PU'
 515 'CONC LAV/TORNA S/EFEITO ART 43 CONST PUB'
 516 'CONC LAV/DENÚNCIA INVASÃO DE ÁREA'
 517 'CONC LAV/RELATORIO ART 43 CONSTITUI PROIT'
 518 'CONC LAV/ÁREA LIVRE 30 DIAS APOS PUBLICA D'
 519 'CONC LAV/VISTORIA REALIZADA -REEMBOLSO PROTOCOLIZADO'
 520 'CONC LAV/GRUPAMENTO MINEIRO CANCELADO PUBL'
 521 'PLG/RENOVAÇÃO PLG SOLICITADA'
 522 'PLG/INDEFERIMENTO PRORROGAÇÃO PRAZO PLG PUBLICADO'
 523 'PLG/RENOVAÇÃO PLG PUBLICADA'
 524 'PLG/ADITAMENTO NOVA SUBSTÂNCIA SOLICITADO'
 525 'PLG/ADITAMENTO NOVA SUBSTÂNCIA AUTORIZADA'
 526 'PLG/ADITAMENTO NOVA SUBSTÂNCIA NÃO AUT PUB'
 527 'PLG/TRANSF DIREITOS -CESSÃO TOTAL NEGADA'
 528 'PLG/TRANSF DIREITOS -CESSÃO PARCIAL NEGADA'
 529 'PLG/BAIXA TRANSCRIÇÃO PLG'
 530 'PLG/EXIGÊNCIA PUBLICADA'
 531 'PLG/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZADA'
 532 'PLG/CANCELAMENTO PLG PUBLICADO'
 533 'AUT PESQ/TRANSF DIREITOS -CESSÃO PARCIAL ANULADA'
 534 'CONC LAV/TORNA S/EFEITO CANCELAMENTO GRUPAM MINEIRO'
 535 'CONC LAV/TORNA S/EFEITO MULTA APLICADA'
 536 'CONC LAV/TRANSF DIREITOS -DISTRATO PROTOCOLIZADO'
 537 'DISPONIB/ANULA DECLARAÇÃO PRIOR EDITAL PESQUISA PUB'
 538 'REQ PESQ/INDEFERIMENTO PLANO ART 9 IN 05/2000 PUB'
 539 'CONC LAV/ARRENDAMENTO AVERBAÇÃO CANCELADA'
 540 'AUT PESQ/TRANSF DIREITOS -CESSÃO PARCIAL EFETIVADA'
 541 'AUT PESQ/RAL ANO BASE APRESENTADO'
 542 'PLG/RAL ANO BASE APRESENTADO'
 543 'CONC LAV/TORNA S/EFEITO APROVAÇÃO RELATÓRIO REAVAL'
 544 'AUT PESQ/TORNA S/EFEITO DESP NEGOU CESSÃO PARC ALV'
 545 'AUT PESQ/TRANSF DIREITOS -CESSÃO PARCIAL PROTOCOLIZADA'
 546 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL REQ LAV PROTOCOL'
 549 'TORNA S/EFEITO NOTIFICAÇÃO CFEM (NF LDP)'
 550 'CONC LAV/TORNA S/EFEITO APROVAÇÃO NOVO PAE PUB'
 551 'CONC LAV/TRANSF DIREITOS -CESSÃO DIREITOS CANCELADA'
 552 'REQ PLG/CONTESTAÇÃO COOPERATIVA NÃO PROVIDA'
 553 'REQ PLG/CONTESTAÇÃO COOPERATIVA PROVIDA'
 554 'CONC LAV/RENÚNCIA CONC LAV/HOMOLOGADA PUBL'
 555 'CONC LAV/ÁREA LIVRE A PARTIR DA PUBLIC'
 556 'CONC LAV/TORNA S/EFEITO NOTIFICAÇÃO CFEM PUB'
 557 'CONC LAV/TRANSF DIREITOS -CESSÃO PARCIAL APROVADA'
 558 'CONC LAV/ARRENDAMENTO PARCIAL AVERBAÇÃO APROVADA'
 559 'CONC LAV/ARRENDAMENTO PARCIAL AVERBAÇÃO EFETIVADA'
 560 'REQ LAV/TORNA S/EFEITO EXIGÊNCIA PUBLICADA'
 561 'AUT PESQ/PRORROGAÇÃO PRAZO REQ LAVRA NEGADO'
 562 'DISPONIB/RENÚNCIA HABILITAÇÃO DISP ART 26 PROT'
 563 'DISPONIB/HOMOLOGIA RENÚNCIA HABILIT ART26 PU'
 564 'REQ LAV/TRANSF DIREITOS -CESSÃO DE DIREITOS ANULADA'
 565 'REQ PLG/ARQUIVAMENTO DEFINITIVO PROCESSO'
 566 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL REQ LAV APROVADA'
 567 'REQ PLG/INDEFERIMENTO DE PLANO PUB'
 568 'REQ PLG/IND ART 4 PORT 284/2000'
 569 'REQ PLG/TORNA S/EFEITO EXIGÊNCIA PUBLICADA'
 570 'REQ PLG/CONTESTAÇÃO COOP NÃO PROVIDA PU'
 571 'PLG/TRANSF DIREITOS -CESSÃO TOTAL APROVADA'
 572 'PLG/TRANSF DIREITOS -CESSÃO TOTAL EFETIVADA'
 573 'REQ PLG/OPÇÃO REGIME AUTORIZAÇÃO PESQ PROTOCOLIZADO'
 574 'REQ PLG/OPÇÃO REGIME AUTORIZAÇÃO PESQ INDEFERIDO'
 575 'REQ PLG/TORNA S/EFEITO DESPACHO INDEFERIMENTO'
 576 'PLG/AUTO INFRACAO MULTA PUBLICADO'
 577 'PLG/MULTA APLICADA PUBLICADA'
 578 'PLG/PAGAMENTO MULTA EFETUADO'
 579 'PLG/SOLICITA ANULACAO AUTO INFRACAO'
 580 'PLG/AUTO INFRACAO ARQUIVADO PUB'
 581 'PLG/TORNA S/EFEITO A PERM LAVRA GARIMP'
 582 'CONC LAV/ARRENDAMENTO TOTAL PROTOCOLIZADO'
 583 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL REQ LAV EFETIVADA'
 584 'PLG/TRANSF DIREITOS -CESSÃO TOTAL PROTOCOLIZADA'
 585 'AUT PESQ/SOLICITA PARC DÉBITO TAH'
 586 'AUT PESQ/INDEFERIMENTO PLANO PEDIDO PARC DÉB TAH'
 587 'AUT PESQ/PARCELAMENTO DÉBITO TAH DEFERIDO'
 588 'AUT PESQ/PAGAMENTO PARCELA DÉB TAH EFETUADO'
 589 'REQ PLG/SOLICITA ANU PRÉVIA CESSÃO TOTAL'
 590 'REQ PLG/AVERBAÇÃO CESSÃO TOTAL EFETIVADA'
 591 'REQ PLG/SOLICITA DISTRATO CESSÃO TOT REQ'
 592 'REQ PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 593 'REQ LICEN/SOLICITA ANU PRÉVIA CESSÃO TOTAL'
 594 'REQ LICEN/AVERBAÇÃO CESSÃO TOTAL EFETIVADA'
 595 'LICEN/TRANSF DIREITOS -CESSÃO TOTAL EFETIVADA'
 596 'CONC LAV/ONERACAO DIREITOS -PENHORA AUTORIZADO'
 597 'CONC LAV/ONERACAO DIREITOS -PENHORA AVERBADO'
 598 'AUT PESQ/ONERACAO DIREITOS -PENHORA AUTORIZADO'

599 'AUT PESQ/ONERAÇÃO DIREITOS -PENHORA AVERBADO'
 600 'PLG/TRANSF DIREITOS -CESSÃO PARCIAL PROTOCOLIZADA'
 601 'PLG/TRANSF DIREITOS -CESSÃO PARCIAL APROVADA'
 602 'PLG/TRANSF DIREITOS -CESSÃO PARCIAL EFETIVADA'
 603 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL REQ LAV NEGADA'
 604 'CONC LAV/ARRENDAMENTO PARCIAL PROTOCOLIZADO'
 605 'CONC LAV/ARRENDAMENTO PARCIAL AVERBAÇÃO NEGADA'
 606 'REQ PLG/IND ART.6º PORT 284/2000 PUB'
 607 'DISPONIBILIDADE DESISTÊNCIA HABILIT EDITAL PUBL'
 608 'CONC LAV/TORNA S/EFEITO AUTO INFRAÇÃO PUBLICADO'
 609 'REQ LAV/ONERAÇÃO DIREITOS LAVRA PROTOCOLIZADA'
 610 'REQ LAV/ONERAÇÃO DIREITOS LAVRA APROVADA'
 611 'REQ LAV/ONERAÇÃO DIREITOS LAVRA AVERBADA'
 612 'REQ PLG/DESISTÊNCIA REQ PLG PROTOCOLIZADA'
 613 'REQ PLG/DESISTÊNCIA REQ PLG HOMOLOGADA PUBLICADA'
 614 'AUT PESQ/TAXA ANUAL HECTARE PAGA A MENOR'
 615 'REQ LAV/LIBERAÇÃO ONERAÇÃO DIREITOS LAVRA PUBLICADA'
 616 'REQ LAV/LIBERAÇÃO ONERAÇÃO DIREITOS LAVRA AVERBADA'
 617 'REQ PESQ/INDEFERE OPÇÃO REQ LICENÇA'
 618 'REQ PESQ/PROCESSO SITUADO EM ÁREA BLOQUEADA'
 619 'REQ PESQ/PROCESSO SITUADO EM ÁREA INDÍGENA'
 620 'AUT PESQ/ÁREA PROTEÇÃO DE FONTE SOLICITADA'
 621 'AUT PESQ/LICENÇA AMBIENTAL OPERAÇÃO APRESENTADA'
 622 'AUT PESQ/LICENÇA AMBIENTAL INSTALAÇÃO APRESENTADA'
 623 'AUT PESQ/GUIA UTILIZAÇÃO RENOVÇÃO SOLICITADA'
 624 'REQ LAV/GUIA UTILIZAÇÃO REQUERIMENTO PROTOC'
 625 'REQ LAV/GUIA UTILIZAÇÃO AUTORIZADA PUBLICADA'
 626 'REQ LAV/GUIA UTILIZAÇÃO INDEFERIDA PUBLICADA'
 627 'CONC LAV/TRANSF DIREITOS -CESSÃO PARCIAL PROTOCOL'
 628 'CONC LAV/TRANSF DIREITOS -CESSÃO PARCIAL EFETIVADA'
 629 'REQ PESQ/ASSENT. CDN/CESSÃO DIREITOS AUT'
 630 'AUT PESQ/ASSENTIMENTO CDN/CESSÃO DIREITOS AUT'
 631 'REQ LAV/ASSENTIMENTO CDN/CESSÃO DIREITOS AUTORIZADO'
 632 'CONC LAV/ASSENTIMENTO CDN/CESSÃO DIREITOS AUTORIZADO'
 633 'CONC LAV/TORNA S/EFEITO INSTAURAÇÃO PROC ADM CADUCIDADE'
 634 'AUT PESQ/COMPLEMENTAÇÃO PGTO TAH EFETUADO'
 635 'AUT PESQ/AUTO INFRAÇÃO MULTA-TAH'
 636 'TORNA S/EFEITO AUTO INFRAÇÃO-TAH'
 637 'ARQUIVAMENTO AUTO INFRAÇÃO-TAH'
 638 'AUT PESQ/AUTO INFRAÇÃO MULTA-RELATÓRIO PESQ'
 639 'AUT PESQ/TORNA S/EFEITO AUTO INFRAÇÃO-REL PESQ'
 640 'AUT PESQ/ARQUIVAMENTO AUTO INFRAÇÃO-REL PESQ'
 641 'AUT PESQ/MULTA APLICADA-TAH'
 642 'AUT PESQ/PAGAMENTO MULTA EFETUADO-TAH'
 643 'TORNA S/EFEITO MULTA APLICADA-TAH'
 644 'AUT PESQ/MULTA APLICADA-RELATÓRIO PESQUISA'
 645 'AUT PESQ/PAGAMENTO MULTA EFETUADO-REL PESQ'
 646 'AUT PESQ/TORNA S/EFEITO MULTA APLICADA-REL PESQ'
 647 'AUT PESQ/INSTAURA PROC ADM CADU ALVARA-TAH'
 648 'AUT PESQ/TORNA S/EFEITO PROC ADM CAD ALV-TAH'
 649 'AUT PESQ/ARQUIVAMENTO PROC ADM CADU ALV-TAH'
 650 'AUT PESQ/ALVARÁ DE PESQUISA CADUCADO -TAH'
 651 'AUT PESQ/TORNA S/EFEITO CADUCIDADE ALV-TAH'
 652 'AUT PESQ/SOLICITA DEVOLUÇÃO PAGAMENTO TAH'
 653 'AUT PESQ/DEVOLUÇÃO PAGAMENTO TAH EFETUADA'
 654 'AUT PESQ/PARCELAMENTO TAH QUITADO'
 655 'AUT PESQ/NOTIFICAÇÃO ADM 11 PGTO DÉBITO TAH'
 656 'AUT PESQ/TORNA S/EFEITO NOTIF ADM 11 PGTO DÉB TAH'
 657 'CONC LAV/TORNA S/EFEITO DESPACHO PUBLICADO'
 658 'LICEN/INSTAURA PROC ADM CANCELAMENTO REGISTRO LICENÇA'
 659 'CONC LAV/TORNA S/EFEITO EXIGÊNCIA PUBLICADA'
 660 'AUT PESQ/PRORROGAÇÃO PRAZO REQ LAVRA SOLICITADO'
 661 'CONC LAV/COMPROVA PAGTO EMOL IMISSÃO POSSE'
 662 'NOTIFICAÇÃO ADM PGTO DÉBITO MULTA'
 663 'SOLICITA PARCELAMENTO DÉBITO MULTA'
 664 'INDEFERE REQ PARCELAMENTO DÉBITO MULTA'
 665 'PARCELAMENTO MULTA DEFERIDO'
 666 'PGTO PARCELA DÉBITO MULTA EFETUADA'
 667 'PARCELAMENTO MULTA QUITADO'
 668 'SOLICITA DEVOLUÇÃO PAGAMENTO MULTA'
 669 'DEVOLUÇÃO PAGAMENTO MULTA EFETUADO'
 670 'DEVOLUÇÃO PAGAMENTO MULTA NEGADO'
 671 'PLG/DESPACHO RETIFICAÇÃO PLG PUB'
 672 'SOLICITA PARCELAMENTO DÉBITO CFEM'
 673 'INDEF PARCELAMENTO DÉBITO CFEM'
 674 'PARCELAMENTO CFEM DEFERIDO'
 675 'PARCELAMENTO CFEM QUITADO'
 676 'LICENÇA AMBIENTAL PROTOCOLIZADA'
 677 'DISPONIBILIDADE DISPONIBILIDADE PARA PLG - EDITAL'
 678 'CASSAÇÃO ANUÊNCIA PRÉVIA CESSÃO DIREITOS'
 679 'MANF/REGISTRO MANIFESTO SOLICITADO'
 680 'MANF/MANIFESTO DE MINA REGISTRADO'
 681 'AUT PESQ/RELATÓRIO PESQ ANALISADO'
 682 'REQ LAV/PAE ANALISADO'
 683 'AUT PESQ/ONERAÇÃO DIREITOS -PENHORA CANCELADA'
 684 'AUT PESQ/ONERAÇÃO DIREITOS -PENHORA CANCELAMENTO AVERBADO'
 685 'CONC LAV/ONERAÇÃO DIREITOS -PENHORA CANCELADA'
 686 'CONC LAV/ONERAÇÃO DIREITOS -PENHORA CANCELAMENTO AVERBADO'
 687 'NOTIFICAÇÃO ADM PAGTO DÉBITO VISTORIA'
 688 'AUT PESQ/OPÇÃO REGIME PERM. LAVRA GARIMP PROT'
 689 'REQ LAV/NOTIFICAÇÃO RECOLHIMENTO CFEM PUBL'
 690 'PAGAMENTO EMOLUMENTOS CESSÃO TOTAL DIREITOS'
 691 'PAGAMENTO EMOLUMENTOS CESSÃO PARCIAL DIREITOS'
 692 'PAGAMENTO EMOLUMENTOS INCORP. FUSÃO CISAÇÃO EMPRESA'
 693 'PAGAMENTO EMOLUMENTOS DEMAIS ATOS AVERBAÇÃO'
 694 'PAGAMENTO VISTORIA FISCALIZAÇÃO EFETUADO'
 695 'REQ LAV/TORNA S/EFEITO DESPACHO INDEF. REQ LAVRA'
 696 'CONC LAV/TORNA S/EFEITO CADUCIDADE LAVRA PUBL'
 698 'MANF/NULIDADE MANIFESTO DE MINA PUBLIC'
 699 'MANF/DECLAR CADU/S/EFEITO MANIFESTO PUBLI'
 700 'REQ LICEN/REQUERIMENTO LICENCIAMENTO PROTOCO'
 701 'LICEN/IND ART 7 IN 01/2001 PUB'
 702 'LICEN/IND ART 22 IN 01/2001 PUB'
 703 'LICEN/IND ART 6 IN 01/2001 PUB'
 704 'LICEN/CANCELAMENTO LICENCIAMENTO PUB'
 705 'LICEN/BAIXA LICENCIAMENTO ESGOTADO PRAZO'
 706 'LICEN/PLANO APROVEITAMENTO ECON APRES'
 707 'LICEN/PLANO APROVEITAMENTO ECON APROV'
 708 'PLG/RENÚNCIA PLG PROTOCOLIZADA'
 709 'PLG/RENÚNCIA PLG HOMOLOGADA PUBLICADA'
 710 'LICEN/CONSULTA ORGAOS DIVERS ENCAMINHADA'
 711 'LICEN/ASSENT ORGAOS DIVERS AUTORIZADO'
 712 'LICEN/ASSENT ORGAOS DIVERS NAO AUTORIZAD'
 713 'PLG/DECLARA NULIDADE PLG'
 714 'PLG/DECLARA CADUCIDADE PLG'
 715 'PLG/INSTAURA PROCESSO DE CADUCIDADE PLG'
 716 'LICEN/EXIGÊNCIA PUBLICADA'
 719 'LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 720 'LICEN/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZAD'
 721 'LICEN/INDEF NÃO CUMPRIMENTO EXIGENC PUBL'
 722 'LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
 723 'LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADA'
 730 'LICEN/LICENCIAMENTO AUTORIZADO PUBLICADO'
 736 'LICEN/DOCUMENTO DIVERSO PROTOCOLIZADO'
 737 'LICEN/ARREND DIR LICENCIAMENTO PROT'
 738 'LICEN/INDEFERIMENTO ART 18 CM PUBLICADO'
 739 'LICEN/IND LIMINAR ART 1 LEI 6567/78 PUBLIC'
 740 'LICEN/INDEFERIMENTO PUBLICADO'
 741 'LICEN/RETIFICAÇÃO REGISTRO DE LICENÇA PUBLICADA'
 742 'LICEN/PRORROGAÇÃO REGISTRO LICENÇA AUTORIZADA'
 743 'LICEN/REEMBOLSO VISTORIA REALIZADA PROTOC'
 744 'LICEN/INDEFERIMENTO PRORROGAÇÃO REGISTRO LICENÇA'
 745 'LICEN/PEDIDO RECONSIDERAÇÃO PROVIDA PUBL'
 746 'LICEN/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 747 'LICEN/PEDIDO RECONSIDERAÇÃO NEGADO PUBLICADO'
 748 'LICEN/TRANSF DIREITOS -CESSÃO TOTAL PROTOCOL'
 749 'LICEN/TRANSF DIREITOS -CESSÃO TOTAL APROVADA'
 750 'LICEN/TRANSF DIREITOS -CESSÃO TOTAL NEGADA'
 751 'LICEN/BAIXA LICENÇA ESGOTADO PRAZO'
 752 'LICEN/ARREND DEREIT LICENC APROVADO PUBLI'
 753 'LICEN/RECURSO AO MINISTRO PROTOCOLIZADO'
 754 'LICEN/RECURSO PROVIDO PUBLICADO'
 755 'LICEN/PRORROGAÇÃO REGISTRO LICENÇA PROTOCOLIZADA'
 756 'LICEN/DESPACHO DIVERSO PUBLICADO'
 757 'LICEN/RECURSO NEGADO PUBLICADO'
 758 'LICEN/TORNA S/EFEITO NOTIFICAÇÃO CFEM PUB'
 759 'LICEN/RAL ANOS ANTERIORES APRESENTADO'
 760 'LICEN/RAL ANO BASE APRESENTADO'
 761 'LICEN/AUTO INFRAÇÃO PUBLICADO'
 762 'LICEN/AUTO INFRAÇÃO ARQUIVADO PUBLICADO'
 763 'LICEN/RELATÓRIO ART 43 CONSTITUIÇÃO PROT'
 764 'LICEN/NEGA ANUÊNCIA CESSÃO TOTAL PUB'

765 'LICEN'TRANSF DIREITOS -CESSÃO PARCIAL NEGADA'
 766 'LICEN'TORNA S/EFEITO EXIGÊNCIA'
 767 'LICEN'TORNA S/EFEITO BAIXA REGISTRO DE LICENÇA PUBL'
 768 'LICEN'TORNA S/EFEITO PRORROGAÇÃO REGISTRO LICENÇA'
 769 'LICEN'TORNA S/EFEITO DESPACHO INDEFERIMENTO PUB'
 770 'LICEN'ADITAMENTO NOVA SUBST AUTORIZADO PUB'
 771 'LICEN'TORNA S/EFEITO LICENCIAMENTO PUB'
 772 'LICEN'NOTIFICAÇÃO RECOLHIMENTO CFEM PUBL'
 773 'LICEN'MULTA APLICADA PUBLICADA'
 774 'LICEN'ADVERTENCIA APLICADA PUBLICADA'
 775 'LICEN'DENÚNCIA INVASÃO DA ÁREA'
 776 'LICEN'TRANSF DIREITOS -CESSÃO PARCIAL APROVADA'
 777 'LICEN'TORNA S/EFEITO DESPACHO NEG RECONSIDERAÇÃO'
 778 'LICEN'INDEF PLANO ART. 9 IN 05/2000 PUBLIC'
 779 'LICEN'DENÚNCIA C/TIT REG LIC IMPROCEDENTE'
 780 'REQ LICEN'DESISTENCIA REQ LICEN PROTOCOLIZADA'
 781 'LICEN'ARQUIVAMENTO PROCESSO LICENCIAMENTO PUBL'
 782 'LICEN'ÁREA BLOQUEADA ART 42 CM PUB'
 783 'REQ LICEN'DESISTENCIA REQ LICEN HOMOLOGADA PUBL'
 784 'LICEN'RENÚNCIA LICENCIAMENTO HOMOLOGADA PUBLICADA'
 785 'LICEN'TORNO S/EFEI HOMOL DES REQ REG LIC'
 786 'LICEN'ONERAÇÃO DIREITOS -PENHOR AVERBADO'
 787 'LICEN'ENGOLOBAMENTO ÁREAS SOLICITADO'
 788 'LICEN'ENGOLOBAMENTO ÁREAS PUBLICADO'
 789 'REQ LICEN/CESSÃO TOTAL REQ. REGISTRO LICEN. PUB'
 790 'LICEN'OPÇÃO REGIME AUTORIZAÇÃO PESQ PROTOC'
 791 'LICEN'OPÇÃO REGIME AUTORIZAÇÃO PESQ INDEFERIDA'
 792 'REQ PLG DOCUMENTO DIVERSO PROTOCOLIZADO'
 794 'AUT PESQ RELATORIO PESQ POSITIVO APRESENTADO'
 795 'AUT PESQ RELATORIO PESQ NEGATIVO APRESENTADO'
 796 'LICEN'TORNA S/EFEITO CANCELAMENTO DO TÍTULO PUB'
 797 'LICEN'TORNA S/EFEITO LICENCIAMENTO ART 43 CONST'
 798 'LICEN'ÁREA LIVRE 30 DIAS APOS PUBLICA'
 799 'LICEN'CANCELAMENTO LICENCIAMENTO PUBLIC'
 800 'ART 43 CONSTT RELACINADO P/ DISTRITOS'
 801 'DISP 43 ADCT ÁREA LIVRE DATA DA PUBLF'
 802 'REQ LAV'TRANSF DIREITOS -CESSÃO PARCIAL DIREITO REQ LAV NEG'
 803 'AUTO DE PARALISAÇÃO LAVRADO'
 805 'PLG'OPÇÃO REGIME AUTORIZAÇÃO PESQ PROTOC'
 806 'REQ LAV/AUTO INFRAÇÃO PUBLICADO'
 807 'REQ LAV/ARQUIVAMENTO AUTO INFRAÇÃO PUBLICADO'
 808 'REQ LAV/DEFESA PROTOCOLIZADA'
 809 'REQ LAV/DEFESA ACEITA PUBLICADA'
 810 'REQ LAV/DEFESA NÃO ACEITA PUBLICADA'
 811 'REQ LAV/MULTA APLICADA PUBLICADA'
 812 'REQ LAV/PAGAMENTO MULTA EFETUADO'
 813 'REQ LAV/TORNA S/EFEITO MULTA APLICADA'
 820 'REQ EXT/REQUERIMENTO PROTOCOLIZADO'
 821 'REQ EXT/INDEFERIMENTO DE PLANO PUBLICADO'
 822 'REQ EXT/INDEFERIMENTO INTERFERENCIA TOTAL'
 823 'REQ EXT/INDEFERIMENTO ÁREA EM PARQUE NAC EST OU MUN'
 824 'REQ EXT/INDEFERIMENTO ÁREA EM RESERVA BIOLÓGICA'
 825 'REQ EXT/EXIGÊNCIA COM PRAZO DE 30 DIAS PUBLICADA'
 826 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA PROTOCOLIZADO'
 827 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
 828 'REQ EXT/TORNA S/EFEITO EXIGÊNCIA PUBLICADA'
 829 'REQ EXT/CUMPRIMENTO DE EXIGÊNCIA PROTOCOLIZADA'
 830 'REQ EXT/INDEFERIMENTO NÃO CUMPRIMENTO DE EXIGÊNCIA'
 831 'REQ EXT/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 832 'REQ EXT/PEDIDO DE RECONSIDERAÇÃO PROVIDO'
 833 'REQ EXT/PEDIDO DE RECONSIDERAÇÃO NEGADO'
 834 'REQ EXT/TORNA S/EFEITO DESPACHO DE INDEFERIMENTO'
 835 'REQ EXT/RECURSO PROTOCOLIZADO'
 836 'REQ EXT/RECURSO PROVIDO PUBLICADO'
 837 'REQ EXT/RECURSO NEGADO PUBLICADO'
 838 'REQ EXT/DESISTENCIA PROTOCOLIZADA'
 839 'REQ EXT/DESCONSIDERAÇÃO DA DESIST PROTOCOLIZADO'
 840 'REQ EXT/DESISTENCIA HOMOLOGADA PUBLICADO'
 841 'REQ EXT/TORNA S/EFEITO HOMOLOG DA DESISTENCIA'
 842 'REQ EXT/ARQUIVAMENTO PROCESSO PUBLICADO'
 843 'REQ EXT/TORNA S/EFEITO ARQUIVAMENTO PROCESSO'
 844 'REQ EXT/ASSENTIMENTO CDN SOLICITADO'
 845 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA PUBLICADO'
 846 'DISPONIBILIDADE EDITAL DISPONIBIL PRES FORA PRAZO'
 901 'RETIFICA O DESPACHO PUBLICADO EM.'
 902 'DESPACHO 9.01 RETIFICATORIO PUBLIC EM.'
 903 'DECISÃO JUDICIAL PROTOCOLIZADA'
 904 'TORNA S/EFEITO NOTIFICAÇÃO DA MULTA'
 905 'TORNA S/EFEITO NOTIFICAÇÃO DA VISTORIA'
 906 'ARQUIVAMENTO IMPOSIÇÃO MULTA - TAH'
 911 'RELACIONADO P/ INCINERACAO-PUBLICADO EM.'
 912 'PROCESSO DESTRUÍDO CONFORME PDI'
 920 'REQ EXT/REGISTRO DE EXTRAÇÃO 01 ANO PUBLICADO'
 921 'REQ EXT/REGISTRO DE EXTRAÇÃO 02 ANOS PUBLICADO'
 922 'REQ EXT/REGISTRO DE EXTRAÇÃO 03 ANOS PUBLICADO'
 923 'REQ EXT/REGISTRO DE EXTRAÇÃO 04 ANOS PUBLICADO'
 924 'REQ EXT/REGISTRO DE EXTRAÇÃO 05 ANOS PUBLICADO'
 925 'REQ EXT/RAL ANO BASE APRESENTADO'
 926 'REQ EXT/PRORROGAÇÃO DO PRAZO POR 04 ANOS'
 927 'REQ EXT/PRORROGAÇÃO DO PRAZO POR 05 ANOS'
 929 'REQ EXT/RENÚNCIA PROTOCOLIZADA'
 930 'REQ EXT/DESCONSIDERAÇÃO DA RENÚNCIA PROTOCOLIZADO'
 931 'REQ EXT/RENÚNCIA HOMOLOGADA'
 932 'REQ EXT/TORNA S/EFEITO HOMOLOG DA RENÚNCIA'
 933 'REQ EXT/ADITAMENTO DE NOVA SUBST PROTOCOLIZADO'
 935 'REQ EXT/ADITAMENTO DE NOVA SUBST AUTORIZADO'
 936 'REQ EXT/ADITAMENTO DE NOVA SUBST NÃO AUTORIZADO'
 937 'REQ EXT/PRORROGAÇÃO PRAZO REG EXTRAÇÃO SOLICITADO'
 938 'REQ EXT/INDEFERIMENTO PRORROGAÇÃO PRAZO REG EXTRAÇÃO PUB'
 939 'REQ EXT/PRORROGAÇÃO DO PRAZO POR 01 ANO'
 940 'REQ EXT/PRORROGAÇÃO DO PRAZO POR 02 ANOS'
 941 'REQ EXT/PRORROGAÇÃO DO PRAZO POR 03 ANOS'
 942 'REQ EXT/TORNA S/EFEITO PRORROGAÇÃO DO PRAZO'
 943 'REQ EXT/CANCELAMENTO REGISTRO EXTRAÇÃO PUBLICADO'
 944 'REQ EXT/TORNA S/EFEITO CANCELAMENTO DO TÍTULO'
 945 'REQ EXT/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 946 'REQ EXT/PEDIDO RECONSIDERAÇÃO PROVIDO'
 947 'REQ EXT/PEDIDO RECONSIDERAÇÃO NEGADO'
 948 'REQ EXT/RECURSO PROTOCOLIZADO'
 949 'REQ EXT/RECURSO PROVIDO PUBLICADO'
 950 'REQ EXT/RECURSO NEGADO PUBLICADO'
 951 'REQ EXT/ARQUIVAMENTO PROCESSO PUBLICADO'
 952 'REQ EXT/TORNA S/EFEITO ARQUIVAMENTO DO PROCESSO'
 953 'REQ EXT/NOTIFICAÇÃO RECOLHIMENTO CFEM PUB'
 954 'REQ EXT/EXIGÊNCIA PUBLICADA'
 955 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
 956 'REQ EXT/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZADO'
 957 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO PUB'
 958 'REQ EXT/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO PUB'
 960 'PLG'ENGOLOBAMENTO DE ÁREAS'
 961 'PLG'ARQUIVAMENTO DE PROCESSO'
 964 'AUT PESQ'ALVARÁ DE PESQUISA 04 ANOS PUBL'
 965 'AUT PESQ'PRORROGAÇÃO PRAZO 04 ANOS PUB'
 1001 'REQ PESQ'OPÇÃO REGIME PERM LAVRA GARIMP PROT'
 1002 'REQ PESQ'OPÇÃO REGIME PERM LAVRA GARIMP AUTORIZADO'
 1003 'REQ PESQ'OPÇÃO REGIME PERM LAVRA GARIMP INDEFERIDO'
 1004 'REQ PESQ'NÃO CONHECE REQUERIMENTO PUBLICADO'
 1005 'REQ PESQ'DENUNCIA INVASÃO DE ÁREA PROTOCOLIZADA'
 1006 'REQ PESQ'VISTORIA LAVRA ILEGAL'
 1007 'AUT PESQ'PRORROGAÇÃO PRAZO ALV - DESISTENCIA PROT'
 1008 'AUT PESQ'ACORDO C/SUPERFICARIO NÃO REALIZADO PROTOC'
 1009 'AUT PESQ'TRANSF DIREITOS -CESSÃO DIREITOS CANCELADA'
 1010 'AUT PESQ'RAL APRESENTA ART'
 1011 'AUT PESQ'TRANSF DIREITOS -ANÚNCIA CESSÃO DIREITOS CASSADA'
 1012 'AUT PESQ'COMUNICAÇÃO DE ACIDENTE AMBIENTAL PROT'
 1013 'AUT PESQ'COMUNICAÇÃO DE ACIDENTE DE TRABALHO PROT'
 1014 'AUT PESQ'COMUNICAÇÃO DE PRESENCIA DE CAVERNA PROT'
 1015 'AUT PESQ'COMUNICAÇÃO DE PRESENCIA DE FOSSIL PROT'
 1016 'AUT PESQ'CUMPRIMENTO EXIGÊNCIA- DIPEM PROT'
 1017 'AUT PESQ'CUMPRIMENTO EXIGÊNCIA- DIPEM RETIF PROT'
 1018 'AUT PESQ'DESINSTERDIÇÃO TRAB PESQ AUTORIZ PUB'
 1019 'AUT PESQ'EXIGÊNCIA - ENTREGA DIPEM'
 1020 'AUT PESQ'EXIGÊNCIA - ENTREGA DIPEM RETIFICADORA'
 1021 'AUT PESQ'GUIA DE EMBARQUE DE AMOSTRAS PROTOCOLIZADA'
 1022 'AUT PESQ'GUIA UTILIZAÇÃO DEVOLVIDA PROTOCOLIZADA'
 1023 'AUT PESQ'ANÁLISE BACTERIOLÓGICA APRESENTADA'
 1024 'AUT PESQ'ANÁLISE LAMIN PROTOCOLIZADA'
 1025 'AUT PESQ'ESTUDO IN LOCO (LAMIN) PROTOCOLIZADO'
 1026 'AUT PESQ'MULTA NÃO INICIO PESQ COMUNICADO'
 1027 'AUT PESQ'OPÇÃO REGIME PERM LAVRA GARIMP INDEFERIDO'
 1028 'AUT PESQ'RAL NÃO ACEITO PUBLICADO'
 1029 'AUT PESQ'RELATORIO PESQ SOBR NÃO APV ART 30 IV CM'

1030 'AUT PESQ/RELATÓRIO DIPEM PROTOCOLIZADO'
1031 'AUT PESQ/RELATÓRIO DIPEM APROVADO'
1032 'AUT PESQ/RELATÓRIO DIPEM NÃO APROVADO'
1033 'AUT PESQ/TÍTULO REVOGADO PUBLICADO'
1034 'AUT PESQ/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
1035 'AUT PESQ/TORNA S/EFEITO MULTA -INICIO PESQ'
1036 'AUT PESQ/TORNA S/EFEITO NOTIFICAÇÃO CFEM PUB'
1037 'AUT PESQ/VISTORIA LAVRA ILEGAL'
1038 'REQ LAV/TRANSF DIREITOS -CESSÃO DE DIREITOS CANCELADA'
1039 'REQ LAV/ARQUIVAMENTO PROCESSO PUBLICADO'
1040 'REQ LAV/TRANSF DIREITOS -ANUENCIA CESSÃO DIREITOS CASSADA'
1041 'REQ LAV/CUMPRIMENTO EXIGÊNCIA LICENÇA AMBIENTAL PROTOC'
1042 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL REQ LAV PROTOCOL'
1043 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL REQ LAV APROVADA'
1044 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL REQ LAV EFETIVADA'
1045 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL REQ LAV NEGADA'
1046 'AUT PESQ/TRANSF DIREITOS -DISTRATO NÃO ACEITO'
1047 'CONC LAV/TRANSF DIREITOS -DISTRATO NÃO ACEITO'
1048 'LICEN/TRANSF DIREITOS -DISTRATO NÃO ACEITO'
1049 'PLG/TRANSF DIREITOS -DISTRATO NÃO ACEITO'
1050 'REQ LAV/ÁREA DESMEMBRADA EM OUTRAS'
1051 'REQ LAV/REQ PROVENIENTE DESMEMBRAMENTO PROTOC'
1052 'REQ LAV/TRANSF DIREITOS -DISTRATO NÃO ACEITO'
1053 'LICEN/CORREÇÃO DE FASE- ÁREA REQ PESQUISA'
1054 'REQ LAV/EXIGÊNCIA LICENÇA AMBIENTAL PUB'
1055 'REQ LAV/GUIA UTILIZAÇÃO DEVOLVIDA PROT'
1056 'REQ LAV/INDENIZAÇÃO AO PESQUISADOR PROTOCOLIZADA'
1057 'REQ LAV/NÃO CONHECE REQUERIMENTO' PUBLICADO'
1058 'AUT PESQ/TRANSF DIREITOS-CESSÃO PARCIAL DIREITO REQ LAV PROT'
1059 'REQ LAV/OFÍCIO INTIMA P/ DEFESA CAD/NULID'
1060 'REQ LAV/INSTAURA PROC ADM INDEF LEI SNUC' PUBLICADO'
1061 'REQ LAV/ARQUIVAMENTO PROC ADM INDEF - LEI SNUC' PUBL'
1062 'REQ LAV/LICENÇA AMBIENTAL- REGISTRO PROTOCOLO ÓRGÃO'
1063 'REQ LAV/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
1064 'REQ LAV/GUIA UTILIZAÇÃO RENOVAÇÃO SOLICITADA'
1065 'REQ LAV/TORNA S/EFEITO INST PROC ADM CADUCIDADE'
1066 'LICEN/PRORROGAÇÃO INÍCIO LAVRA SOLICITADO'
1067 'REQ LAV/NOTIFICAÇÃO CFEM PUB - TORNA S/EFEITO'
1068 'REQ LAV/VISTORIA LAVRA ILEGAL'
1069 'CONC LAV/COMUNICAÇÃO DE ACIDENTE AMBIENTAL'
1070 'CONC LAV/COMUNICAÇÃO DE ACIDENTE DE TRABALHO'
1071 'CONC LAV/COMUNICAÇÃO DE PRESENÇA DE CAVERNA'
1072 'CONC LAV/COMUNICAÇÃO DE PRESENÇA DE FOSSIL'
1073 'CONC LAV/BALANÇO MINERAL PROTOCOLIZADO'
1074 'CONC LAV/ANÁLISE LAMIN PROTOCOLIZADO'
1075 'CONC LAV/ARRENDAMENTO TOTAL AVERBAÇÃO NEGADA'
1076 'CONC LAV/RAL APRESENTA ART'
1077 'CONC LAV/AUTO INFRAÇÃO ADVERTENCIA PUBLI'
1078 'CONC LAV/AUTO INFRAÇÃO MULTA PUBLICADA'
1079 'CONC LAV/TRANSF DIREITOS -ANUENCIA CESSÃO CASSADA'
1080 'CONC LAV/COBRANCA JUDICIAL DE MULTA PUB'
1081 'CONC LAV/COMUNICAÇÃO OCORR OUTRA SUBSTANCIA PROTOCOLIZADO'
1082 'CONC LAV/CONSORCIO MINERAÇÃO - INCLUSÃO ÁREA PROTOCOL'
1083 'CONC LAV/DESMEMBRAMENTO DE ÁREA APROVADO'
1084 'CONC LAV/DESMEMBRAMENTO DE ÁREA NEGADO'
1085 'CONC LAV/DESMEMBRAMENTO DE ÁREA PROTOC'
1086 'CONC LAV/DESMEMBRAMENTO INICIATIVA - DNP/PM PUB'
1087 'CONC LAV/ASSENTIMENTO CDN/ARRENDAMENTO ENCAMINHADO'
1088 'CONC LAV/ASSENTIMENTO CDN/ARRENDAMENTO AUTORIZADO'
1089 'CONC LAV/ASSENTIMENTO CDN/ARRENDAMENTO NEGADO'
1090 'CONC LAV/VISTORIA IN LOCO'
1091 'CONC LAV/GUIA UTILIZAÇÃO DEVOLVIDA PROTOCOLIZADA'
1092 'CONC LAV/ENLOBAMENTO DE ÁREAS NEGADO PUB'
1093 'CONC LAV/ENLOBAMENTO DE ÁREAS PROTOCOLIZADO'
1094 'CONC LAV/ESTUDO IN LOCO (LAMIN) PROTOCOLIZADO'
1095 'CONC LAV/GUIA UTILIZAÇÃO AUTORIZADA PUBLICADA'
1096 'CONC LAV/GUIA UTILIZAÇÃO INDEFERIDA PUBLICADA'
1097 'CONC LAV/GUIA UTILIZAÇÃO REQUERIMENTO PROTOC'
1098 'CONC LAV/LIBERAÇÃO ONERAÇÃO DIREITOS AVERBADO'
1099 'CONC LAV/LIBERAÇÃO ONERAÇÃO DIREITOS PUBLICADO'
1100 'CONC LAV/PAGAMENTO MULTA MISSÃO DE POSSE PROTOC'
1101 'CONC LAV/NÃO CONHECE REQUERIMENTO' PUBLICADO'
1102 'CONC LAV/OFÍCIO DE INTIMAÇÃO DE DESMEMBRAMENTO PUB'
1103 'CONC LAV/OFÍCIO INTIMA P/ DEFESA CAD/NULID' PUBLICADO'
1104 'CONC LAV/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
1105 'CONC LAV/RELATÓRIO PESQ NOVA SUBSTANCIA PROTOCOLIZADO'
1106 'CONC LAV/RELATÓRIO PESQ NOVA SUBSTANCIA APROVADO'
1107 'CONC LAV/RELATÓRIO PESQ NOVA SUBSTANCIA NÃO APROVADO'
1108 'CONC LAV/ONERAÇÃO DIREITOS LAVRA PROTOCOLIZADA'
1109 'CONC LAV/GUIA UTILIZAÇÃO RENOVAÇÃO PROTOCOLIZADA'
1110 'CONC LAV/OFÍCIO DE INTIMAÇÃO DE DESMEMB. TORNA S/ EFEITO'
1111 'CONC LAV/VISTORIA LAVRA ILEGAL'
1112 'CONC LAV/CUMPRIMENTO INTIMAÇÃO DESMEMBRAMENTO APROVADO'
1113 'CONC LAV/CUMPRIMENTO INTIMAÇÃO DESMEMBRAMENTO FORA DO PRAZO'
1114 'CONC LAV/CUMPRIMENTO INTIMAÇÃO DESMEMBRAMENTO NEGADO'
1115 'CONC LAV/CUMPRIMENTO INTIMAÇÃO DESMEMBRAMENTO PROTOC'
1116 'DISPONIB/NÃO CONHECE REQUERIMENTO HABILITAÇÃO'
1117 'DISPONIB/HOMOLOGA DESIST HABIL EDIT DISP LAVRA PUB'
1118 'LICEN/PRORROGAÇÃO INÍCIO LAVRA AUTORIZADO'
1119 'DISPONIB/DESISTÊNCIA HABILIT EDITAL DISP PESQ PROTOC'
1120 'DISPONIB/DESISTÊNCIA HABILIT EDITAL DISP LAVRA PROTOC'
1121 'LICEN/PRORROGAÇÃO INÍCIO LAVRA NAO AUTORIZADO'
1122 'DISPONIB/ANULA DECLARAÇÃO PRIOR EDITAL LAVRA PUBLI'
1123 'DISPONIB/CONSID PRIORITARIO- EDITAL PLG PUBLI'
1124 'DISPONIB/INDEF HABILIT EDIT DISPONIB ÁREA PLG PUB'
1125 'DISPONIB/HABILIT EDITAL DISPONIB ÁREA PLG PROT'
1126 'DISPONIB/TORNA S/EFEITO EDITAL DISPONIB -ÁREA PLG'
1127 'REQ EXT/ÁREA BLOQUEADA ART 42 CM PUBLIC'
1128 'REQ EXT/ÁREA BLOQUEADA-INUNDACAO PUB'
1129 'REQ EXT/ASSENTIMENTO CDN AUTORIZADO'
1130 'REQ EXT/ASSENTIMENTO CDN NEGADO'
1131 'REQ EXT/DENÚNCIA C/REQUERENTE PROTOCOLI'
1132 'REQ EXT/NÃO CONHECE REQUERIMENTO PUBLICADO'
1133 'REQ EXT/PROCESSO SITUADO EM ÁREA BLOQUEADA'
1134 'REQ EXT/PROCESSO SITUADO EM ÁREA INDÍGENA'
1135 'REQ EXT/DENÚNCIA INVASÃO DE ÁREA PROTOCOLIZADA'
1136 'REQ EXT/DESPACHO DIVERSO PUBLICADO'
1137 'REQ EXT/VISTORIA LAVRA ILEGAL'
1138 'REQ EXT/COMUNICAÇÃO DE ACIDENTE AMBIENTAL PROTOCOLIZADO'
1139 'REQ EXT/COMUNICAÇÃO DE ACIDENTE DE TRABALHO PROTOCOLIZADO'
1140 'REQ EXT/COMUNICAÇÃO DE PRESENÇA DE CAVERNA PROTOCOLIZADO'
1141 'REQ EXT/COMUNICAÇÃO DE PRESENÇA DE FOSSIL PROTOCOLIZADO'
1142 'REQ EXT/RAL APRESENTA ART'
1143 'REQ EXT/TORNA S/EFEITO NOTIFICAÇÃO CFEM PUB'
1144 'REQ LICEN/PROCESSO LOCALIZADO EM FAIXA DE FRONTEIRA'
1145 'REQ LICEN/ÁREA BLOQUEADA ART 42 CM PUBLIC'
1146 'REQ LICEN/ÁREA BLOQUEADA-INUNDACAO PUB'
1147 'REQ LICEN/ARQUIVAMENTO PROCESSO PUBLICADO'
1148 'REQ LICEN/AUTO DE PARALISAÇÃO LAVRADO'
1149 'REQ LICEN/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZAD'
1150 'REQ LICEN/DECISÃO JUDICIAL PROTOCOLIZADA'
1151 'REQ LICEN/DENÚNCIA C/REQUERENTE PROTOCOLI'
1152 'REQ LICEN/DENÚNCIA INVASÃO DE ÁREA PROTOCOLIZADO'
1153 'REQ LICEN/DESPACHO DIVERSO PUBLICADO'
1154 'REQ LICEN/DOCUMENTO DIVERSO PROTOCOLIZADO'
1155 'REQ LICEN/EXIGÊNCIA PUBLICADA'
1156 'REQ LICEN/NÃO CONHECE REQUERIMENTO PUBLICADO'
1157 'REQ LICEN/OPÇÃO REGIME AUTORIZAÇÃO PESQ INDEFERIDA'
1158 'REQ LICEN/OPÇÃO REGIME AUTORIZAÇÃO PESQ AUTORIZADA'
1159 'REQ LICEN/OPÇÃO REGIME AUTORIZAÇÃO PESQ PROTOCOLIZADO'
1160 'REQ LICEN/PEDIDO RECONSIDERAÇÃO NEGADO PUB'
1161 'REQ LICEN/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
1162 'REQ LICEN/PEDIDO RECONSIDERAÇÃO PROVIDA PUBLI'
1163 'REQ LICEN/PROCESSO SITUADO EM ÁREA BLOQUEADA'
1164 'REQ LICEN/PROCESSO SITUADO EM ÁREA INDÍGENA'
1165 'REQ LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADA'
1166 'REQ LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
1167 'REQ LICEN/PROTOCOLO ÓRGÃO AMBIENTAL PROTOCOLIZADO'
1168 'REQ LICEN/RECONSTITUIÇÃO DE PROCESSO AUTORIZADA'
1169 'REQ LICEN/RECURSO PROTOCOLIZADO'
1170 'REQ LICEN/RECURSO NEGADO PUBLICADO'
1171 'REQ LICEN/RECURSO PROVIDO PUBLICADO'
1172 'REQ LICEN/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
1173 'REQ LICEN/TORNA S/EFEITO ARQUIVAMENTO PROCESSO'
1174 'REQ LICEN/VISTORIA LAVRA ILEGAL'
1175 'LICEN/ADITAMENTO NOVA SUBST NÃO AUTORIZADO PUB'
1176 'LICEN/ADITAMENTO NOVA SUBST PROTOCOLIZADO'
1177 'LICEN/TRANSF DIREITOS -CESSÃO DE DIREITOS CANCELADA'
1178 'LICEN/ARQUIVAMENTO PROC ADM CANCELAMENTO REG LICEN'
1179 'LICEN/AUTO INFRAÇÃO ADVERTENCIA PUBLI'
1180 'LICEN/AUTO INFRAÇÃO MULTA PUBLICADA'
1181 'LICEN/TRANSF DIREITOS -CESSÃO PARCIAL EFETIVADA'

1182 'LICEN/TRANSF DIREITOS -CESSÃO PARCIAL PROTOCOL'
 1183 'LICEN/ONERAÇÃO DIREITOS -PENHORA CANCELADA'
 1184 'LICEN/ONERAÇÃO DIREITOS -PENHORA CANCELAMENTO AVERBADO'
 1185 'LICEN/TRANSF DIREITOS -ANÚNCIA CESSÃO CASSADA'
 1186 'LICEN/COBRANCA JUDICIAL DE MULTA'
 1187 'LICEN/COMUNICAÇÃO DE ACIDENTE AMBIENTAL PROTOCOLIZADO'
 1188 'LICEN/COMUNICAÇÃO DE ACIDENTE DE TRABALHO PROTOCOLIZADO'
 1189 'LICEN/COMUNICAÇÃO DE PRESENÇA DE CAVERNA PROTOCOLIZADO'
 1190 'LICEN/COMUNICAÇÃO DE PRESENÇA DE FOSSIL PROTOCOLIZADO'
 1191 'LICEN/COMUNICAÇÃO OCORR OUTRA SUBSTANCIA PROTOCOLIZADO'
 1192 'LICEN/DEFESA ACEITA PUBLICADA'
 1193 'LICEN/DEFESA NÃO ACEITA PUBLICADA'
 1194 'LICEN/DEFESA PROTOCOLIZADA'
 1195 'LICEN/DENÚNCIA CONTRA TITULAR PROTOCOLIZADA'
 1196 'LICEN/DESINTERDIÇÃO LAVRA AUTORIZ PUB'
 1197 'LICEN/ENGOBAMENTO DE ÁREAS NEGADO'
 1198 'LICEN/COMUNICAÇÃO INICIO DE LAVRA PROTOCOLIZADA'
 1199 'LICEN/INTERDIÇÃO DA LAVRA PUBLICADA'
 1200 'LICEN/ONERAÇÃO DIREITOS -PENHORA AUTORIZADO'
 1201 'LICEN/PAGAMENTO DE MULTA EFETUADO'
 1202 'LICEN/NÃO CONHECE REQUERIMENTO PUBLICADO'
 1203 'LICEN/SUSPENSÃO TRABALHOS LAVRA AUTORIZADO PUBL'
 1204 'LICEN/SUSPENSÃO TRABALHOS LAVRA NEGADO PUBL'
 1205 'LICEN/SUSPENSÃO TRABALHOS LAVRA SOLICITADO'
 1206 'LICEN/PLANO DE LAVRA PROTOCOLIZADO'
 1207 'LICEN/REDUÇÃO DE ÁREA APROVADA'
 1208 'LICEN/REDUÇÃO DE ÁREA NEGADA'
 1209 'LICEN/REDUÇÃO DE ÁREA SOLICITADA'
 1210 'LICEN/RENÚNCIA LICENCIAMENTO PROTOCOLIZADO'
 1211 'LICEN/RETIFICAÇÃO REGISTRO DE LICENÇA NEGADA'
 1212 'LICEN/RETIFICAÇÃO REGISTRO DE LICENÇA APROVADA'
 1213 'LICEN/RETIFICAÇÃO REGISTRO DE LICENÇA REQUERIDA'
 1214 'LICEN/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
 1215 'LICEN/VISTORIA LAVRA ILEGAL'
 1216 'LICEN/VISTORIA LAVRA IRREGULARIDADES'
 1217 'REQ PLG/DECLARAÇÃO DE APTIDÃO EMITIDA'
 1218 'REQ PLG/ÁREA BLOQUEADA ART 42 CM PUBLICADO'
 1219 'REQ PLG/DENÚNCIA CONTRA REQUERENTE PROTOCOLIZADO'
 1220 'REQ PLG/NÃO CONHECE REQUERIMENTO PUBLICADO'
 1221 'REQ PLG/RECURSO AO MINISTRO PROTOCOLIZADO'
 1222 'REQ PLG/RECURSO NEGADO PUBLICADO'
 1223 'REQ PLG/RECURSO PROVIDO PUBLICADO'
 1224 'REQ PLG/VISTORIA LAVRA ILEGAL'
 1225 'PLG/COMUNICAÇÃO DE ACIDENTE AMBIENTAL'
 1226 'PLG/COMUNICAÇÃO DE ACIDENTE DE TRABALHO'
 1227 'PLG/COMUNICAÇÃO DE PRESENÇA DE CAVERNA'
 1228 'PLG/COMUNICAÇÃO DE PRESENÇA DE FOSSIL'
 1229 'PLG/ADVERTENCIA APLICADA PUBLICADA'
 1230 'PLG/TRANSF DIREITOS -CESSÃO DE DIREITOS CANCELADA'
 1231 'PLG/ÁREA BLOQUEADA ART 42 CM PUBLIC'
 1232 'PLG/RAL APRESENTA ART'
 1233 'PLG/AUTO INSCRIÇÃO ADVERTENCIA PUBLI'
 1234 'PLG/TRANSF DIREITOS -ANÚNCIA CESSÃO CASSADA'
 1235 'PLG/COBRANCA JUDICIAL DE MULTA'
 1236 'PLG/COMUNICAÇÃO OCORR OUTRA SUBSTANCIA'
 1237 'PLG/DEFESA ACEITA PUBLICADA'
 1238 'PLG/DEFESA NÃO ACEITA PUBLICADA'
 1239 'PLG/DEFESA PROTOCOLIZADA'
 1240 'PLG/DENÚNCIA CONTRA TITULAR PROTOCOLIZADA'
 1241 'PLG/DESINTERDIÇÃO LAVRA AUTORIZ PUB'
 1242 'PLG/ENGOBAMENTO DE ÁREAS NEGADO'
 1243 'PLG/TÍTULO ENGOBADO POR OUTRO TÍTULO'
 1244 'PLG/ENGOBAMENTO DE ÁREAS PROTOCOLIZADO'
 1245 'PLG/COMUNICAÇÃO DE INICIO DE LAVRA PROTOCOLIZADO'
 1246 'PLG/INSTAURA PROC ADM CANCELAMENTO PLG'
 1247 'PLG/INTERDIÇÃO DA LAVRA PUBLICADA'
 1248 'PLG/NÃO CONHECE REQUERIMENTO PUBLICADO'
 1249 'PLG/NOTIFICAÇÃO RECOLHIMENTO CFEM PUBL'
 1250 'PLG/OPÇÃO REGIME AUTORIZAÇÃO PESQ INDEFERIDO'
 1251 'PLG/PEDIDO RECONSIDERAÇÃO PROTOCOLIZADO'
 1252 'PLG/PEDIDO RECONS NEGADO PUB'
 1253 'PLG/PEDIDO RECONS PROVIDO PUB'
 1254 'PLG/PEDIDO SUSPENSÃO LAV AUTORIZ PUBL'
 1255 'PLG/PEDIDO SUSPENSÃO LAV NEGADO PUBL'
 1256 'PLG/PEDIDO SUSPENSÃO LAVRA PROTOCOL'
 1257 'PLG/ARQUIVAMENTO PROC ADM CAD/NUL PLG PUBL'
 1258 'PLG/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
 1259 'PLG/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDEIDA'
 1260 'PLG/RAL ANOS ANTERIORES APRESENTADO'
 1261 'PLG/RECURSO AO MINISTRO PROTOCOLIZADO'
 1262 'PLG/RECURSO NEGADO PUBLICADO'
 1263 'PLG/RECURSO PROVIDO PUBLICADO'
 1264 'PLG/RETIFICAÇÃO PLG NEGADA'
 1265 'PLG/RETIFICAÇÃO PLG AUTORIZADA'
 1266 'PLG/RETIFICAÇÃO PLG PROTOCOLIZADA'
 1267 'PLG/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
 1268 'PLG/RETIFICAÇÃO COORDENADA SOLICITADA'
 1269 'PLG/DENÚNCIA INVASÃO DA ÁREA'
 1270 'PLG/TORNA S/EFEITO INST PROC ADM NULIDADE'
 1271 'PLG/VISTORIA LAVRA IRREGULARIDADES'
 1272 'LICEN/TÍTULO ENGOBADO POR OUTRO TÍTULO'
 1273 'AUT PESQ/REDUÇÃO DE ÁREA PROTOCOLIZADO'
 1274 'REQ PESQ/REQ PROVENIENTE DE CESSÃO PARCIAL PROTOCOLIZADO'
 1275 'REQ LAV/REQ PROVENIENTE DE CESSÃO PARCIAL PROTOCOLIZADO'
 1276 'REQ PLG/REQ PROVENIENTE DE CESSÃO PARCIAL PROTOCOLIZADO'
 1277 'REQ LICEN/REQ PROVENIENTE DE CESSÃO PARCIAL PROTOCOLIZADO'
 1278 'CONC LAV/PROVENIENTE DE ARRENDAMENTO PARCIAL PROTOCOLIZADO'
 1279 'CONC LAV/PROVENIENTE DE ARRENDAMENTO TOTAL PROTOCOLIZADO'
 1280 'REQ LAV/RETIFICAÇÃO DA APROVAÇÃO RELATÓRIO FINAL PUB'
 1281 'REQ LICEN/INDEFERIMENTO SEM ONERAÇÃO PORT 266/2008'
 1282 'REQ LICEN/INDEFERIMENTO COM ONERAÇÃO PORT 266/2008'
 1283 'REQ LICEN/DECLARAÇÃO DE APTIDÃO EMITIDA'
 1284 'REQ LICEN/TORNA S/EFEITO EXIGÊNCIA'
 1285 'LICEN/OPÇÃO REGIME AUTORIZAÇÃO PESQ AUTORIZADA'
 1286 'LICEN/INSTAURA PROC ADM NULIDADE REGISTRO LICENÇA'
 1287 'LICEN/INSTAURA PROC ADM CASSAÇÃO REGISTRO LICENÇA'
 1288 'LICEN/REGISTRO DE LICENÇA ANULADO'
 1289 'LICEN/REGISTRO DE LICENÇA CASSADO'
 1290 'LICEN/ARQUIVAMENTO PROC ADM NULIDADE REGISTRO LICENÇA'
 1291 'LICEN/ARQUIVAMENTO PROC ADM CASSAÇÃO REGISTRO LICENCIAMENTO'
 1292 'LICEN/TORNA S/EFEITO CASSAÇÃO REGISTRO DE LICENÇA PUBLI'
 1293 'LICEN/NOTIFICAÇÃO ADMINISTRATIVA ENCAMINHADA'
 1294 'REQ PLG/VISTORIA IN LOCO'
 1295 'REQ PLG/ASSENTIMENTO CDN AUTORIZADO'
 1296 'REQ PLG/ASSENTIMENTO CDN NEGADO'
 1297 'REQ PLG/ASSENTIMENTO CDN SOLICITADO'
 1298 'PLG/TORNA S/EFEITO EXIGÊNCIA PUBLIC'
 1299 'PLG/OPÇÃO REGIME AUTORIZAÇÃO PESQ AUTORIZADO'
 1300 'CONC LAV/ARRENDAMENTO PRORROGAÇÃO PROTOCOLIZADO'
 1301 'CONC LAV/ARRENDAMENTO PRORROGAÇÃO AUTORIZADA'
 1302 'CONC LAV/ARRENDAMENTO PRORROGAÇÃO NEGADA'
 1303 'CONC LAV/ARRENDAMENTO DESISTÊNCIA PROTOCOLIZADA'
 1304 'CONC LAV/ARRENDAMENTO -RELATÓRIO ESTADO DA MINA PROTOCOLIZADO'
 1305 'REQ EXT/BAIXA TRANSCRIÇÃO DO REGISTRO EXTRAÇÃO'
 1306 'REQ PESQ/BLOQUEIO TEMPORARIO'
 1307 'AUT PESQ/BLOQUEIO TEMPORARIO'
 1308 'REQ LAV/BLOQUEIO TEMPORARIO'
 1309 'CONC LAV/BLOQUEIO TEMPORARIO'
 1310 'REQ PLG/BLOQUEIO TEMPORARIO'
 1311 'PLG/BLOQUEIO TEMPORARIO'
 1312 'LICEN/BLOQUEIO TEMPORARIO'
 1313 'DISPONIB/BLOQUEIO TEMPORARIO'
 1314 'MANF/BLOQUEIO TEMPORARIO'
 1315 'DISPONIB/PROPOSTA ÚNICA - EDITAL ENCERRADO'
 1316 'REQ EXT/BLOQUEIO TEMPORARIO'
 1317 'REQ EXT/BLOQUEIO TEMPORARIO'
 1318 'REQ LICEN/BLOQUEIO TEMPORARIO'
 1319 'LICEN/OFÍCIO INTIMA P/ DEFESA'
 1320 'LICEN/TRANSF DIREITOS -DISTRATO PROTOCOLIZADO'
 1321 'LICEN/TORNA S/EFEITO DESPACHO NULIDADE DO TÍTULO'
 1322 'PLG/TORNA S/EFEITO INST PROC ADM'
 1323 'PLG/OFÍCIO INTIMA P/ DEFESA'
 1324 'PLG/ARQUIVAMENTO PROC ADM CANCELAMENTO PUBI'
 1325 'PLG/INSTAURA PROC ADM NULIDADE PLG PUBLI'
 1326 'PLG/TORNA S/EFEITO DESP CANCEL DO TÍTULO'
 1327 'PLG/TORNA S/EFEITO DESP NULID DO TÍTULO'
 1328 'PLG/TORNA S/EFEITO INST PROC ADM'
 1329 'REQ EXT/ARQUIVAMENTO PROC ADM CANCELAMENTO'
 1330 'REQ EXT/DESPACHO DECL NULID REG EXTRAÇÃO PUBI'
 1331 'REQ EXT/INSTAURA PROC ADM CANCELAMENTO REG EXTRAÇÃO'
 1332 'REQ EXT/OFÍCIO INTIMA P/ DEFESA'
 1333 'REQ EXT/ARQUIVAMENTO PROC ADM NULIDADE REG EXTRAÇÃO PUBI'

1334 'REG EXT/INSTAURA PROC ADM NULIDADE REG EXTRAÇÃO PUB'
 1335 'REG EXT/TORNA S/ EFEITO DESP NULID DO TITULO'
 1336 'REG EXT/TORNA S/EFEITO INST PROC ADM'
 1337 'CONC LAV/ANALISE BACTERIOLÓGICA APRESENTADA'
 1338 'CONC LAV/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
 1339 'REQ PLG/INDEFERIMENTO POR INTERFERENCIA TOTAL'
 1340 'REQ PESQ/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1341 'AUT PESQ/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1342 'REQ LICEN/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1343 'LICEN/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1344 'REQ PLG/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1345 'PLG/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1346 'REG EXT/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1347 'REG EXT/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1348 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA REQ PESQ'
 1349 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA AUT PESQ'
 1350 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA REQ LICEN'
 1351 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA LICEN'
 1352 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA REQ PLG'
 1353 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA PLG'
 1354 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA REQ EXT'
 1355 'DISPONIB/TORNA S/EFEITO DISPONIB ART 26- ÁREA REG EXT'
 1356 'REQ PESQ/RECURSO PROTOCOLIZADO'
 1357 'REQ PESQ/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1358 'REQ PESQ/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1359 'AUT PESQ/RECURSO AO MINISTRO PROTOCOLIZADO'
 1360 'AUT PESQ/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1361 'AUT PESQ/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1362 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL DIREITO REQ LAV APRV'
 1363 'REQ LAV/TRANSF DIREITOS -CESSÃO PARCIAL DIREITO REQ LAV EFET'
 1364 'REQ LAV/TRANSF DIREITOS -DISTRATO PROTOCOLIZADO'
 1365 'CONC LAV/RECURSO AO MINISTRO PROTOCOLIZADO'
 1366 'CONC LAV/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1367 'CONC LAV/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1368 'REQ LICEN/RECURSO AO MINISTRO PROTOCOLIZADO'
 1369 'REQ LICEN/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1370 'REQ LICEN/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1371 'LICEN/RECURSO PROTOCOLIZADO'
 1372 'LICEN/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1373 'LICEN/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1374 'REQ PLG/RECURSO PROTOCOLIZADO'
 1375 'REQ PLG/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1376 'REQ PLG/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1377 'PLG/RECURSO PROTOCOLIZADO'
 1378 'PLG/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1379 'PLG/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1380 'REQ EXT/RECURSO AO MINISTRO PROTOCOLIZADO'
 1381 'REQ EXT/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1382 'REQ EXT/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1383 'REG EXT/RECURSO AO MINISTRO PROTOCOLIZADO'
 1384 'REG EXT/RECURSO AO MINISTRO NEGADO PUBLICADO'
 1385 'REG EXT/RECURSO AO MINISTRO PROVIDO PUBLICADO'
 1386 'REQ PESQ/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1387 'AUT PESQ/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1388 'REQ LAV/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1389 'CONC LAV/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1390 'REQ LICEN/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1391 'LICEN/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1392 'REQ PLG/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1393 'PLG/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1394 'REQ EXT/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1395 'REG EXT/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 1396 'REQ PESQ/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1397 'AUT PESQ/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1398 'REQ LAV/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1399 'CONC LAV/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1400 'REQ LICEN/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1401 'LICEN/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1402 'REQ PLG/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1403 'PLG/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1404 'REQ EXT/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1405 'REG EXT/LICENÇA AMBIENTAL PROTOCOLIZADA'
 1406 'AUT PESQ/ONERAÇÃO DIREITOS -PENHORA PROTOCOLIZADO'
 1407 'AUT PESQ/AUTO INFRAÇÃO MULTA INICIO PESQ NÃO COMUNICADO'
 1408 'AUT PESQ/ONERAÇÃO DIREITOS -PENHORA NEGADO'
 1409 'AUT PESQ/TORNA S/EFEITO AUTO INFRAÇÃO -INICIO DE PESQ'
 1410 'AUT PESQ/LIBERAÇÃO PENHORA PROTOCOLIZADO'
 1411 'AUT PESQ/LIBERAÇÃO PENHORA APROVADO'
 1412 'AUT PESQ/LIBERAÇÃO PENHORA NEGADO'
 1413 'AUT PESQ/LIBERAÇÃO PENHORA AVERBADO'
 1414 'CONC LAV/ONERAÇÃO DIREITOS -PENHORA PROTOCOLIZADO'
 1415 'REQ LICEN/TORNA S/EFEITO DESPACHO PUBLICADO'
 1416 'CONC LAV/ONERAÇÃO DIREITOS -PENHORA NEGADO'
 1417 'LICEN/TORNA S/EFEITO DESPACHO PUBLICADO'
 1418 'CONC LAV/LIBERAÇÃO PENHORA PROTOCOLIZADO'
 1419 'CONC LAV/LIBERAÇÃO PENHORA APROVADO(A)'
 1420 'CONC LAV/LIBERAÇÃO PENHORA NEGADO'
 1421 'CONC LAV/LIBERAÇÃO PENHORA AVERBADO'
 1422 'LICEN/ONERAÇÃO DIREITOS -PENHOR PROTOCOLIZADO'
 1423 'LICEN/ONERAÇÃO DIREITOS -PENHOR APROVADO(A)'
 1424 'LICEN/ONERAÇÃO DIREITOS -PENHOR NEGADO'
 1425 'LICEN/TRANSF DIREITOS -CESSÃO DE DIREITOS ANULADA'
 1426 'LICEN/ONERAÇÃO DIREITOS -CAUÇÃO PROTOCOLIZADO'
 1427 'LICEN/ONERAÇÃO DIREITOS -CAUÇÃO APROVADO(A)'
 1428 'LICEN/ONERAÇÃO DIREITOS -CAUÇÃO NEGADO'
 1429 'LICEN/ONERAÇÃO DIREITOS -CAUÇÃO AVERBADO'
 1430 'LICEN/ONERAÇÃO DIREITOS -HIPOTECA PROTOCOLIZADO'
 1431 'LICEN/ONERAÇÃO DIREITOS -HIPOTECA APROVADO(A)'
 1432 'LICEN/ONERAÇÃO DIREITOS -HIPOTECA NEGADO'
 1433 'LICEN/ONERAÇÃO DIREITOS -HIPOTECA AVERBADO'
 1434 'LICEN/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO PROTOCOLIZADO'
 1435 'LICEN/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO APROVADO(A)'
 1436 'LICEN/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO NEGADO'
 1437 'LICEN/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO AVERBADO'
 1438 'LICEN/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO PROTOC'
 1439 'LICEN/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO APROV'
 1440 'LICEN/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO NEGADO'
 1441 'LICEN/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO AVERBADO'
 1442 'LICEN/LIBERAÇÃO PENHOR PROTOCOLIZADO'
 1443 'LICEN/LIBERAÇÃO PENHOR APROVADO(A)'
 1444 'LICEN/LIBERAÇÃO PENHOR NEGADO'
 1445 'LICEN/LIBERAÇÃO PENHOR AVERBADO'
 1446 'LICEN/LIBERAÇÃO CAUÇÃO PROTOCOLIZADO'
 1447 'LICEN/LIBERAÇÃO CAUÇÃO APROVADO(A)'
 1448 'LICEN/LIBERAÇÃO CAUÇÃO NEGADO'
 1449 'LICEN/LIBERAÇÃO CAUÇÃO AVERBADO'
 1450 'LICEN/LIBERAÇÃO HIPOTECA PROTOCOLIZADO'
 1451 'LICEN/LIBERAÇÃO HIPOTECA APROVADO(A)'
 1452 'LICEN/LIBERAÇÃO HIPOTECA NEGADO'
 1453 'LICEN/LIBERAÇÃO CÉDULA CRÉDITO PROTOCOLIZADO'
 1454 'LICEN/LIBERAÇÃO CÉDULA CRÉDITO APROVADO(A)'
 1455 'LICEN/LIBERAÇÃO CÉDULA CRÉDITO NEGADO'
 1456 'LICEN/LIBERAÇÃO CÉDULA CRÉDITO AVERBADO'
 1458 'LICEN/LIBERAÇÃO CONTRATO DE FINANCIAMENTO PROTOCOLIZADO'
 1459 'LICEN/LIBERAÇÃO CONTRATO DE FINANCIAMENTO APROVADO(A)'
 1460 'LICEN/LIBERAÇÃO CONTRATO DE FINANCIAMENTO NEGADO'
 1461 'LICEN/LIBERAÇÃO CONTRATO DE FINANCIAMENTO AVERBADO'
 1462 'CONC LAV/ONERAÇÃO DIREITOS -PENHOR PROTOCOLIZADO'
 1463 'CONC LAV/ONERAÇÃO DIREITOS -PENHOR APROVADO'
 1464 'CONC LAV/ONERAÇÃO DIREITOS -PENHOR NEGADO'
 1465 'CONC LAV/ONERAÇÃO DIREITOS -PENHOR AVERBADO'
 1466 'CONC LAV/ONERAÇÃO DIREITOS -CAUÇÃO PROTOCOLIZADO'
 1467 'CONC LAV/ONERAÇÃO DIREITOS -CAUÇÃO APROVADO'
 1468 'CONC LAV/ONERAÇÃO DIREITOS -CAUÇÃO NEGADO'
 1469 'CONC LAV/ONERAÇÃO DIREITOS -CAUÇÃO AVERBADO'
 1470 'CONC LAV/ONERAÇÃO DIREITOS -HIPOTECA PROTOCOLIZADO'
 1471 'CONC LAV/ONERAÇÃO DIREITOS -HIPOTECA APROVADO'
 1472 'CONC LAV/ONERAÇÃO DIREITOS -HIPOTECA NEGADO'
 1473 'CONC LAV/ONERAÇÃO DIREITOS -HIPOTECA AVERBADO'
 1474 'CONC LAV/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO PROTOCOL'
 1475 'CONC LAV/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO APROVADA'
 1476 'CONC LAV/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO NEGADA'
 1477 'CONC LAV/ONERAÇÃO DIREITOS -CÉDULA CRÉDITO AVERBADA'
 1478 'CONC LAV/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO PROTO'
 1479 'CONC LAV/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO APROV'
 1480 'CONC LAV/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO NEGAD'
 1481 'CONC LAV/ONERAÇÃO DIREITOS -CONTRATO FINANCIAMENTO AVERB'
 1482 'CONC LAV/LIBERAÇÃO PENHOR PROTOCOLIZADO'
 1483 'CONC LAV/LIBERAÇÃO PENHOR APROVADO(A)'
 1484 'CONC LAV/LIBERAÇÃO PENHOR NEGADO'
 1485 'CONC LAV/LIBERAÇÃO PENHOR AVERBADO'

1486 'CONC LAV/LIBERAÇÃO CAUÇÃO PROTOCOLIZADO'
 1487 'CONC LAV/LIBERAÇÃO CAUÇÃO APROVADO(A)'
 1488 'CONC LAV/LIBERAÇÃO CAUÇÃO NEGADO'
 1489 'CONC LAV/LIBERAÇÃO CAUÇÃO AVERBADO'
 1490 'CONC LAV/LIBERAÇÃO HIPOTECA PROTOCOLIZADO'
 1491 'CONC LAV/LIBERAÇÃO HIPOTECA APROVADO(A)'
 1492 'CONC LAV/LIBERAÇÃO HIPOTECA NEGADO'
 1493 'CONC LAV/LIBERAÇÃO HIPOTECA AVERBADO'
 1494 'CONC LAV/LIBERAÇÃO CÉDULA CRÉDITO PROTOCOLIZADO'
 1495 'CONC LAV/LIBERAÇÃO CÉDULA CRÉDITO APROVADO(A)'
 1496 'CONC LAV/LIBERAÇÃO CÉDULA CRÉDITO NEGADO'
 1497 'CONC LAV/LIBERAÇÃO CÉDULA CRÉDITO AVERBADO'
 1498 'CONC LAV/LIBERAÇÃO CONTRATO FINANCIAMENTO PROTOCOLIZADO'
 1499 'CONC LAV/LIBERAÇÃO CONTRATO FINANCIAMENTO APROVADO'
 1500 'CONC LAV/LIBERAÇÃO CONTRATO FINANCIAMENTO NEGADO'
 1501 'CONC LAV/LIBERAÇÃO CONTRATO FINANCIAMENTO AVERBADO'
 1502 'REQ PESQ/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1503 'REQ PESQ/TRANSF DIREITOS -CISÃO APROVADO'
 1504 'REQ PESQ/TRANSF DIREITOS -CISÃO AVERBADO'
 1505 'REQ PESQ/TRANSF DIREITOS -CISÃO NEGADO'
 1506 'REQ PESQ/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1507 'REQ PESQ/TRANSF DIREITOS -FUSÃO APROVADA'
 1508 'REQ PESQ/TRANSF DIREITOS -FUSÃO NEGADO'
 1509 'REQ PESQ/TRANSF DIREITOS -FUSÃO AVERBADO'
 1510 'REQ PESQ/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1511 'REQ PESQ/TRANSF DIREITOS -INCORPORAÇÃO APROVADO'
 1512 'REQ PESQ/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1513 'REQ PESQ/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1514 'REQ PESQ/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1515 'REQ PESQ/TRANSF DIREITOS -FALÊNCIA APROVADO'
 1516 'REQ PESQ/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1517 'REQ PESQ/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1518 'REQ PESQ/TRANSF DIREITOS -SUCESSÃO CAUSAMORTIS PROTOCOLIZADO'
 1519 'REQ PESQ/TRANSF DIREITOS -SUCESSÃO CAUSAMORTIS APROVADO'
 1520 'REQ PESQ/TRANSF DIREITOS -SUCESSÃO CAUSAMORTIS NEGADO'
 1521 'REQ PESQ/TRANSF DIREITOS -SUCESSÃO CAUSAMORTIS AVERBADO'
 1522 'AUT PESQ/TRANSF DIREITOS -CISÃO PROTOCOLIZADA'
 1523 'AUT PESQ/TRANSF DIREITOS -CISÃO APROVADA'
 1524 'AUT PESQ/TRANSF DIREITOS -CISÃO AVERBADA'
 1525 'AUT PESQ/TRANSF DIREITOS -CISÃO NEGADO'
 1526 'AUT PESQ/TRANSF DIREITOS -FUSÃO PROTOCOLIZADA'
 1527 'AUT PESQ/TRANSF DIREITOS -FUSÃO APROVADA'
 1528 'AUT PESQ/TRANSF DIREITOS -FUSÃO NEGADO'
 1529 'AUT PESQ/TRANSF DIREITOS -FUSÃO AVERBADO'
 1530 'AUT PESQ/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADA'
 1531 'AUT PESQ/TRANSF DIREITOS -INCORPORAÇÃO APROVADA'
 1532 'AUT PESQ/TRANSF DIREITOS -INCORPORAÇÃO NEGADA'
 1533 'AUT PESQ/TRANSF DIREITOS -INCORPORAÇÃO AVERBADA'
 1534 'AUT PESQ/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1535 'AUT PESQ/TRANSF DIREITOS -FALÊNCIA APROVADO'
 1536 'AUT PESQ/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1537 'AUT PESQ/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1538 'AUT PESQ/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1539 'AUT PESQ/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADA'
 1540 'AUT PESQ/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1541 'AUT PESQ/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1542 'REQ LAV/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1543 'REQ LAV/TRANSF DIREITOS -CISÃO APROVADO'
 1544 'REQ LAV/TRANSF DIREITOS -CISÃO AVERBADO'
 1545 'REQ LAV/TRANSF DIREITOS -CISÃO NEGADO'
 1546 'REQ LAV/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1547 'REQ LAV/TRANSF DIREITOS -FUSÃO APROVADO'
 1548 'REQ LAV/TRANSF DIREITOS -FUSÃO NEGADO'
 1549 'REQ LAV/TRANSF DIREITOS -FUSÃO AVERBADO'
 1550 'REQ LAV/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1551 'REQ LAV/TRANSF DIREITOS -INCORPORAÇÃO APROVADO'
 1552 'REQ LAV/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1553 'REQ LAV/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1554 'REQ LAV/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1555 'REQ LAV/TRANSF DIREITOS -FALÊNCIA APROVADO'
 1556 'REQ LAV/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1557 'REQ LAV/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1558 'REQ LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1559 'REQ LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADO'
 1560 'REQ LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1561 'REQ LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1562 'CONC LAV/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1563 'CONC LAV/TRANSF DIREITOS -CISÃO APROVADO'
 1564 'CONC LAV/TRANSF DIREITOS -CISÃO AVERBADO'
 1565 'CONC LAV/TRANSF DIREITOS -CISÃO NEGADO'
 1566 'CONC LAV/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1567 'CONC LAV/TRANSF DIREITOS -FUSÃO APROVADO'
 1568 'CONC LAV/TRANSF DIREITOS -FUSÃO NEGADO'
 1569 'CONC LAV/TRANSF DIREITOS -FUSÃO AVERBADO'
 1570 'CONC LAV/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADA'
 1571 'CONC LAV/TRANSF DIREITOS -INCORPORAÇÃO APROVADA'
 1572 'CONC LAV/TRANSF DIREITOS -INCORPORAÇÃO NEGADA'
 1573 'CONC LAV/TRANSF DIREITOS -INCORPORAÇÃO AVERBADA'
 1574 'CONC LAV/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1575 'CONC LAV/TRANSF DIREITOS -FALÊNCIA APROVADO'
 1576 'CONC LAV/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1577 'CONC LAV/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1578 'CONC LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1579 'CONC LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADA'
 1580 'CONC LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1581 'CONC LAV/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1582 'REQ LICEN/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1583 'REQ LICEN/TRANSF DIREITOS -CISÃO APROVADO'
 1584 'REQ LICEN/TRANSF DIREITOS -CISÃO AVERBADO'
 1585 'REQ LICEN/TRANSF DIREITOS -CISÃO NEGADO'
 1586 'REQ LICEN/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1587 'REQ LICEN/TRANSF DIREITOS -FUSÃO APROVADO(A)'
 1588 'REQ LICEN/TRANSF DIREITOS -FUSÃO NEGADO'
 1589 'REQ LICEN/TRANSF DIREITOS -FUSÃO AVERBADO'
 1590 'REQ LICEN/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1591 'REQ LICEN/TRANSF DIREITOS -INCORPORAÇÃO APROVADO'
 1592 'REQ LICEN/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1593 'REQ LICEN/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1594 'REQ LICEN/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1595 'REQ LICEN/TRANSF DIREITOS -FALÊNCIA APROVADO(A)'
 1596 'REQ LICEN/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1597 'REQ LICEN/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1598 'REQ LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1599 'REQ LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADO'
 1600 'REQ LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1601 'REQ LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1602 'LICEN/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1603 'LICEN/TRANSF DIREITOS -CISÃO APROVADO(A)'
 1604 'LICEN/TRANSF DIREITOS -CISÃO AVERBADO'
 1605 'LICEN/TRANSF DIREITOS -CISÃO NEGADO'
 1606 'LICEN/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1607 'LICEN/TRANSF DIREITOS -FUSÃO APROVADO(A)'
 1608 'LICEN/TRANSF DIREITOS -FUSÃO NEGADO'
 1609 'LICEN/TRANSF DIREITOS -FUSÃO AVERBADO'
 1610 'LICEN/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1611 'LICEN/TRANSF DIREITOS -INCORPORAÇÃO APROVADA'
 1612 'LICEN/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1613 'LICEN/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1614 'LICEN/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1615 'LICEN/TRANSF DIREITOS -FALÊNCIA APROVADO'
 1616 'LICEN/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1617 'LICEN/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1618 'LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1619 'LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADO(A)'
 1620 'LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1621 'LICEN/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1622 'REQ PLG/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1623 'REQ PLG/TRANSF DIREITOS -CISÃO APROVADO(A)'
 1624 'REQ PLG/TRANSF DIREITOS -CISÃO AVERBADO'
 1625 'REQ PLG/TRANSF DIREITOS -CISÃO NEGADO'
 1626 'REQ PLG/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1627 'REQ PLG/TRANSF DIREITOS -FUSÃO APROVADO(A)'
 1628 'REQ PLG/TRANSF DIREITOS -FUSÃO NEGADO'
 1629 'REQ PLG/TRANSF DIREITOS -FUSÃO AVERBADO'
 1630 'REQ PLG/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1631 'REQ PLG/TRANSF DIREITOS -INCORPORAÇÃO APROVADO(A)'
 1632 'REQ PLG/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1633 'REQ PLG/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1634 'REQ PLG/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1635 'REQ PLG/TRANSF DIREITOS -FALÊNCIA APROVADO(A)'
 1636 'REQ PLG/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1637 'REQ PLG/TRANSF DIREITOS -FALÊNCIA AVERBADO'

1638 'REQ PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOC'
 1639 'REQ PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADO'
 1640 'REQ PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1641 'REQ PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1642 'PLG/TRANSF DIREITOS -CISÃO PROTOCOLIZADO'
 1643 'PLG/TRANSF DIREITOS -CISÃO APROVADO(A)'
 1644 'PLG/TRANSF DIREITOS -CISÃO AVERBADO'
 1645 'PLG/TRANSF DIREITOS -CISÃO NEGADO'
 1646 'PLG/TRANSF DIREITOS -FUSÃO PROTOCOLIZADO'
 1647 'PLG/TRANSF DIREITOS -FUSÃO APROVADO(A)'
 1648 'PLG/TRANSF DIREITOS -FUSÃO NEGADO'
 1649 'PLG/TRANSF DIREITOS -FUSÃO AVERBADO'
 1650 'PLG/TRANSF DIREITOS -INCORPORAÇÃO PROTOCOLIZADO'
 1651 'PLG/TRANSF DIREITOS -INCORPORAÇÃO APROVADO(A)'
 1652 'PLG/TRANSF DIREITOS -INCORPORAÇÃO NEGADO'
 1653 'PLG/TRANSF DIREITOS -INCORPORAÇÃO AVERBADO'
 1654 'PLG/TRANSF DIREITOS -FALÊNCIA PROTOCOLIZADO'
 1655 'PLG/TRANSF DIREITOS -FALÊNCIA APROVADO(A)'
 1656 'PLG/TRANSF DIREITOS -FALÊNCIA NEGADO'
 1657 'PLG/TRANSF DIREITOS -FALÊNCIA AVERBADO'
 1658 'PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS PROTOCOLIZADO'
 1659 'PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS APROVADO'
 1660 'PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS NEGADO'
 1661 'PLG/TRANSF DIREITOS -SUCESSÃO CAUSA MORTIS AVERBADO'
 1662 'REQ LAV/EDITAL DISPONIBILIDADE PESQUISA'
 1663 'CONC LAV/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 1664 'REQ LAV/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 1665 'CONC LAV/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 1666 'DISPONIB/TORNA S/EFEITO EDITAL DISPONIB -ÁREA REQ LAV'
 1667 'DISPONIB/TORNA S/EFEITO EDITAL DISPONIB -ÁREA CONC LAV'
 1668 'PLG/DOCUMENTO DIVERSO PROTOCOLIZADO'
 1669 'REQ LICEN/TORNA S/ EFEITO INDEFERIMENTO COM ONERAÇÃO'
 1670 'REQ LICEN/TORNA S/ EFEITO INDEFERIMENTO SEM ONERAÇÃO'
 1671 'LICEN/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 1672 'REQ PLG/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 1673 'PLG/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 1674 'PLG/TORNA S/EFEITO BAIXA TITULO PUB'
 1675 'AUT PESQ/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 1676 'CONC LAV/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 1677 'CONC LAV/TORNA S/EFEITO BAIXA TITULO LAVRA'
 1678 'DISPONIB/ARQUIVAMENTO PROCESSO PUBLICADO'
 1679 'REQ LAV/RAL APRESENTA ART'
 1680 'LICEN/RAL APRESENTA ART'
 1681 'AUT PESQ/RAL ANALISADO'
 1682 'REQ LAV/RAL ANALISADO'
 1683 'CONC LAV/RAL ANALISADO'
 1684 'LICEN/RAL ANALISADO'
 1685 'PLG/RAL ANALISADO'
 1686 'REQ EXTR/RAL ANALISADO'
 1687 'REQ LAV/RAL NÃO ACEITO PUBLICADO'
 1688 'LICEN/RAL NÃO ACEITO PUBLICADO'
 1689 'PLG/RAL NÃO ACEITO PUBLICADO'
 1690 'REQ EXTR/RAL NÃO ACEITO PUBLICADO'
 1691 'AUT PESQ/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
 1692 'REQ LAV/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
 1693 'CONC LAV/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
 1694 'LICEN/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
 1695 'PLG/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
 1696 'AUT PESQ/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
 1697 'REQ LAV/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
 1698 'CONC LAV/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
 1699 'LICEN/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
 1700 'PLG/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
 1701 'AUT PESQ/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
 1702 'REQ LAV/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
 1703 'CONC LAV/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
 1704 'LICEN/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
 1705 'PLG/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
 1706 'AUT PESQ/RAL AUTO INFRAÇÃO ARQUIVADO'
 1707 'REQ LAV/RAL AUTO DE INFRAÇÃO ARQUIVADO'
 1708 'CONC LAV/RAL AUTO INFRAÇÃO ARQUIVADO'
 1709 'LICEN/RAL AUTO DE INFRAÇÃO ARQUIVADO'
 1710 'PLG/RAL AUTO DE INFRAÇÃO ARQUIVADO'
 1711 'AUT PESQ/RAL MULTA APLICADA'
 1712 'REQ LAV/RAL MULTA APLICADA'
 1713 'CONC LAV/RAL MULTA APLICADA'
 1714 'LICEN/RAL MULTA APLICADA'
 1715 'PLG/RAL MULTA APLICADA'
 1716 'AUT PESQ/RAL PAGAMENTO MULTA EFETUADO'
 1717 'REQ LAV/RAL PAGAMENTO MULTA EFETUADO'
 1718 'CONC LAV/RAL PAGAMENTO MULTA EFETUADO'
 1719 'LICEN/RAL PAGAMENTO MULTA EFETUADO'
 1720 'PLG/RAL PAGAMENTO MULTA EFETUADO'
 1721 'AUT PESQ/RAL TORNA SEM EFEITO MULTA APLICADA'
 1722 'REQ LAV/RAL TORNA SEM EFEITO MULTA APLICADA'
 1723 'CONC LAV/RAL TORNA SEM EFEITO MULTA APLICADA'
 1724 'LICEN/RAL TORNA SEM EFEITO MULTA APLICADA'
 1725 'PLG/RAL TORNA SEM EFEITO MULTA APLICADA'
 1726 'AUT PESQ/RAL EXIGÊNCIA DE APRESENTAÇÃO'
 1727 'REQ LAV/RAL EXIGÊNCIA DE APRESENTAÇÃO'
 1728 'CONC LAV/RAL EXIGÊNCIA DE APRESENTAÇÃO'
 1729 'LICEN/RAL EXIGÊNCIA DE APRESENTAÇÃO'
 1730 'PLG/RAL EXIGÊNCIA DE APRESENTAÇÃO'
 1731 'AUT PESQ/RAL CUMPRIMENTO DE EXIGÊNCIA'
 1732 'REQ LAV/RAL CUMPRIMENTO DE EXIGÊNCIA'
 1733 'CONC LAV/RAL CUMPRIMENTO DE EXIGÊNCIA'
 1734 'LICEN/RAL CUMPRIMENTO DE EXIGÊNCIA'
 1735 'PLG/RAL CUMPRIMENTO DE EXIGÊNCIA'
 1736 'AUT PESQ/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 1737 'REQ LAV/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 1738 'CONC LAV/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 1739 'LICEN/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 1740 'PLG/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 1741 'AUT PESQ/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
 1742 'REQ LAV/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
 1743 'CONC LAV/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
 1744 'LICEN/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
 1745 'PLG/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
 1746 'AUT PESQ/RAL RECURSO MULTA PROTOCOLIZADO'
 1747 'REQ LAV/RAL RECURSO MULTA PROTOCOLIZADO'
 1748 'CONC LAV/RAL RECURSO MULTA PROTOCOLIZADO'
 1749 'LICEN/RAL RECURSO MULTA PROTOCOLIZADO'
 1750 'PLG/RAL RECURSO MULTA PROTOCOLIZADO'
 1751 'AUT PESQ/RAL RECURSO MULTA PROVIDO'
 1752 'REQ LAV/RAL RECURSO MULTA PROVIDO'
 1753 'CONC LAV/RAL RECURSO MULTA PROVIDO'
 1754 'LICEN/RAL RECURSO MULTA PROVIDO'
 1755 'PLG/RAL RECURSO MULTA PROVIDO'
 1756 'AUT PESQ/RAL RECURSO MULTA NEGADO'
 1757 'REQ LAV/RAL RECURSO MULTA NEGADO'
 1758 'CONC LAV/RAL RECURSO MULTA NEGADO'
 1759 'LICEN/RAL RECURSO MULTA NEGADO'
 1760 'PLG/RAL RECURSO MULTA NEGADO'
 1761 'AUT PESQ/RAL ANOS ANTERIORES APRESENTADO'
 1762 'REQ LAV/RAL ANOS ANTERIORES APRESENTADO'
 1763 'REQ EXTR/RAL ANOS ANTERIORES APRESENTADO'
 1764 'REQ LAV/RAL ANO BASE APRESENTADO'
 1765 'AUT PESQ/RAL RETIFICADOR ANOS ANTERIORES'
 1766 'REQ LAV/RAL RETIFICADOR ANOS ANTERIORES'
 1767 'CONC LAV/RAL RETIFICADOR ANOS ANTERIORES'
 1768 'LICEN/RAL RETIFICADOR ANOS ANTERIORES'
 1769 'PLG/RAL RETIFICADOR ANOS ANTERIORES'
 1770 'REQ EXTR/RAL RETIFICADOR ANOS ANTERIORES'
 1771 'AUT PESQ/RAL RETIFICADOR ANO BASE'
 1772 'REQ LAV/RAL RETIFICADOR ANO BASE'
 1773 'CONC LAV/RAL RETIFICADOR ANO BASE'
 1774 'LICEN/RAL RETIFICADOR ANO BASE'
 1775 'PLG/RAL RETIFICADOR ANO BASE'
 1776 'REQ EXTR/RAL RETIFICADOR ANO BASE'
 1777 'AUT PESQ/GUIA UTILIZAÇÃO CANCELADA PUBLICADA'
 1778 'REQ LAV/GUIA UTILIZAÇÃO CANCELADA PUBLICADA'
 1779 'CONC LAV/GUIA UTILIZAÇÃO CANCELADA PUBLICADA'
 1780 'REQ PESQ/TORNA S/EFEITO CANCELAMENTO DO TITULO'
 1781 'REQ LAV/REQUERIMENTO LAVRA PROTOCOL FORA DO PRAZO'
 1782 'AUT PESQ/RETIFICAÇÃO DA APROVAÇÃO DO RELATORIO FINAL'
 1783 'REQ LAV/ENLOBOAMENTO ÁREAS PESQUISADAS SOLICITADA'
 1784 'REQ LAV/RETIFICAÇÃO APROVO RELATORIO FINAL SOLICITADA'
 1785 'CONC LAV/PORTARIA ENLOBOANDO ÁREAS PESQUISADAS'
 1786 'REQ LAV/ÁREA ENLOBOADA POR PORTARIA'
 1787 'REQ LAV/DESISTÊNCIA DIREITO REQ LAVRA PROTOCOLIZADO'
 1788 'REQ LAV/DESISTENCIA DIREITO REQ LAVRA HOMOLOGADA PUBP'
 1789 'REQ LICEN/TORNA S/EFEITO CANCELAMENTO REGISTRO LICENÇA'

1790 'LICEN/ONERAÇÃO DIREITOS -PENHORA AVERBADA'
 1791 'LICEN/ONERAÇÃO DIREITOS -PENHORA NEGADA'
 1792 'LICEN/ONERAÇÃO DIREITOS -PENHORA PROTOCOLIZADA'
 1793 'LICEN/LIBERAÇÃO PENHORA APROVADO(A)'
 1794 'LICEN/LIBERAÇÃO PENHORA AVERBADA'
 1795 'LICEN/LIBERAÇÃO PENHORA NEGADA'
 1796 'LICEN/LIBERAÇÃO PENHORA PROTOCOLIZADA'
 1797 'PLG/TRANSF DIREITOS - DISTRATO PROTOCOLIZADO'
 1798 'PLG/TRANSF DIREITOS -CESSÃO DE DIREITOS ANULADA'
 1799 'CONC LAV/EXIGÊNCIA LICENÇA AMBIENTAL PUB'
 1800 'REQ PESQ/REQ PROVENIENTE DESMEMBRAMENTO PROTOC'
 1801 'REQ LICEN/EXIGÊNCIA ÁREA REMANESCENTE PUBLICADA'
 1802 'DISPONIB/ÁREA DESCARTADA DISPONIB P/ PESQUISA - EDITAL'
 1803 'DISPONIB/JULGAMENTO HABILITAÇÃO PUBLICADO'
 1804 'DISPONIB/ANULA JULGAMENTO HABILITAÇÃO PUB'
 1805 'DISPONIB/RECURSO- DIRETOR GERAL PROTOCOLIZADO'
 1806 'DISPONIB/RECURSO- DIRETOR GERAL NEGADO PUBL'
 1807 'DISPONIB/RECURSO- DIRETOR GERAL PROVIDO PUBL'
 1808 'DISPONIB/DESCCLASSIFICAÇÃO PROPOSTA DISPONIB PUB'
 1809 'DISPONIB/EXCLUSÃO DE PROCESSO EDITAL PUB'
 1810 'ARQUIVAMENTO IMPOSIÇÃO MULTA PUBLICADA'
 1811 'ÁREA BLOQUEADA JUDICIALMENTE'
 1812 'ÁREA DESBLOQUEADA JUDICIALMENTE'
 1813 'CONC LAV/EDITAL IMISSÃO POSSE ANULADO'
 1814 'DISPONIB/EDITAL DISPONIB ART 26 CM PUBLICADO'
 1815 'AUT PESQ/BAIXA TRANS: ALVARÁ- MUDANÇA DE REGIME'
 1816 'LICEN/BAIXA TRANS:RICÃO TÍTULO- MUDANÇA DE REGIME'
 1817 'AUT PESQ/TRANSF DIREITOS -DISTRATO PROTOCOLIZADO'
 1818 'REQ PESQ/TRANSF DIREITOS -ANTERIOR PORT 199/06 APROVADO'
 1819 'REQ PESQ/TRANSF DIREITOS -ANTERIOR PORT 199/06 NEGADO'
 1820 'REQ PESQ/TRANSF DIREITOS -ANTERIOR PORT 199/06 EFETIVADO'
 1821 'REQ LICEN/TORNA S/EFEITO NULIDADE DO TÍTULO'
 1822 'LICEN/TORNA S/EFEITO MULTA APLICADA'
 1823 'AUT PESQ/OPÇÃO REGIME LICENCIAMENTO AUTORIZADA'
 1824 'REQ PESQ/CORREÇÃO DE FASE- ÁREA DISPONIBILIDADE'
 1825 'AUT PESQ/CORREÇÃO DE FASE- ÁREA DISPONIBILIDADE'
 1826 'DISPONIB/CORREÇÃO DE FASE- ÁREA REQ LAVRA'
 1827 'DISPONIB/ÁREA DESCARTADA EM ESTUDO'
 1828 'DISPONIB/ÁREA DESCARTADA LIBERADA PARA EDITAL'
 1829 'AUT PESQ/CORREÇÃO DE FASE- ÁREA LICENCIAMENTO'
 1830 'LICEN/CORREÇÃO DE FASE- ÁREA AUTORIZAÇÃO PESQUISA'
 1831 'DISPONIB/CORREÇÃO DE FASE- ÁREA REQ PESQ'
 1832 'REQ LAV/TORNA S/EFEITO ARQUIVAMENTO PROCESSO'
 1833 'AUT PESQ/REGIME COMPARTILHADO- LICEN'
 1834 'REQ LAV/REGIME COMPARTILHADO- LICEN'
 1835 'LICEN/REGIME COMPARTILHADO- AUT PESQ'
 1836 'DISPONIB/ÁREA DESCARTADA DISPONIB PARA PLG - EDITAL'
 1837 'NÃO CONHECE RECONSIDERAÇÃO RECURSO PUB'
 1838 'AUT PESQ/TRANSF DIREITOS - CESSÃO TOTAL CADEIA SUCESSÓRIA'
 1839 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL DIR REQ LAV EM CADEIA'
 1840 'REQ LAV/TRANSF DIREITOS -CESSÃO TOTAL REQ LAV EM CADEIA'
 1841 'CONC LAV/TRANSF DIREITOS -CESSÃO TOTAL CADEIA SUCESSÓRIA'
 1842 'DISPONIB/AUTO INFRAÇÃO MULTA PUBLICADO'
 1843 'DISPONIB/MULTA APLICADA PUBLICADA'
 1844 'DISPONIB/ARQUIVAMENTO AUTO INFRAÇÃO PUBLICADO'
 1845 'DISPONIB/DEFESA APRESENTADA'
 1846 'DISPONIB/DEFESA ACEITA'
 1847 'DISPONIB/DEFESA NÃO ACEITA'
 1848 'DISPONIB/TORNA S/ EFEITO AUTO INFRAÇÃO'
 1849 'DISPONIB/TORNA S/ EFEITO MULTA APLICADA'
 1850 'CONC LAV/PORTARIA DESMEMBRADA ÁREAS PESQUISADAS PUB'
 1851 'PLG/TRANSF DIREITOS - CESSÃO TOTAL CADEIA SUCESSÓRIA'
 1852 'REQ PLG/TRANSF DIREITOS -ANTERIOR PORT 199/06 APROVADO'
 1853 'REQ PLG/TRANSF DIREITOS -ANTERIOR PORT 199/06 EFETIVADO'
 1854 'REQ PLG/TRANSF DIREITOS -ANTERIOR PORT 199/06 NEGADO'
 1855 'LICEN/REGIME COMPARTILHADO- REQ LAV'
 1856 'REQ PESQ/TRANSF DIREITOS -ANULADA'
 1857 'CONC LAV/GRUPAMENTO MINEIRO PROC ADM PRINCIPAL AUTORIZ PUBL'
 1858 'DISPONIB/ANULA ARQUIVAMENTO PROCESSO PUBL'
 1859 'REQ LICEN/PLANO APROVEITAMENTO ECON APRES'
 1860 'REQ LICEN/PLANO DE LAVRA PROTOCOLIZADO'
 1861 'CONC LAV/GRUPAMENTO MINEIRO DESISTENCIA PROTOC'
 1862 'CONC LAV/GRUPAMENTO MINEIRO PROC ADM PRINCIPAL ARQUIVADO PUB'
 1863 'REQ PESQ/OPÇÃO REGIME LICENCIAMENTO APROVADO'
 1864 'DISPONIB/TORNA S/ EFEITO DESPACHO PUBLICADO'
 1865 'NÃO CONHECE SOLICITAÇÃO - FALTA PREVISÃO LEGAL PUB'
 1866 'REQ PESQ/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 1867 'REQ PLG/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 1868 'PLG/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 1869 'AUT PESQ/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 1870 'CONC LAV/ÁREA DISPONIBILIDADE - EDITAL'
 1871 'DISPONIB/INDEF NÃO CUMPRIMENTO DE INTIMAÇÃO ART.44/PORT268'
 1872 'AUT PESQ/ARQUIVAMENTO AUTO INFRAÇÃO- INÍCIO DE PESQ'
 1873 'LICEN/TORNA SEM EFEITO AUTO INFRAÇÃO'
 1874 'PLG/TORNA SEM EFEITO AUTO INFRAÇÃO'
 1875 'PLG/TORNA SEM EFEITO MULTA APLICADA'
 1876 'REQ LAV/TORNA SEM EFEITO AUTO INFRAÇÃO'
 1877 'REESTUDO DE ÁREAS EM ANÁLISE'
 1878 'REESTUDO DE ÁREAS CONCLUÍDO'
 1879 'REQ PESQ/REQ PROVENIENTE DE OPÇÃO DE ÁREA PROTOC'
 1880 'REQ EXT/DOKUMENTO DIVERSO PROTOCOLIZADO'
 1881 'REQ EXT/DOKUMENTO DIVERSO PROTOCOLIZADO'
 1882 'REQ LAV/CORREÇÃO DE FASE- ÁREA AUTORIZAÇÃO PESQUISA'
 1883 'DISPONIB/ÁREA DESBLOQUEADA DISPONIB PARA PLG - EDITAL'
 1884 'AUT PESQ/REL PESQ PROVENIENTE CESSÃO PARCIAL PROT'
 1885 'AUT PESQ/CORREÇÃO DE FASE- ÁREA REQUERIMENTO LAVRA'
 1886 'REQ PESQ/CORREÇÃO DE FASE- ÁREA AUTORIZAÇÃO PESQUISA'
 1887 'DISPONIB/RECURSO MINISTRO PROTOCOLIZADO'
 1888 'DISPONIB/RECURSO MINISTRO NEGADO PUBL'
 1889 'DISPONIB/RECURSO MINISTRO PROVIDO PUBLICADO'
 1890 'ONERAÇÃO DIREITOS - CAUÇÃO - LIBERAÇÃO APROVADA'
 1891 'ONERAÇÃO DIREITOS - CAUÇÃO - LIBERAÇÃO AVERBADA'
 1892 'ONERAÇÃO DIREITOS - CAUÇÃO - LIBERAÇÃO NEGADA'
 1893 'ONERAÇÃO DIREITOS - CAUÇÃO - LIBERAÇÃO PROTOCOLIZADA'
 1894 'ONERAÇÃO DIREITOS - CAUÇÃO APROVADO'
 1895 'ONERAÇÃO DIREITOS - CAUÇÃO AVERBADO'
 1896 'ONERAÇÃO DIREITOS - CAUÇÃO NEGADO'
 1897 'ONERAÇÃO DIREITOS - CAUÇÃO PROTOCOLIZADO'
 1898 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO - LIBERAÇÃO APROVADA'
 1899 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO - LIBERAÇÃO AVERBADA'
 1900 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO - LIBERAÇÃO NEGADA'
 1901 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO - LIBERAÇÃO PROTOCOLIZADA'
 1902 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO APROVADA'
 1903 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO AVERBADA'
 1904 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO NEGADA'
 1905 'ONERAÇÃO DIREITOS - CÉDULA CRÉDITO PROTOCOLIZADA'
 1906 'ONERAÇÃO DIREITOS - CONTRATO DE FINANC - LIBERAÇÃO APROVADA'
 1907 'ONERAÇÃO DIREITOS - CONTRATO DE FINANC - LIBERAÇÃO AVERBADA'
 1908 'ONERAÇÃO DIREITOS - CONTRATO DE FINANC - LIBERAÇÃO NEGADA'
 1909 'ONERAÇÃO DIREITOS - CONTRATO DE FINANC - LIBERAÇÃO PROTOC'
 1910 'ONERAÇÃO DIREITOS - CONTRATO FINANCIAMENTO APROVADO'
 1911 'ONERAÇÃO DIREITOS - CONTRATO FINANCIAMENTO AVERBADO'
 1912 'ONERAÇÃO DIREITOS - CONTRATO FINANCIAMENTO NEGADO'
 1913 'ONERAÇÃO DIREITOS - CONTRATO FINANCIAMENTO PROTOCOLIZADO'
 1914 'ONERAÇÃO DIREITOS - HIPOTECA - LIBERAÇÃO APROVADA'
 1915 'ONERAÇÃO DIREITOS - HIPOTECA - LIBERAÇÃO AVERBADA'
 1916 'ONERAÇÃO DIREITOS - HIPOTECA - LIBERAÇÃO NEGADA'
 1917 'ONERAÇÃO DIREITOS - HIPOTECA - LIBERAÇÃO PROTOCOLIZADA'
 1918 'ONERAÇÃO DIREITOS - HIPOTECA APROVADA'
 1919 'ONERAÇÃO DIREITOS - HIPOTECA AVERBADA'
 1920 'ONERAÇÃO DIREITOS - HIPOTECA NEGADA'
 1921 'ONERAÇÃO DIREITOS - HIPOTECA PROTOCOLIZADA'
 1922 'ONERAÇÃO DIREITOS - PENHOR - LIBERAÇÃO APROVADA'
 1923 'ONERAÇÃO DIREITOS - PENHOR - LIBERAÇÃO AVERBADA'
 1924 'ONERAÇÃO DIREITOS - PENHOR - LIBERAÇÃO NEGADA'
 1925 'ONERAÇÃO DIREITOS - PENHOR - LIBERAÇÃO PROTOCOLIZADA'
 1926 'ONERAÇÃO DIREITOS - PENHOR APROVADO'
 1927 'ONERAÇÃO DIREITOS - PENHOR AVERBADO'
 1928 'ONERAÇÃO DIREITOS - PENHOR NEGADO'
 1929 'ONERAÇÃO DIREITOS - PENHOR PROTOCOLIZADO'
 1930 'ONERAÇÃO DIREITOS - PENHORA - LIBERAÇÃO APROVADA'
 1931 'ONERAÇÃO DIREITOS - PENHORA - LIBERAÇÃO AVERBADA'
 1932 'ONERAÇÃO DIREITOS - PENHORA - LIBERAÇÃO NEGADA'
 1933 'ONERAÇÃO DIREITOS - PENHORA - LIBERAÇÃO PROTOCOLIZADA'
 1934 'ONERAÇÃO DIREITOS - PENHORA AUTORIZADA'
 1935 'ONERAÇÃO DIREITOS - PENHORA AVERBADA'
 1936 'ONERAÇÃO DIREITOS - PENHORA NEGADA'
 1937 'ONERAÇÃO DIREITOS - PENHORA PROTOCOLIZADA'
 1938 'TRANSF DIREITOS - CISAÓ APROVADA'
 1939 'TRANSF DIREITOS - CISAÓ AVERBADA'
 1940 'TRANSF DIREITOS - CISAÓ NEGADO'
 1941 'TRANSF DIREITOS - CISAÓ PROTOCOLIZADA'

1942 'TRANSF DIREITOS - FALÊNCIA APROVADO'
 1943 'TRANSF DIREITOS - FALÊNCIA AVERBADO'
 1944 'TRANSF DIREITOS - FALÊNCIA NEGADO'
 1945 'TRANSF DIREITOS - FALÊNCIA PROTOCOLIZADO'
 1946 'TRANSF DIREITOS - FUSÃO APROVADA'
 1947 'TRANSF DIREITOS - FUSÃO AVERBADA'
 1948 'TRANSF DIREITOS - FUSÃO NEGADA'
 1949 'TRANSF DIREITOS - FUSÃO PROTOCOLIZADA'
 1950 'TRANSF DIREITOS - INCORPORAÇÃO APROVADA'
 1951 'TRANSF DIREITOS - INCORPORAÇÃO AVERBADA'
 1952 'TRANSF DIREITOS - INCORPORAÇÃO NEGADA'
 1953 'TRANSF DIREITOS - INCORPORAÇÃO PROTOCOLIZADA'
 1954 'TRANSF DIREITOS - SUCESSÃO CAUSA MORTIS APROVADA'
 1955 'TRANSF DIREITOS - SUCESSÃO CAUSA MORTIS AVERBADA'
 1956 'TRANSF DIREITOS - SUCESSÃO CAUSA MORTIS NEGADA'
 1957 'TRANSF DIREITOS - SUCESSÃO CAUSA MORTIS PROTOCOLIZADA'
 1958 'REQ LAV/ÁREA SERVIDÃO SOLICITADA'
 1959 'REQ LAV/ÁREA SERVIDÃO NÃO CONCEDIDA PUB'
 1960 'REQ LAV/ÁREA SERVIDÃO CONCEDIDA PUB'
 1961 'REQ PESQ/ÁREA SERVIDÃO SOLICITADA'
 1962 'REQ PESQ/ÁREA SERVIDÃO NÃO CONCEDIDA PUB'
 1963 'REQ PESQ/ÁREA SERVIDÃO CONCEDIDA PUB'
 1964 'REQ LAV/ADVERTÊNCIA PUBLICADA'
 1965 'REQ PESQ/PROCESSO SITUADO UNIDADE DE CONSERVAÇÃO'
 1966 'AUT PESQ/TRANSF DIREITOS - DISTRATO ACEITO'
 1967 'CONC LAV/TRANSF DIREITOS - DISTRATO ACEITO'
 1968 'LICEN TRANSF DIREITOS - DISTRATO ACEITO'
 1969 'PLG/TRANSF DIREITOS - DISTRATO ACEITO'
 1970 'REQ LAV/TRANSF DIREITOS - DISTRATO ACEITO'
 1971 'PLG/DESPACHO PUBLICADO'
 1972 'AUT PESQ/CORREÇÃO DE FASE- ÁREA REQ LICENCIAMENTO'
 1973 'CONC LAV/ARRENDAMENTO PRORROGAÇÃO AVERBADA'
 1974 'SUSPENSÃO DE ANÁLISE - CONFLITO PROJ ENERGETICO'
 1975 'SUSPENSÃO DE ANÁLISE CANCELADA'
 1976 'REQ PESQ/OPÇÃO REGIME DESISTENCIA PROTOCOLIZADA'
 1977 'REQ PESQ/OPÇÃO REGIME DESISTENCIA HOMOLOGADA PUB'
 1978 'REQ PESQ/OPÇÃO REGIME DESISTENCIA PROTOCOLIZADA'
 1979 'REQ PLG/OPÇÃO REGIME DESISTENCIA HOMOLOGADA PUB'
 1980 'REQ LICEN/OPÇÃO REGIME DESISTENCIA PROTOCOLIZADA'
 1981 'REQ LICEN/OPÇÃO REGIME DESISTENCIA HOMOLOGADA PUB'
 1982 'ÁREA DESBLOQUEADA PUBLICADA'
 1983 'REQ LAV/AUTOINFRAÇÃO ADVERTÊNCIA PUBLICADO'
 1984 'ANULA PUBLICAÇÃO POR DUPLICIDADE'
 1985 'CONC LAV/DESPACHO RETIFICAÇÃO PORTARIA PUBLICADO'
 1986 'REQ LAV/OPÇÃO REGIME LICENCIAMENTO PROT'
 1987 'REQ LAV/OPÇÃO REGIME LICENCIAMENTO AUTORIZADO'
 1988 'REQ LAV/OPÇÃO REGIME LICENC INDEFERIDO PUB'
 1989 'CONC LAV/OPÇÃO REGIME LICENCIAMENTO PROT'
 1990 'CONC LAV/OPÇÃO REGIME LICENCIAMENTO AUTORIZADO'
 1991 'CONC LAV/OPÇÃO REGIME LICENC INDEFERIDO PUB'
 1992 'CONC LAV/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG PROT'
 1993 'CONC LAV/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG ACEITO'
 1994 'CONC LAV/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG NÃO ACEITO'
 1995 'CONC LAV/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA PROT'
 1996 'CONC LAV/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA ACEITO'
 1997 'CONC LAV/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA NÃO ACEITO'
 1998 'CONC LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE PROT'
 1999 'CONC LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
 2000 'CONC LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE NÃO ACEITO'
 2001 'CONC LAV/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC PROT'
 2002 'CONC LAV/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC ACEITO'
 2003 'CONC LAV/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC NÃO ACEITO'
 2004 'REQ LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE PROT'
 2005 'REQ LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
 2006 'REQ LAV/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE NÃO ACEITO'
 2007 'LICEN/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC PROT'
 2008 'LICEN/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC ACEITO'
 2009 'LICEN/BARRAGENS RESUMO CONCL FIM INSPEÇÃO ESPEC NÃO ACEITO'
 2010 'LICEN/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG PROT'
 2011 'LICEN/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG ACEITO'
 2012 'LICEN/BARRAGENS CRONOGRAMA IMPLANT PLANO SEG NÃO ACEITO'
 2013 'LICEN/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA PROT'
 2014 'LICEN/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA ACEITO'
 2015 'LICEN/BARRAGENS RESUMO EXECUT REVISÃO PERIODICA NÃO ACEITO'
 2016 'LICEN/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE PROT'
 2017 'LICEN/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
 2018 'LICEN/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE NÃO ACEITO'
 2019 'CONC LAV/BARRAGENS EXIGENCIA PUBLICADA'
 2020 'CONC LAV/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2021 'CONC LAV/BARRAGENS PRORROG PRAZO EXIGÊNCIA SOLICITADO'
 2022 'CONC LAV/BARRAGENS PRORROG PRAZO EXIGÊNCIA NEGADO'
 2023 'CONC LAV/BARRAGENS PRORROG PRAZO EXIGÊNCIA CONCEDIDO'
 2024 'REQ LAV/BARRAGENS EXIGENCIA PUBLICADA'
 2025 'REQ LAV/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2026 'REQ LAV/BARRAGENS PRORROG PRAZO EXIGENCIA SOLICITADO'
 2027 'REQ LAV/BARRAGENS PRORROG PRAZO EXIGÊNCIA NEGADO'
 2028 'REQ LAV/BARRAGENS PRORROG PRAZO EXIGÊNCIA CONCEDIDO'
 2029 'LICEN/BARRAGENS EXIGENCIA PUBLICADA'
 2030 'LICEN/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2031 'REQ PLG/TORNA S/EFEITO DESPACHO PUBLICADO'
 2032 'LICEN/BARRAGENS PRORROG PRAZO EXIGÊNCIA SOLICITADO'
 2033 'LICEN/BARRAGENS PRORROG PRAZO EXIGÊNCIA NEGADO'
 2034 'LICEN/BARRAGENS PRORROG PRAZO EXIGÊNCIA CONCEDIDO'
 2035 'REQ PESQ/INDEF INTERF ÁREA AMBIENTAL - LEI DO SNUC PUB'
 2036 'REQ LICEN/INDEF INTERF ÁREA AMBIENTAL - LEI DO SNUC PUB'
 2037 'REQ PLG/INDEF INTERF ÁREA AMBIENTAL - LEI DO SNUC PUB'
 2038 'REQ EXT/INDEF INTERF ÁREA AMBIENTAL - LEI DO SNUC PUB'
 2039 'REQ LAV/INDEF INTERF ÁREA AMBIENTAL - LEI DO SNUC PUB'
 2040 'REQ LAV/OFÍCIO INTIMA P/ DEFESA INDEF - LEI DO SNUC'
 2041 'AUT PESQ/OFÍCIO INTIMA P/ DEFESA DECAIMENTO'
 2042 'AUT PESQ/INST PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2043 'AUT PESQ/ARQUIV PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2044 'AUT PESQ/DECLARAÇÃO DE DECAIMENTO ALV PESQ PUB'
 2045 'AUT PESQ/OFÍCIO INTIMA P/ DEFESA ARQUIV REL PESQ - LEI DO SNUC'
 2046 'AUT PESQ/INST PROC ADM ARQUIV REL PESQ - LEI DO SNUC'
 2047 'AUT PESQ/ARQUIV PROC ADM REL PESQ - LEI DO SNUC PUB'
 2048 'AUT PESQ/RELATORIO PESQ ARQUIVADO - LEI DO SNUC PUB'
 2049 'CONC LAV/OFÍCIO INTIMA P/ DEFESA DECAIMENTO'
 2050 'CONC LAV/INST PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2051 'CONC LAV/ARQUIV PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2052 'CONC LAV/PORTARIA DE DECAIMENTO DA LAVRA PUBLICADO'
 2053 'LICEN/OFÍCIO INTIMA P/ DEFESA DECAIMENTO'
 2054 'LICEN/INSTAURAÇÃO PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2055 'LICEN/ARQUIV PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2056 'LICEN/DECLARAÇÃO DECAIMENTO REGISTRO DE LICENÇA PUB'
 2057 'PLG/OFÍCIO INTIMA P/ DEFESA DECAIMENTO'
 2058 'PLG/INST PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2059 'PLG/ARQUIV PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2060 'PLG/DECLARAÇÃO DECAIMENTO DA PLG PUBLICADO'
 2061 'REQ EXT/OFÍCIO INTIMA P/ DEFESA DECAIMENTO'
 2062 'REQ EXT/INST PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2063 'REQ EXT/ARQUIV PROC ADM DECAIMENTO - LEI DO SNUC PUB'
 2064 'REQ EXT/DECLARAÇÃO DECAIMENTO REG DE EXTRAÇÃO PUB'
 2065 'PROTESTO JUDICIAL'
 2066 'REQ PLG/OPÇÃO REGIME AUTORIZAÇÃO PESQ AUTORIZADO'
 2067 'AUT PESQ/OPÇÃO REGIME PERM LAVRA GARIMP AUTORIZADO'
 2068 'AUT PESQ/TÍTULO DECLARADO CADUCO PUBLICADO'
 2069 'REQ PLG/DESPACHO PUBLICADO'
 2070 'TRANSF DIREITOS - INCORPORAÇÃO ANULADA'
 2071 'CONC LAV/ARRENDAMENTO ARQUIVAMENTO PROCESSO PUB'
 2072 'CONC LAV/BARRAGENS EXIGENCIA AÇÃO EMERGENCIAL PUB'
 2073 'REQ LAV/RECURSO PROTOCOLIZADO'
 2074 'REQ LAV/RECURSO PROVIDO PUBLICADO'
 2075 'REQ LAV/RECURSO NEGADO PUBLICADO'
 2076 'REQ LICEN/OPÇÃO REGIME EXIGENCIA PUBLICADA'
 2077 'LICEN/OPÇÃO REGIME EXIGENCIA PUBLICADA'
 2078 'REQ PLG/OPÇÃO REGIME EXIGENCIA PUBLICADA'
 2079 'PLG/OPÇÃO REGIME EXIGENCIA PUBLICADA'
 2080 'REQ PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA PROTOCOLIZADA'
 2081 'REQ PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA AUTORIZADA'
 2082 'REQ PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA NEGADA'
 2083 'PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA PROTOCOLIZADO'
 2084 'PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA AUTORIZADA'
 2085 'PLG/OPÇÃO REGIME PRORROGAÇÃO EXIGENCIA NEGADA'
 2086 'DISPONIB/JULGAMENTO HABILITAÇÃO PROPONENTE HABILITADO'
 2087 'DISPONIB/JULGAMENTO HABILITAÇÃO PROPONENTE INABILITADO'
 2088 'DISPONIB/JULGAMENTO PROPOSTAS - ORDEM CLASSIFICAÇÃO'
 2089 'CONC LAV/BARRAGENS PROTOC ENTREGA PAEBM À DEFESA CIVIL'
 2090 'CONC LAV/BARRAGENS PROTOC ENTREGA PAEBM À PREFEITURAS'
 2091 'LICEN/BARRAGENS PROTOC ENTREGA PAEBM À DEFESA CIVIL'
 2092 'LICEN/BARRAGENS PROTOC ENTREGA PAEBM À PREFEITURAS'
 2093 'PLG/BARRAGENS PROTOC ENTREGA PAEBM À DEFESA CIVIL'

2094 'PLG BARRAGENS PROTOC ENTREGA PAEBM À PREFEITURAS'
2095 'REQ LICEN/INDEFERIMENTO COM ONERAÇÃO'
2096 'REQ LICEN/INDEFERIMENTO SEM ONERAÇÃO'
2097 'CONC LAV/ARRENDAMENTO - DISTRATO PROTOCOLIZADO'
2098 'CONC LAV/ARRENDAMENTO - DISTRATO ACEITO'
2099 'CONC LAV/ARRENDAMENTO - DISTRATO NÃO ACEITO'
2100 'TERMO DE COMPROMISSO GERADO'
2101 'REQ PESQ/TERMO DE COMPROMISSO ASSINADO'
2102 'REQ PESQ/INDEFERIMENTO ÁREA BLOQUEADA - RENCA PUB'
2103 'REQ LICEN/INDEFERIMENTO ÁREA BLOQUEADA - RENCA PUB'
2104 'REQ PLG/INDEFERIMENTO ÁREA BLOQUEADA - RENCA PUB'
2105 'REQ PESQ/ARQUIVAMENTO PROCESSO PUBL/ÁREA ONERADA'
2106 'REQ LAV/EXIGÊNCIA LICENÇA AMBIENTAL PUB'
2107 'REQ LAV/LICENÇA AMBIENTAL - COMPROVANTE PAR 6 ART 41 CM PROTOC'
2108 'DISPON/INDEF NÃO CUMPRIMENTO DE INTIMAÇÃO'
2109 'AUT PESQ/REL PESQ ARQ ART 30 III CM - LIBERADA P EDITAL PUB'
2110 'REQ PESQ/TORNA S/EFEITO HOM DESIST PUB - VÍCIO DE LEGALIDADE'
2111 'REQ PLG/PROTOCOLO ORGÃO AMBIENTAL PROTOCOLADO'
2112 'REQ PLG/EXIGÊNCIA OPÇÃO DE ÁREA'
2113 'REQ PLG/EXIGÊNCIA PARA APRESENTAR LICENÇA AMBIENTAL'
2114 'AUT PESQ/TORNA S/EFEITO HOM RENUN PUB - VÍCIO DE LEGALIDADE'
2115 'REQUERIMENTO DE ÁREA DE BLOQUEIO'
2116 'AUT PESQ/BAIXA ALVARÁ - LIBERADA PARA EDITAL'
2117 'PLG/BAIXA PLG - LIBERADA PARA EDITAL'
2118 'LICEN/BAIXA LICENCIAMENTO - LIBERADA PARA EDITAL'
2119 'AUT PESQ/CORREÇÃO DE FASE- ÁREA REQ PESQUISA'
2120 'REQ LAV/CORREÇÃO DE FASE- ÁREA CONCESSÃO DE LAVRA'
2121 'LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA AUTORIZADA'
2122 'LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA NEGADA'
2123 'LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA PROTOCOLIZADO'
2124 'REQ LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA AUTORIZADA'
2125 'REQ LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA NEGADA'
2126 'REQ LICEN/OPÇÃO REGIME PRORROGAÇÃO EXIGÊNCIA PROT'
2127 'CONC LAV/PLANO DE LAVRA APRESENTADO'
2128 'AUT PESQ/SUSPENSÃO JUDICIAL DO ALVARÁ DE PESQUISA'
2129 'AUT PESQ/SUSPENSÃO JUDICIAL DO ALVARÁ DE PESQUISA - ENCERRADA'
2130 'CONC LAV/SUSPENSÃO JUDICIAL DA PORTARIA DE LAVRA'
2131 'CONC LAV/SUSPENSÃO JUDICIAL DA PORTARIA DE LAVRA - ENCERRADA'
2132 'CONC LAV/PORTARIA CONCESSÃO DE LAVRA ANM PUB'
2133 'CONC LAV/PORTARIA RETIFICAÇÃO CONCESSÃO DE LAVRA ANM PUB'
2134 'CONC LAV/PORTARIA NULIDADE CONCESSÃO DE LAVRA ANM PUB'
2135 'CONC LAV/PORTARIA CADUCADA CONCESSÃO DE LAVRA ANM PUB'
2137 'CONC LAV/RETOMADA DOS TRABALHOS LAVRA AUTORIZADO PUB'
2138 'CONC LAV/RETOMADA DOS TRABALHOS LAVRA COMUNICADO PROT'
2139 'REQ LAV/INDEFERIMENTO REQ LAVRA - ANM PUB'
2140 'CONC LAV/PORTARIA NULIDADE CONCESSÃO - VÍCIO COMPETÊNCIA PUB'
2141 'CONC LAV/PORTARIA CEDIDA PARCIALMENTE EM OUTRAS ANM PUB'
2142 'CONC LAV/PORTARIA CESSÃO PARCIAL DE OUTRA ANM PUB'
2145 'REQ EXT/RAL AUTO DE INFRAÇÃO NÃO ENTREGA PUBLIC'
2146 'REQ EXT/RAL TORNA SEM EFEITO AUTO DE INFRAÇÃO'
2147 'REQ EXT/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
2148 'REQ EXT/RAL AUTO INFRAÇÃO ARQUIVADO'
2149 'REQ EXT/RAL MULTA APLICADA'
2150 'REQ EXT/RAL PAGAMENTO MULTA EFETUADO'
2151 'REQ EXT/RAL TORNA SEM EFEITO MULTA APLICADA'
2152 'REQ EXT/RAL EXIGÊNCIA DE APRESENTAÇÃO'
2153 'REQ EXT/RAL CUMPRIMENTO DE EXIGÊNCIA'
2154 'REQ EXT/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
2155 'REQ EXT/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
2156 'REQ EXT/RAL RECURSO MULTA PROTOCOLIZADO'
2157 'REQ EXT/RAL RECURSO MULTA PROVIDO'
2158 'REQ EXT/RAL RECURSO MULTA NEGADO'
2159 'REQ PESQ/DESISTÊNCIA PARCIAL REQ PESQ PROTOCOLIZADA'
2160 'REQ PESQ/DESISTÊNCIA PARCIAL REQ PESQ HOMOLOGADA PUB'
2161 'AUT PESQ/RENÚNCIA PARCIAL AUT PESQ PROTOCOLIZADA'
2162 'AUT PESQ/RENÚNCIA PARCIAL AUT PESQ HOMOLOGADA PUB'
2163 'REQ LAV/DESISTÊNCIA PARCIAL REQ LAVRA PROTOCOLIZ'
2164 'REQ LAV/DESISTÊNCIA PARCIAL REQ LAVRA HOMOLOGADA PUB'
2165 'CONC LAV/RENÚNCIA PARCIAL CONCESSÃO LAVRA PROTOC'
2166 'CONC LAV/RENÚNCIA PARCIAL CONC LAV/ HOMOLOGADA PUB'
2167 'REQ LICEN/DESISTÊNCIA PARCIAL REQ LICEN PROTOCOLIZADA'
2168 'REQ LICEN/DESISTÊNCIA PARCIAL REQ LICEN HOMOLOGADA PUB'
2169 'LICEN/RENÚNCIA PARCIAL LICENCIAMENTO PROTOCOLIZADO'
2170 'LICEN/RENÚNCIA PARCIAL LICENCIAMENTO HOMOLOGADA PUB'
2171 'REQ PLG/DESISTÊNCIA PARCIAL REQ PLG PROTOCOLIZADA'
2172 'REQ PLG/DESISTÊNCIA PARCIAL REQ PLG HOMOLOGADA PUB'
2173 'PLG/RENÚNCIA PARCIAL PLG PROTOCOLIZADA'
2174 'PLG/RENÚNCIA PARCIAL PLG HOMOLOGADA PUB'
2175 'AUT PESQ/APROVA LAUDO PARA CONSTITUIÇÃO DE SERVIDÃO PUB'
2176 'REQ LAV/APROVA LAUDO PARA CONSTITUIÇÃO DE SERVIDÃO PUB'
2177 'CONC LAV/APROVA LAUDO PARA CONSTITUIÇÃO DE SERVIDÃO PUB'
2178 'CONC LAV/AUTO DE INFRAÇÃO FISC CFEM APLICADA PUBLICADA'
2179 'CONC LAV/MULTA FISC CFEM APLICADA PUBLICADA'
2180 'LICEN/AUTO DE INFRAÇÃO FISC CFEM APLICADA PUBLICADA'
2181 'CONC LAV/PORTARIA DE LAVRA CANCELADA DECISÃO JUDICIAL PUB'
2182 'LICEN/MULTA FISC CFEM APLICADA PUBLICADA'
2183 'PLG/AUTO DE INFRAÇÃO FISC CFEM APLICADA PUBLICADA'
2184 'PLG/MULTA FISC CFEM APLICADA PUBLICADA'
2185 'REQ EXT/AUTO DE INFRAÇÃO FISC CFEM APLICADA PUBLICADA'
2186 'REQ EXT/MULTA FISC CFEM APLICADA PUBLICADA'
2187 'AUT PESQ/INDEF PRORROGAÇÃO PRAZO ALVARÁ - LEI SNUC PUB'
2188 'CONC LAV/COMUNICAÇÃO SOBRE RETIFICAÇÃO DE ÁREA'
2189 'AUT PESQ/COMUNICAÇÃO SOBRE RETIFICAÇÃO DE ÁREA'
2190 'REQ LAV/COMUNICAÇÃO SOBRE RETIFICAÇÃO DE ÁREA'
2191 'CONC LAV/EXIGÊNCIA ARRENDATARIO'
2192 'CONC LAV/DECLARA ÁREA DE UTILIDADE PÚBLICA P FINS DE SERV'
2193 'AUT PESQ/TORNA S/EFEITO DECAIMENTO - LEI DO SNUC PUB'
2194 'REQ PESQ/INDEFERIMENTO DE PLANO ART 14 DECRETO 9.406 PUB'
2195 'CONC LAV/TRANSF DIREITOS - CESSÃO DIREITOS CANCELADA ANM'
2196 'CONC LAV/TRANSF DIREITOS - CESSÃO PARCIAL APROVADA ANM'
2197 'CONC LAV/TRANSF DIREITOS - CESSÃO PARCIAL NEGADA ANM'
2198 'CONC LAV/TRANSF DIREITOS - CESSÃO PARCIAL EFETIVADA ANM'
2199 'CONC LAV/TRANSF DIREITOS - CESSÃO TOTAL APROVADA ANM'
2200 'CONC LAV/TRANSF DIREITOS - CESSÃO TOTAL CAD SUCESSORIA ANM'
2201 'CONC LAV/TRANSF DIREITOS - CESSÃO TOTAL NEGADA ANM'
2202 'CONC LAV/TRANSF DIREITOS - CESSÃO TOTAL EFETIVADA ANM'
2203 'DIR REQ LAVRA/DOCUMENTO DIVERSO PROTOCOLIZADO'
2204 'DIR REQ LAVRA/DENÚNCIA DE INVASÃO DA ÁREA'
2205 'DIR REQ LAVRA/DEFESA APRESENTADA'
2206 'DIR REQ LAVRA/RECURSO PROTOCOLIZADO'
2207 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO EXIGÊNCIA SOLICITADO'
2208 'DIR REQ LAVRA/CUMPRIMENTO EXIGÊNCIA PROTOCOLIZADO'
2209 'DIR REQ LAVRA/GUIA UTILIZAÇÃO REQUERIMENTO PROTOC'
2210 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO REQ LAVRA SOLICITADO'
2211 'DIR REQ LAVRA/RAL APRESENTA ART'
2212 'DIR REQ LAVRA/GUIA UTILIZAÇÃO DE VOLVIDA PROTOCOLIZADA'
2213 'DIR REQ LAVRA/TRANSF DIREITOS - CESSÃO PARCIAL PROT'
2214 'DIR REQ LAVRA/RECURSO AO MINISTRO PROTOCOLIZADO'
2215 'DIR REQ LAVRA/LICENÇA AMBIENTAL PROTOCOLIZADA'
2216 'DIR REQ LAVRA/RAL AUTO DE INFRAÇÃO DEFESA APRESENTADA'
2217 'DIR REQ LAVRA/RAL CUMPRIMENTO DE EXIGÊNCIA'
2218 'DIR REQ LAVRA/RAL RETIFICADOR CUMPRIMENTO DE EXIGÊNCIA'
2219 'DIR REQ LAVRA/RAL RECURSO MULTA PROTOCOLIZADO'
2220 'DIR REQ LAVRA/TRANSF DIREITOS - DISTRATO PROTOCOLIZADO'
2221 'DIR REQ LAVRA/SIGILO INFORMAÇÃO MINERÁRIA - REQUERIDA'
2222 'DIR REQ LAVRA/TRANSF DIREITOS - CESSÃO TOTAL PROT'
2223 'DIR REQ LAVRA/DESISTÊNCIA DIREITO REQ LAVRA PROTOCOLIZADO'
2224 'DIR REQ LAVRA/EXIGÊNCIA PUBLICADA'
2225 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO EXIGÊNCIA CONCEDIDO'
2226 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO EXIGÊNCIA NEGADO'
2227 'DIR REQ LAVRA/DEFESA ACEITA PUBLICADA'
2228 'DIR REQ LAVRA/DEFESA NÃO ACEITA PUBLICADA'
2229 'DIR REQ LAVRA/DENÚNCIA CONTRA TITULAR DA ÁREA PROTOC'
2230 'DIR REQ LAVRA/DESISTÊNCIA DIREITO REQ LAVRA HOMOLOGADA PUB'
2231 'DIR REQ LAVRA/DESISTÊNCIA PARCIAL DIR REQ LAV HOMOLOGADA PUB'
2232 'DIR REQ LAVRA/DESISTÊNCIA PARCIAL DIREITO REQ LAVRA PROTOCOLIZADO'
2233 'DIR REQ LAVRA/NÃO CONHECE REQUERIMENTO PUBLICADO'
2234 'DIR REQ LAVRA/DESPACHO PUBLICADO'
2235 'DIR REQ LAVRA/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
2236 'DIR REQ LAVRA/GUIA UTILIZAÇÃO RENOVACÃO SOLICITADA'
2237 'DIR REQ LAVRA/GUIA UTILIZAÇÃO AUTORIZADA PUBLICADA'
2238 'DIR REQ LAVRA/GUIA UTILIZAÇÃO CANCELADA PUBLICADA'
2239 'DIR REQ LAVRA/GUIA UTILIZAÇÃO INDEFERIDA PUBLICADA'
2240 'DIR REQ LAVRA/INTERDIÇÃO LAVRA ILEGAL'
2241 'DIR REQ LAVRA/LICENÇA AMBIENTAL INSTALAÇÃO APRESENTADA'
2242 'DIR REQ LAVRA/LICENÇA AMBIENTAL OPERAÇÃO APRESENTADA'
2243 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO REQ LAVRA- 01 ANO PUB'
2244 'DIR REQ LAVRA/PRORROGAÇÃO PRAZO REQ LAVRA NEGADO'
2245 'DIR REQ LAVRA/RECURSO AO MINISTRO NEGADO PUBLICADO'
2246 'DIR REQ LAVRA/RECURSO AO MINISTRO PROVIDO PUBLICADO'
2247 'DIR REQ LAVRA/RECURSO NEGADO PUBLICADO'
2248 'DIR REQ LAVRA/RECURSO PROVIDO PUBLICADO'

2249 'DIR REQ LAVRA/REGIME COMPARTILHADO- LICEN'
 2250 'DIR REQ LAVRA/RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2251 'DIR REQ LAVRA/TORNA S/EFEITO DESPACHO PUBLICADO'
 2252 'DIR REQ LAVRA/TRANSF DIREITOS -CANCELAMENTO SOLICITADO'
 2253 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO DIREITOS CANCELADA'
 2254 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO PARCIAL ANULADA'
 2255 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO PARCIAL APROVADA'
 2256 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO PARCIAL EFETIVADA'
 2257 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO PARCIAL NEGADA'
 2258 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO TOTAL ANULADA'
 2259 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO TOTAL APROVADA'
 2260 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO TOTAL EFETIVADA'
 2261 'DIR REQ LAVRA/TRANSF DIREITOS -CESSÃO TOTAL NEGADA'
 2262 'DIR REQ LAVRA/CORREÇÃO DE FASE- ÁREA REQUERIMENTO LAVRA'
 2263 'DIR REQ LAVRA/TORNA S/EFEITO ARQUIVAMENTO PROCESSO PUB'
 2264 'DIR REQ LAVRA/TORNA S/EFEITO DESP APROV REL PUB'
 2265 'DIR REQ LAVRA/TORNA S/EFEITO EXIGÊNCIA PUB'
 2266 'DIR REQ LAVRA/ANÁLISE LAMIN PROTOCOLIZADA'
 2267 'DIR REQ LAVRA/ESTUDO IN LOCO (LAMIN) PROTOCOLIZADO'
 2268 'DIR REQ LAVRA/CORREÇÃO DE FASE- ÁREA AUTORIZAÇÃO PESQUISA'
 2269 'REQ PESQ/ESTUDO IN LOCO (LAMIN) PROTOCOLIZADO'
 2270 'REQ LAV/ESTUDO IN LOCO (LAMIN) PROTOCOLIZADO'
 2271 'REQ PESQ/ANÁLISE LAMIN PROTOCOLIZADO'
 2272 'REQ LAV/ANÁLISE LAMIN PROTOCOLIZADO'
 2273 'DIR REQ LAVRA/RETIFICAÇÃO ÁREA DO REL FINAL APROVADO PUB'
 2274 'DIR REQ LAVRA/RETIFICAÇÃO ÁREA REL FINAL APROVADO PROT'
 2275 'APTO DISP/ÁREA APTA PARA DISPONIBILIDADE'
 2276 'AUT PESQ/CORREÇÃO DE FASE- ÁREA DIREITO REQUERER A LAVRA'
 2277 'DISPONIB/CUMPRIMENTO DE EXIGENCIA PROTOC'
 2278 'DIR REQ LAVRA/ASSENTIMENTO CDN AUTORIZADO'
 2279 'DIR REQ LAVRA/ASSENTIMENTO CDN NÃO AUTORIZADO'
 2280 'DIR REQ LAVRA/ASSENTIMENTO CDN SOLICITADO'
 2281 'DIR REQ LAVRA/VISTORIA LAVRA ILEGAL'
 2282 'DIR REQ LAVRA/AUTOINFRAÇÃO ADVERTÊNCIA PUBLICADA'
 2283 'DIR REQ LAVRA/ADVERTÊNCIA PUBLICADA'
 2284 'DIR REQ LAVRA/AUTO INFRAÇÃO PUBLICADO'
 2285 'DIR REQ LAVRA/MULTA APLICADA PUBLICADA'
 2286 'DIR REQ LAVRA/TORNA SEM EFEITO AUTO INFRAÇÃO'
 2287 'DIR REQ LAVRA/ARQUIVAMENTO AUTO INFRAÇÃO PUBLICADO'
 2288 'DIR REQ LAVRA/TORNA S/EFEITO MULTA APLICADA'
 2289 'DIR REQ LAVRA/ARQUIVAMENTO PROCESSO PUBLICADO'
 2292 'AUT PESQ/ANULA PUBLICAÇÃO ALVARA POR DUPLICIDADE'
 2293 'DISPONIB/ABERTURA DE PROCESSO DECLARADO PRIORITÁRIO PROTOCOL'
 2294 'DIR REQ LAVRA/REQ PROVENIENTE CESSÃO PARCIAL REL APROV PROT'
 2295 'DIR REQ LAVRA/RAL RETIFICADOR EXIGÊNCIA DE APRESENTAÇÃO'
 2296 'REQ LAV/TORNA S/EFEITO DESPACHO PUBLICADO'
 2297 'PLG/TORNA S/EFEITO DESPACHO PUBLICADO'
 2298 'REQ EXT/TORNA S/ EFEITO DESPACHO PUBLICADO'
 2299 'TORNA S/EFEITO DESPACHO PUBLICADO'
 2300 'AUT PESQ/BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2301 'AUT PESQ/BARRAGENS DESINTERDIÇÃO NEGADA'
 2302 'AUT PESQ/BARRAGENS DESINTERDIÇÃO PUB'
 2303 'AUT PESQ/BARRAGENS INTERDIÇÃO PUB'
 2304 'DISPONIB/EDITAL OFERTA PUBLICA PARA PLG'
 2305 'DISPONIB/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 2306 'REQ PESQ/TORNA S/EFEITO DESPACHO INDEFERIMENTO- REPEM'
 2307 'REQ PESQ/DECISÃO JUDICIAL PROTOCOLIZADA'
 2308 'AUT PESQ/DECISÃO JUDICIAL PROTOCOLIZADA'
 2309 'DIR REQ LAV/DECISÃO JUDICIAL PROTOCOLIZADA'
 2310 'DISPONIB/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2311 'PLG/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2312 'PLG/BARRAGENS PRORROG PRAZO EXIGENCIA SOLICITADO'
 2313 'CONC LAV/ BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2314 'LICEN/BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2315 'PLG/BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2316 'REQ LAV/ BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2317 'REQ LAV/BARRAGENS PROTOC ENTREGA PAEBM A DEFESA CIVIL'
 2318 'REQ LAV/BARRAGENS PROTOC ENTREGA PAEBM A PREFEITURAS'
 2319 'REQ PESQ/ASSENTIMENTO CDN CASSADO'
 2320 'REQ PLG/ASSENTIMENTO CDN CASSADO'
 2321 'REQ EXT/ASSENTIMENTO CDN CASSADO'
 2322 'AUT PESQ/GUIA UTILIZAÇÃO PRORROGAÇÃO SOLICITADA'
 2323 'AUT PESQ/GUIA UTILIZAÇÃO PRORROGAÇÃO 01 ANO PUBL'
 2324 'AUT PESQ/GUIA UTILIZAÇÃO PRORROGAÇÃO 02 ANOS PUB'
 2325 'AUT PESQ/GUIA UTILIZAÇÃO PRORROGAÇÃO 03 ANOS PUB'
 2326 'DIR REQ LAVRA/GUIA UTILIZAÇÃO PRORROGAÇÃO SOLICITADA'
 2327 'DIR REQ LAVRA/GUIA UTILIZAÇÃO PRORROGAÇÃO 01 ANO PUBL'
 2328 'DIR REQ LAVRA/GUIA UTILIZAÇÃO PRORROGAÇÃO 02 ANOS PUBL'
 2329 'DIR REQ LAVRA/GUIA UTILIZAÇÃO PRORROGAÇÃO 03 ANOS PUB'
 2330 'REQ LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO SOLICITADA'
 2331 'REQ LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 01 ANO PUB'
 2332 'REQ LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 02 ANOS PUB'
 2333 'REQ LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 03 ANOS PUB'
 2334 'CONC LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO SOLICITADA'
 2335 'CONC LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 01 ANO PUB'
 2336 'CONC LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 02 ANOS PUB'
 2337 'CONC LAV/GUIA UTILIZAÇÃO PRORROGAÇÃO 03 ANOS PUB'
 2338 'DISPONIB/EDITAL OFERTA PUBLICA PARA PESQUISA'
 2339 'DISPONIB/EDITAL OFERTA PUBLICA PARA LAVRA'
 2340 'REQ PESQ/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2341 'AUT PESQ/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2342 'REQ LICEN/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2343 'LICEN/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2344 'REQ PLG/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2345 'PLG/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2346 'REQ EXT/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2347 'REQ EXT/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2348 'REQ PESQ/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2349 'AUT PESQ/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2350 'REQ LAV/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2351 'CONC LAV/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2352 'REQ LICEN/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2353 'LICEN/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2354 'REQ PLG/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2355 'PLG/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2356 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2357 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA- REQUERIDA'
 2358 'REQ LAV/DECISÃO JUDICIAL PROTOCOLIZADA'
 2359 'CONC LAV/DECISÃO JUDICIAL PROTOCOLIZADA'
 2360 'APTO DISP/DECISÃO JUDICIAL PROTOCOLIZADA'
 2361 'DISPONIB/DECISÃO JUDICIAL PROTOCOLIZADA'
 2362 'CONC LAV/BARRAGENS EXIGENCIA PRAZO ESPECIAL PUB'
 2363 'CONC LAV/BARRAGENS INTERDIÇÃO PUB'
 2364 'CONC LAV/BARRAGENS DESINTERDIÇÃO NEGADA'
 2365 'CONC LAV/BARRAGENS DESINTERDIÇÃO PUB'
 2366 'CONC LAV/BARRAGENS REITERA EXIGENCIA PUB'
 2367 'CONC LAV/BARRAGENS PRORROG PRAZO EXIGENCIA CONCEDIDO'
 2368 'CONC LAV/BARRAGENS PRORROG EXIGENCIA PRAZO OFICIO'
 2369 'PLG/BARRAGENS PRORROG PRAZO EXIGENCIA NEGADO'
 2370 'PLG/BARRAGENS PRORROG PRAZO EXIGENCIA CONCEDIDO'
 2371 'PLG/BARRAGENS EXIGENCIA PRAZO ESPECIAL PUB'
 2372 'PLG/BARRAGENS EXIGENCIA PUBLICADA'
 2373 'PLG/BARRAGENS INTERDIÇÃO PUB'
 2374 'PLG/BARRAGENS DESINTERDIÇÃO NEGADA'
 2375 'PLG/BARRAGENS DESINTERDIÇÃO PUB'
 2376 'PLG/BARRAGENS REITERA EXIGENCIA PUB'
 2377 'PLG/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
 2378 'PLG/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE NÃO ACEITO'
 2379 'PLG/BARRAGENS PRORROG EXIGENCIA PRAZO OFICIO'
 2380 'LICEN/BARRAGENS EXIGENCIA PRAZO ESPECIAL PUB'
 2381 'LICEN/BARRAGENS INTERDIÇÃO PUB'
 2382 'LICEN/BARRAGENS DESINTERDIÇÃO NEGADA'
 2383 'LICEN/BARRAGENS DESINTERDIÇÃO PUB'
 2384 'LICEN/BARRAGENS REITERA EXIGENCIA PUB'
 2385 'LICEN/BARRAGENS PRORROG PRAZO EXIGENCIA CONCEDIDO'
 2386 'LICEN/BARRAGENS PRORROG EXIGENCIA PRAZO OFICIO'
 2387 'REQ LAV/BARRAGENS INTERDIÇÃO PUB'
 2388 'REQ LAV/BARRAGENS DESINTERDIÇÃO NEGADA'
 2389 'REQ LAV/BARRAGENS DESINTERDIÇÃO PUB'
 2390 'REQ LAV/BARRAGENS REITERA EXIGENCIA PUB'
 2391 'REQ LAV/BARRAGENS EXIGENCIA PRAZO ESPECIAL PUB'
 2392 'REQ LAV/BARRAGENS PRORROG PRAZO EXIGENCIA CONCEDIDO'
 2393 'REQ LAV/BARRAGENS PRORROG EXIGENCIA PRAZO OFICIO'
 2394 'CONC LAV/BARRAGENS AUTO DE INFRAÇÃO PUB'
 2395 'PLG/BARRAGENS AUTO DE INFRAÇÃO PUB'
 2396 'REQ LAV/BARRAGENS AUTO DE INFRAÇÃO PUB'
 2397 'LICEN/BARRAGENS AUTO DE INFRAÇÃO PUB'
 2398 'CONC LAV/BARRAGENS TORNA S/ EFEITO AUTO INFRAÇÃO PUB'
 2399 'PLG/BARRAGENS TORNA S/ EFEITO AUTO INFRAÇÃO PUB'
 2400 'REQ LAV/BARRAGENS TORNA S/ EFEITO AUTO INFRAÇÃO PUB'
 2401 'LICEN/BARRAGENS TORNA S/ EFEITO AUTO INFRAÇÃO PUB'
 2402 'CONC LAV/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'

2403 'PLG/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'
2404 'REQ LAV/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'
2405 'LICEN/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'
2406 'CONC LAV/BARRAGENS DEFESA ACEITA PUB'
2407 'PLG/BARRAGENS DEFESA ACEITA PUB'
2408 'REQ LAV/BARRAGENS DEFESA ACEITA PUB'
2409 'LICEN/BARRAGENS DEFESA ACEITA PUB'
2410 'CONC LAV/BARRAGENS DEFESA NÃO ACEITA PUB'
2411 'PLG/BARRAGENS DEFESA NÃO ACEITA PUB'
2412 'REQ LAV/BARRAGENS DEFESA NÃO ACEITA PUB'
2413 'LICEN/BARRAGENS DEFESA NÃO ACEITA PUB'
2414 'CONC LAV/BARRAGENS MULTA APLICADA PUB'
2415 'PLG/BARRAGENS MULTA APLICADA PUB'
2416 'REQ LAV/BARRAGENS MULTA APLICADA PUB'
2417 'LICEN/BARRAGENS MULTA APLICADA PUB'
2418 'CONC LAV/BARRAGENS TORNA S/ EFEITO MULTA PUB'
2419 'PLG/BARRAGENS TORNA S/ EFEITO MULTA PUB'
2420 'REQ LAV/BARRAGENS TORNA S/ EFEITO MULTA PUB'
2421 'LICEN/BARRAGENS TORNA S/ EFEITO MULTA PUB'
2422 'CONC LAV/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
2423 'PLG/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
2424 'REQ LAV/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
2425 'LICEN/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
2426 'CONC LAV/BARRAGENS RECURSO PROVIDO PUB'
2427 'PLG/BARRAGENS RECURSO PROVIDO PUB'
2428 'REQ LAV/BARRAGENS RECURSO PROVIDO PUB'
2429 'LICEN/BARRAGENS RECURSO PROVIDO PUB'
2430 'CONC LAV/BARRAGENS RECURSO NEGADO PUB'
2431 'PLG/BARRAGENS RECURSO NEGADO PUB'
2432 'REQ LAV/BARRAGENS RECURSO NEGADO PUB'
2433 'LICEN/BARRAGENS RECURSO NEGADO PUB'
2434 'REQ LICEN/DECISÃO JUDICIAL PROTOCOLIZADA'
2435 'LICEN/DECISÃO JUDICIAL PROTOCOLIZADA'
2436 'REQ PLG/DECISÃO JUDICIAL PROTOCOLIZADA'
2437 'PLG/DECISÃO JUDICIAL PROTOCOLIZADA'
2438 'REQ EXT/DECISÃO JUDICIAL PROTOCOLIZADA'
2439 'REG EXT/DECISÃO JUDICIAL PROTOCOLIZADA'
2440 'REQ PESQ/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2441 'REQ PESQ/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2442 'REQ PLG/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2443 'REQ PLG/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2444 'AUT PESQ/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2445 'AUT PESQ/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2446 'CONC LAV/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2447 'CONC LAV/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2448 'DIR REQ LAVRA/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2449 'DIR REQ LAVRA/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2450 'LICEN/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2451 'LICEN/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2452 'PLG/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2453 'PLG/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2454 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2455 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2456 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2457 'REQ EXT/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2458 'REQ LAV/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2459 'REQ LAV/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2460 'REQ LICEN/SIGILO INFORMAÇÃO MINERÁRIA - INDEFERIDO'
2461 'REQ LICEN/SIGILO INFORMAÇÃO MINERÁRIA - DEFERIDO'
2462 'AUT PESQ/ASSENTIMENTO CDN CASSADO/CESSÃO DIREITOS'
2463 'DISPONIB/LEILÃO ELET/PROPOSTA PAGA SEM REQ/RETORNO DISP'
2464 'DISPONIB/LEILÃO ELET/PROPOSTA NÃO PAGA/RETORNO DISP'
2465 'DISPONIB/MANIFESTAÇÃO ÚNICA'
2466 'DISPONIB/MANIFESTAÇÃO ÚNICA/SEM PROTOC REQ/ÁREA LIVRE'
2467 'DISPONIB/LEILÃO ELET/ONICO ÁREA PARA LAVRA'
2468 'DISPONIB/LEILÃO ELET/ONICO ÁREA PARA PESQUISA'
2469 'DISPONIB/LEILÃO ELET/ONICO ÁREA PARA PLG'
2470 'DISPONIB/LEILÃO ELET/SEM REGISTRO PROPOSTA/ÁREA LIVRE'
2471 'DISPONIB/LEILÃO ELET/PROPOSTA PAGA/SEM PROTOC REQ/ÁREA LIVRE'
2472 'DISPONIB/LEILÃO ELET/PROP UNICA/FINAN NÃO PAGA/ÁREA LIVRE'
2473 'DISPONIB/LEILÃO ELET/PROPOSTAS FINAN NÃO PAGAS/ÁREA LIVRE'
2474 'AUT PESQ/FISCALIZAÇÃO REMOTA CONCLUIDA'
2475 'DIR REQ LAVRA/FISCALIZAÇÃO REMOTA CONCLUIDA'
2476 'REQ LAV/FISCALIZAÇÃO REMOTA CONCLUIDA'
2477 'CONC LAV/FISCALIZAÇÃO REMOTA CONCLUIDA'
2478 'LICEN/FISCALIZAÇÃO REMOTA CONCLUIDA'
2479 'PLG/FISCALIZAÇÃO REMOTA CONCLUIDA'
2480 'REQ EXT/FISCALIZAÇÃO REMOTA CONCLUIDA'
2481 'AUT PESQ/VENCIMENTO ALVARÁ ALTERADO RESOLUÇÃO 76/2021 - COVID'
2482 'DIR REQ LAVRA/ASSENTIMENTO CDN CASSADO'
2483 'DIR REQ LAVRA/ASSENTIMENTO CDN CASSADO/CESSÃO DIREITOS'
2484 'REQ LAV/ASSENTIMENTO CDN CASSADO'
2485 'REQ LAV/ASSENTIMENTO CDN CASSADO/CESSÃO DIREITOS'
2486 'CONC LAV/ASSENTIMENTO CDN CASSADO/CESSÃO DIREITOS'
2487 'CONC LAV/ASSENTIMENTO CDN CASSADO/ARRENDAMENTO'
2488 'REQ LAV/DECLARAÇÃO DE APTIDÃO EMISSÃO'
2489 'AUT PESQ/DECLARAÇÃO DE RESULTADOS DE EXPLORAÇÃO'
2490 'AUT PESQ/DECLARAÇÃO DE RECURSOS MINERAIS'
2491 'AUT PESQ/DECLARAÇÃO DE RESERVAS MINERAIS'
2492 'DIR REQ LAVRA/DECLARAÇÃO DE RESULTADOS DE EXPLORAÇÃO'
2493 'DIR REQ LAVRA/DECLARAÇÃO DE RECURSOS MINERAIS'
2494 'DIR REQ LAVRA/DECLARAÇÃO DE RESERVAS MINERAIS'
2495 'REQ LAV/DECLARAÇÃO DE RESULTADOS DE EXPLORAÇÃO'
2496 'REQ LAV/DECLARAÇÃO DE RECURSOS MINERAIS'
2497 'REQ LAV/DECLARAÇÃO DE RESERVAS MINERAIS'
2498 'CONC LAV/BARRAGENS NÃO CONHECE REQUERIMENTO PUBLICADO'
2499 'REQ EXT/DECLARAÇÃO DE APTIDÃO EMISSÃO'
2500 'CONC LAV/DECLARAÇÃO DE RESULTADOS DE EXPLORAÇÃO'
2501 'CONC LAV/DECLARAÇÃO DE RECURSOS MINERAIS'
2502 'CONC LAV/DECLARAÇÃO DE RESERVAS MINERAIS'
2503 'CONC LAV/PLANO DE FECHAMENTO DE MINA ANALISADO'
2504 'CONC LAV/PLANO DE FECHAMENTO DE MINA APROVADO'
2505 'LICEN/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
2506 'LICEN/PLANO DE FECHAMENTO DE MINA ANALISADO'
2507 'LICEN/PLANO DE FECHAMENTO DE MINA APROVADO'
2508 'PLG/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
2509 'PLG/PLANO DE FECHAMENTO DE MINA ANALISADO'
2510 'PLG/PLANO DE FECHAMENTO DE MINA APROVADO'
2511 'REQ EXT/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
2512 'REQ EXT/PLANO DE FECHAMENTO DE MINA ANALISADO'
2513 'REQ EXT/PLANO DE FECHAMENTO DE MINA APROVADO'
2514 'AUT PESQ/BARRAGENS EMBARGO PUBLICADO'
2515 'CONC LAV/BARRAGENS EMBARGO PUBLICADO'
2516 'LICEN/BARRAGENS EMBARGO PUBLICADO'
2517 'PLG/BARRAGENS EMBARGO PUBLICADO'
2518 'REQ LAV/BARRAGENS EMBARGO PUBLICADO'
2519 'AUT PESQ/BARRAGENS DESEMBARGO SOLICITADO PROT'
2520 'CONC LAV/BARRAGENS DESEMBARGO SOLICITADO PROT'
2521 'LICEN/BARRAGENS DESEMBARGO SOLICITADO PROT'
2522 'PLG/BARRAGENS DESEMBARGO SOLICITADO PROT'
2523 'REQ LAV/BARRAGENS DESEMBARGO SOLICITADO PROT'
2524 'AUT PESQ/BARRAGENS DESEMBARGO NEGADO PUBLICADO'
2525 'CONC LAV/BARRAGENS DESEMBARGO NEGADO PUBLICADO'
2526 'LICEN/BARRAGENS DESEMBARGO NEGADO PUBLICADO'
2527 'PLG/BARRAGENS DESEMBARGO NEGADO PUBLICADO'
2528 'REQ LAV/BARRAGENS DESEMBARGO NEGADO PUBLICADO'
2529 'AUT PESQ/BARRAGENS DESEMBARGO PUBLICADO'
2530 'CONC LAV/BARRAGENS DESEMBARGO PUBLICADO'
2531 'LICEN/BARRAGENS DESEMBARGO PUBLICADO'
2532 'PLG/BARRAGENS DESEMBARGO PUBLICADO'
2533 'REQ LAV/BARRAGENS DESEMBARGO PUBLICADO'
2534 'AUT PESQ/BARRAGENS ANÁLISE PROCESSUAL CONCLUIDA'
2535 'CONC LAV/BARRAGENS ANÁLISE PROCESSUAL CONCLUIDA'
2536 'LICEN/BARRAGENS ANÁLISE PROCESSUAL CONCLUIDA'
2537 'PLG/BARRAGENS ANÁLISE PROCESSUAL CONCLUIDA'
2538 'REQ LAV/BARRAGENS ANÁLISE PROCESSUAL CONCLUIDA'
2539 'AUT PESQ/BARRAGENS AUTO DE INFRAÇÃO PUB'
2540 'AUT PESQ/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
2541 'AUT PESQ/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE NÃO ACEITO'
2542 'AUT PESQ/BARRAGENS DEFESA ACEITA PUB'
2543 'AUT PESQ/BARRAGENS DEFESA NÃO ACEITA PUB'
2544 'AUT PESQ/BARRAGENS EXIGÊNCIA PRAZO ESPECIAL PUB'
2545 'AUT PESQ/BARRAGENS EXIGÊNCIA PRAZO OFÍCIO'
2546 'AUT PESQ/BARRAGENS EXIGÊNCIA PUBLICADA'
2547 'AUT PESQ/BARRAGENS MULTA APLICADA PUB'
2548 'AUT PESQ/BARRAGENS PRORROG EXIGÊNCIA PRAZO OFÍCIO'
2549 'AUT PESQ/BARRAGENS PRORROG PRAZO EXIGÊNCIA CONCEDIDO'
2550 'AUT PESQ/BARRAGENS RECURSO NEGADO PUB'
2551 'AUT PESQ/BARRAGENS RECURSO PROVIDO PUB'
2552 'AUT PESQ/BARRAGENS REITERA EXIGÊNCIA PUB'
2553 'AUT PESQ/BARRAGENS TORNA S/ EFEITO AUTO DE INFRAÇÃO PUB'
2554 'AUT PESQ/BARRAGENS TORNA S/ EFEITO MULTA PUB'

2555 'AUT PESQ/BARRAGENS NÃO CONHECE REQUERIMENTO PUBLICADO'
 2556 'DIR REQ LAVRA/BARRAGENS DECLAR CONDIÇÃO ESTABILIDADE ACEITO'
 2557 'DIR REQ LAVRA/BARRAGENS DCE NÃO ACEITO'
 2558 'DIR REQ LAVRA/BARRAGENS EXIGENCIA PUBLICADA'
 2559 'DIR REQ LAVRA/BARRAGENS PRORROG PRAZO EXIGENCIA NEGADO'
 2560 'DIR REQ LAVRA/BARRAGENS EXIGENCIA PRAZO ESPECIAL PUB'
 2561 'DIR REQ LAVRA/BARRAGENS EXIGENCIA PRAZO OFICIO'
 2562 'DIR REQ LAVRA/BARRAGENS DESINTERDIÇÃO NEGADA'
 2563 'DIR REQ LAVRA/BARRAGENS DESINTERDIÇÃO PUB'
 2564 'DIR REQ LAVRA/BARRAGENS REITERA EXIGENCIA PUB'
 2565 'DIR REQ LAVRA/BARRAGENS PRORROG PRAZO EXIGENCIA CONCEDIDO'
 2566 'DIR REQ LAVRA/BARRAGENS PRORROG EXIGENCIA PRAZO OFICIO'
 2567 'DIR REQ LAVRA/BARRAGENS AUTO DE INFRAÇÃO PUB'
 2568 'DIR REQ LAVRA/BARRAGENS TORNA S/ EFEITO AUTO DE INFRAÇÃO PUB'
 2569 'DIR REQ LAVRA/BARRAGENS DEFESA ACEITA PUB'
 2570 'DIR REQ LAVRA/BARRAGENS DEFESA NÃO ACEITA PUB'
 2571 'DIR REQ LAVRA/BARRAGENS MULTA APLICADA PUB'
 2572 'DIR REQ LAVRA/BARRAGENS TORNA S/EFEITO MULTA PUB'
 2573 'DIR REQ LAVRA/BARRAGENS RECURSO NEGADO PUB'
 2574 'DIR REQ LAVRA/BARRAGENS RECURSO PROVIDO PUB'
 2575 'DIR REQ LAVRA/BARRAGENS EMBARGO PUBLICADO'
 2576 'DIR REQ LAVRA/BARRAGENS DESEMBARGO PUBLICADO'
 2577 'DIR REQ LAVRA/BARRAGENS DESEMBARGO NEGADO'
 2578 'DIR REQ LAVRA/BARRAGENS NÃO CONHECE REQUERIMENTO PUBLICADO'
 2579 'LICEN/BARRAGENS NAO CONHECE REQUERIMENTO PUBLICADO'
 2580 'PLG/BARRAGENS NAO CONHECE REQUERIMENTO PUBLICADO'
 2581 'REQ LAV/BARRAGENS NAO CONHECE REQUERIMENTO PUBLICADO'
 2582 'DIR REQ LAVRA/BARRAGENS ANALISE PROCESSUAL CONCLUIDA'
 2583 'AUT PESQ/BARRAGENS PRORROG PRAZO EXIGENCIA NEGADO'
 2584 'AUT PESQ/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2585 'AUT PESQ/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'
 2586 'AUT PESQ/BARRAGENS PRORROG PRAZO EXIGENCIA SOLICITADO'
 2587 'AUT PESQ/BARRAGENS PROTOC ENTREGA PAEBM À DEFESA CIVIL'
 2588 'AUT PESQ/BARRAGENS PROTOC ENTREGA PAEBM À PREFEITURAS'
 2589 'AUT PESQ/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
 2590 'DIR REQ LAVRA/BARRAGENS CUMPRIMENTO DE EXIGENCIA PROTOC'
 2591 'DIR REQ LAVRA/BARRAGENS PRORROG PRAZO EXIGENCIA SOLICITADO'
 2592 'DIR REQ LAVRA/BARRAGENS PROTOC ENTREGA PAEBM À DEFESA CIVIL'
 2593 'DIR REQ LAVRA/BARRAGENS PROTOC ENTREGA PAEBM À PREFEITURAS'
 2594 'DIR REQ LAVRA/BARRAGENS SOLICITA DESINTERDIÇÃO PROT'
 2595 'DIR REQ LAVRA/BARRAGENS DESEMBARGO SOLICITADO PROT'
 2596 'DIR REQ LAVRA/BARRAGENS DEFESA AUTO INFRAÇÃO PROTOCOLIZADA'
 2597 'DIR REQ LAVRA/BARRAGENS RECURSO MULTA PROTOCOLIZADO'
 2598 'AUT PESQ/BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2599 'CONC LAV/BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2600 'REQ PESQ/ANULA PUBLICAÇÃO - REPEM'
 2601 'DIR REQ LAVRA/BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2602 'LICEN BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2603 'PLG/BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2604 'REQ LAV/BARRAGENS TORNA SEM EFEITO DESPACHO PUBLICADO'
 2605 'AUT PESQ/BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2606 'CONC LAV/BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2607 'DIR REQ LAVRA/BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2608 'LICEN BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2609 'PLG/BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2610 'REQ LAV/BARRAGENS RETIFICAÇÃO DE DESPACHO PUBLICADO'
 2611 'CONC LAV/PORTARIA CONCESSÃO DE LAVRA GER/ANM'
 2612 'REQ PESQ/PEDIDO RECONSIDERAÇÃO PROVIDA - SUPERINTENDENTE'
 2613 'REQ PESQ/PEDIDO RECONSIDERAÇÃO NEGADA - SUPERINTENDENTE'
 2614 'REQ LAV/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2615 'REQ LICEN/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2616 'REQ PLG/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2617 'REQ EXT/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2618 'CONC LAV/PORTARIA ENLOBANDO ÁREAS PESQUISADAS - ANM'
 2619 'AUT PESQ/GUIA DE UTILIZAÇÃO PFM PROTOCOLIZADO'
 2620 'AUT PESQ/GUIA DE UTILIZAÇÃO PFM APROVADO'
 2621 'DIR REQ LAVRA/GUIA DE UTILIZAÇÃO PFM PROTOCOLIZADO'
 2622 'DIR REQ LAVRA/GUIA DE UTILIZAÇÃO PFM APROVADO'
 2623 'REQ LAV/GUIA DE UTILIZAÇÃO PFM PROTOCOLIZADO'
 2624 'REQ LAV/GUIA DE UTILIZAÇÃO PFM AUTORIZADO'
 2625 'REQ LAV/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
 2626 'REQ LICEN/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
 2627 'REQ PLG/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
 2628 'REQ EXT/PLANO DE FECHAMENTO DE MINA PROTOCOLIZADO'
 2629 'AUT PESQ/GUIA DE UTILIZAÇÃO RELAT EXEC PFM PROTOCOLIZADO'
 2630 'AUT PESQ/GUIA DE UTILIZAÇÃO RELAT EXEC PFM APROVADO'
 2631 'DIR REQ LAVRA/GUIA DE UTILIZAÇÃO RELAT EXEC PFM PROTOC'
 2632 'DIR REQ LAVRA/GUIA DE UTILIZAÇÃO RELAT EXEC PFM APROVADO'
 2633 'REQ LAV/GUIA DE UTILIZAÇÃO RELAT EXEC PFM PROTOCOLIZADO'
 2634 'REQ LAV/GUIA DE UTILIZAÇÃO RELAT EXEC PFM APROVADO'
 2635 'CONC LAV/RELAT EXEC PFM PROTOCOLIZADO'
 2636 'CONC LAV/RELAT EXEC PFM APROVADO'
 2637 'LICEN/RELAT EXEC PFM PROTOCOLIZADO'
 2638 'LICEN/RELAT EXEC PFM APROVADO'
 2639 'PLG/RELAT EXEC PFM PROTOCOLIZADO'
 2640 'PLG/RELAT EXEC PFM APROVADO'
 2641 'REQ EXT/RELAT EXEC PFM PROTOCOLIZADO'
 2642 'REQ EXT/RELAT EXEC PFM APROVADO'
 2643 'AUT PESQ/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2644 'DIR REQ LAVRA/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2645 'CONC LAV/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2646 'LICEN/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2647 'PLG/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2648 'REQ EXT/RECURSO 2ª INSTÂNCIA PROVIDO PUBLICADO'
 2649 'DISPONIB/ÁREA CONQUISTADA - AVALIAÇÃO SOCIAL - PLG'
 2650 'DISPONIB/ÁREA SUSPENS A'
 2663 'CONC LAV/ÁREA DISPONIBILIDADE PARA PESQUISA - EDITAL'
 2664 'REQ LAV/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 2665 'CONC LAV/ÁREA DISPONIBILIDADE PARA LAVRA - EDITAL'
 2677 'DISPONIB/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 2802 'DISPONIB/ÁREA DESCARTADA DISPONIB P/ PESQUISA - EDITAL'
 2836 'DISPONIB/ÁREA DESCARTADA DISPONIB PARA PLG - EDITAL'
 2866 'REQ PESQ/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 2867 'REQ PLG/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 2868 'PLG/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 2869 'AUT PESQ/ÁREA DISPONIBILIDADE PARA PLG - EDITAL'
 2870 'CONC LAV/TORNA SEM EFEITO PORTARIA'
 2883 'DISPONIB/ÁREA DESBLOQUEADA DISPONIB PARA PLG - EDITAL'
 2890 'CONC LAV/BARRAGENS EXIGENCIA PRAZO OFICIO PUB'
 2891 'CONC LAV/EXIGENCIA BARRAGEM - PORT MME 21/2019 PUB'
 2892 'CONC LAV/EXIGENCIA BARRAGEM - CONS MINIST - RES 01/2019'
 2893 'CONC LAV/CUMPRIMENTO DE EXIGENCIA BARRAGEM - ANM PROTOC'
 2894 'CONC LAV/CUMP EXIGENCIA BARRAGEM-PORT MME 21/2019 PROTOC'
 2895 'CONC LAV/CUMP EXIGENCIA BARRAGEM CONS MINST-RES 01/2019 PROT'
 2896 'PLG/BARRAGENS EXIGENCIA PRAZO OFICIO PUB'
 2897 'CONC LAV/EXIG BARRAGEM-PORT MME 21/19 CONS MINIS 01/19 PUB'
 2898 'CONC LAV/CUMP EXIG BARRAGEM-PORT MME 21/19 CONS MINIS 01/19'
 2899 'PLG/CUMPRIMENTO EXIGENCIA BARRAGEM - ANM PROTOC'
 2900 'LICEN/BARRAGENS EXIGENCIA PRAZO OFICIO PUB'
 2901 'LICEN/CUMPRIMENTO EXIGENCIA BARRAGEM - ANM PROTOC'
 2902 'REQ LAV/BARRAGENS EXIGENCIA PRAZO OFICIO PUB'
 2903 'REQ LAV/EXIGENCIA BARRAGEM - ANM - PROTOC'
 2904 'SIGILO INFORMAÇÃO MINERARIA- REQUERIDA'
 2905 'SIGILO INFORMAÇÃO MINERARIA- DEFERIDA'
 2906 'SIGILO INFORMAÇÃO MINERARIA - INDEFERIDA'
 2907 'REQ EXT/AUTO INFRAÇÃO MULTA PUBLICADA'
 2908 'REQ EXT/MULTA APLICADA PUBLICADA'
 2909 'CONC LAV/PRORROGAÇÃO DE EXIGENCIA BARRAGEM - OF CIRC 02/2019'
 2910 'REQ LAV/PRORROGAÇÃO DE EXIGENCIA BARRAGEM - OF CIRC 02/2019'
 2911 'PLG/PRORROGAÇÃO DE EXIGENCIA BARRAGEM - OF CIRC 02/2019'
 2912 'LICEN/PRORROGAÇÃO DE EXIGENCIA BARRAGEM - OF CIRC 02/2019'
 2913 'CONC LAV/PORTARIA CADUCADA CONCESSÃO DE LAVRA MME PUB'
 2914 'CONC LAV/ADITAMENTO NOVA SUBST AUTORIZADO PUB ANM'
 2915 'CONC LAV/ADITAMENTO NOVA SUBST NÃO AUTORIZADO PUB ANM'
 2916 'ART. 57 AUT PESQ/RECURSO NEGADO PUBLICADO'
 2917 'ART. 59 AUT PESQ/RECURSO NEGADO PUBLICADO'
 2918 'ART. 60 AUT PESQ/RECURSO NEGADO PUBLICADO'.

* Convert event date field from string to date (YYYY/MM/DD) creating a new variable called event_dt.
 COMPUTE event_dt=number(DTEvento, SDATE10).
 VARIABLE LABELS event_dt "Event date".
 VARIABLE LEVEL event_dt (SCALE).
 FORMATS event_dt (SDATE10).

```
VARIABLE WIDTH event_dt(10).
EXECUTE.
```

```
SORT CASES BY DSProcesso(A).
```

```
*Save dataset as SPSS .dat file.
```

```
SAVE OUTFILE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent.sav'.
/drop DTEvento.
```

```
* Get data from Mining Titles granted by ANM.
```

```
PRESERVE.
SET DECIMAL COMMA.
GET DATA /TYPE=TXT
/FILE="E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessoTitulo.txt"
/ENCODING='LOCALE'
/DELCASE=LINE
/DELIMITERS=";"
/ARRANGEMENT=DELIMITED
/FIRSTCASE=2
/LEADINGSPACES IGNORE=YES
/DATATYPEMIN PERCENTAGE=95.0
/VARIABLES=
DSProcesso AUTO
NRTitulo AUTO
IDDocumentoLegal AUTO
IDTipoDocumentoLegal AUTO
IDSituacaoDocumentoLegal AUTO
DTPublicacao SDATE10
DTVencimento SDATE10
/MAP.
RESTORE.
```

```
CACHE.
EXECUTE.
DATASET NAME ProcessTitle WINDOW=FRONT.
```

```
VALUE LABELS
```

```
IDTipoDocumentoLegal
```

```
1 'Research Permit'
```

```
2 'Artisanal Mining Permit'
```

```
3 'License Registration'
```

```
4 'Mining Concession'
```

```
5 'Deposit Manifest'
```

```
6 'Mine Manifest'
```

```
7 'Mining Group Registration'
```

```
8 'Permission for Geological Recognition'
```

```
9 'Mining Consortium Decree'
```

```
10 'Aggregation'
```

```
11 'Extraction Log'
```

```
99 '***'
```

```
/IDDocumentoLegal
```

```
101 'REPC REQUERIMENTO DE PESQUISA COMPLETO'
```

```
102 'REPI REQUERIMENTO DE PESQUISA INCOMPLETO'
```

```
103 'RLGL REQUERIMENTO DE LAVRA GARIMPEIRA'
```

```
104 'RGRU REQUERIMENTO DE GRUPAMENTO MINEIRO'
```

```
105 'RCON REQUERIMENTO DE CONSORCIO DE MINERAÇÃO'
```

```
106 'PLCM REQUERIMENTO DE LICENCIAMENTO'
```

107 'RERG REQUERIMENTO DE RECONHECIMENTO GEOLÓGICO'
 108 'RGRU REQUERIMENTO DE GRUPAMENTO MINEIRO'
 176 'AUT PESQ/ALVARÁ DE PESQUISA DE CESSÃO'
 201 'ALVR ALVARÁ DE PESQUISA'
 202 'ARET ALVARÁ DE PESQUISA RETIFICADO'
 203 'NALV ALVARÁ DE PESQUISA RENOVADO'
 204 'NAV1 ALVARÁ DE PESQUISA RENOVADO POR 1 ANO'
 205 'NAV2 ALVARÁ DE PESQUISA RENOVADO POR 2 ANOS'
 206 'NAV3 ALVARÁ DE PESQUISA RENOVADO POR 3 ANOS'
 301 'DISP ÁREA EM DISPONIBILIDADE PARA PESQUISA'
 302 'DISL ÁREA EM DISPONIBILIDADE PARA LAVRA'
 303 'ANUL ALVARÁ DE PESQUISA DECLARADO NULO'
 304 'ACAD ALVARÁ DE PESQUISA CADU/S.EFEITO/REVOGAD'
 305 'CADU CONCESSÃO CADUCADA/SEM EFEITO/REVOGADA'
 306 'CANU CONCESSÃO DECLARADA NULA'
 307 'MANC MANIFESTO DE MINA CADU/S.EFEITO/REVOGADO'
 308 'MANU MANIFESTO DE MINA DECLARADO NULO'
 309 'MJAZ MANIFESTO DE JAZIDA'
 310 'CEPO CONCESSÃO ENGLOBADA POR OUTRA'
 321 'APU1 AUT PESQ/ALVARÁ DE PESQUISA 01 ANO PUBL'
 322 'APU2 AUT PESQ/ALVARÁ DE PESQUISA 02 ANOS PUBL'
 323 'APU3 AUT PESQ/ALVARÁ DE PESQUISA 03 ANOS PUB'
 324 'APR1 AUT PESQ/PRORROGAÇÃO PRAZO 01 ANO PUBL'
 325 'APR2 AUT PESQ/PRORROGAÇÃO PRAZO 02 ANOS PUBL'
 326 'APR3 AUT PESQ/PRORROGAÇÃO PRAZO 03 ANOS PUBL'
 327 'RET1 AUT PESQ/DESPACHO RETIFICAÇÃO ALVARÁ PUB'
 328 'ADSP DISPONIB/ÁREA DISPONÍVEL ART 26 CM PUBL'
 401 'CLAV CONCESSÃO DE LAVRA'
 402 'CLAR CONCESSÃO DE LAVRA RETIFICADA'
 403 'MANF MANIFESTO DE MINA'
 404 'CDES CONCESSÃO DESMEMBRADA DE OUTRA'
 405 'PLGR CONC LAV/PERMISSÃO DE LAVRA GARIMPEIRA'
 406 'CEOU CONCESSÃO QUE ENGLOBOU OUTRA'
 601 'CONS CONSÓRCIO DE MINERAÇÃO'
 701 'LCMN LICENCIAMENTO'
 801 'RECG PERMISSÃO DE RECONHECIMENTO GEOLÓGICO'
 901 'REGEXT REGISTRO DE EXTRAÇÃO 1 ANO PUBL'
 902 'REGEXT REGISTRO DE EXTRAÇÃO 2 ANOS PUBL'
 903 'REGEXT REGISTRO DE EXTRAÇÃO 3 ANOS PUBL'
 904 'REGEXT REGISTRO DE EXTRAÇÃO 4 ANOS PUBL'
 905 'REGEXT REGISTRO DE EXTRAÇÃO 5 ANOS PUBL'
 906 'REG EXT/PRORROGAÇÃO DO PRAZO POR 01 ANO'
 907 'REG EXT/PRORROGAÇÃO DO PRAZO POR 02 ANOS'
 908 'REG EXT/PRORROGAÇÃO DO PRAZO POR 03 ANOS'
 909 'REG EXT/PRORROGAÇÃO DO PRAZO POR 04 ANOS'
 910 'REG EXT/PRORROGAÇÃO DO PRAZO POR 05 ANOS'
 911 'REGISTRO DE EXTRAÇÃO CANCELADO'
 912 'PERMISSÃO LAVRA GARIMPEIRA CANCELADA'
 913 'REGISTRO DE LICENÇA CANCELADO'
 914 'LCMN LICENCIAMENTO'
 915 'PERMISSÃO LAVRA GARIMPEIRA RENOVADA 5 ANOS'
 964 'APU4 AUT PESQ/ALVARÁ DE PESQUISA 04 ANOS PUB'
 965 'APR4 AUT PESQ/PRORROGAÇÃO PRAZO 04 ANOS PUBL'
 966 'ALVARÁ SUSPENSO JUDICIALMENTE'
 967 'SUSPENSÃO JUDICIAL ALVARÁ ENCERRADA'
 968 'PORTARIA DE LAVRA SUSPENSA JUDICIALMENTE'
 969 'SUSPENSÃO JUDICIAL DA PORTARIA DE LAVRA ENCERRADA'
 1330 'REGISTRO DE EXTRAÇÃO ANULADO'
 2132 'CLAV CONCESSÃO DE LAVRA'
 2133 'CLAR CONCESSÃO DE LAVRA RETIFICADA'


```

2134 'CANU CONCESSÃO DECLARADA NULA'
2135 'CADU CONCESSÃO CADUCADA/SEM EFEITO/REVOGADA'
2140 'CANU CONCESSÃO DECLARADA NULA'
2141 'CLCP CONC LAV CESSÃO PARCIAL EM OUTRAS'
2142 'CLCP CONC LAV CESSÃO PARCIAL DE OUTRA'
2481 'VENCIMENTO ALVARÁ ALTERADO RESOLUÇÃO 76/2021 - COVID'
2611 'CLAV CONCESSÃO DE LAVRA'
2618 'CONC LAV/PORTARIA ENGLOBANDO ÁREAS PESQUISADAS - ANM'
/IDSituacaoDocumentoLegal
1 'Awarded'
2 'Renewed'
3 'Extended'
4 'Rectified'
5 'Null'
6 'Expired / No effect / Repealed'
7 'Canceled'
8 'Revoked'
9 'Suspended'
10 'Suspension ended'
11 'Extended due to the Covid-19 Pandemic'
99 'Granted (pre-load)'.

```

*Fix title numbers.

```

IF NRTitulo<0 NRTitulo=NRTitulo*(-1).
STRING title_n(A8).
COMPUTE title_n= STRING(NRTitulo,F8).
COMPUTE title_n = replace(title_n,' ','').
EXECUTE.

```

*Add metadata to the variables.

```

VARIABLE LABELS
DSPROCESSO "ANM process number"
/NRTitulo 'Title number'
/IDDocumentoLegal 'Title specification'
/IDTipoDocumentoLegal 'Title type'
/IDSituacaoDocumentoLegal 'Title situation'
/DTPublicacao 'Title publication date'
/DTVencimento 'Title expiration date'
/title_n 'Title number - string'.

```

*Sort cases by main ID.

```

SORT CASES BY DSProcesso.

```

*Save mining process titles dataset.

```

SAVE OUTFILE ='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle.sav'.
EXECUTE.

```

* Get data from mined substances.

```

PRESERVE.
SET DECIMAL COMMA.

```

```

GET DATA /TYPE=TXT
/FILE="E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessoSubstancia.txt"
/ENCODING='LOCALE'
/DELCASE=LINE
/DELIMITERS=";"
/ARRANGEMENT=DELIMITED

```

```
/FIRSTCASE=2
/DATATYPEMIN PERCENTAGE=95.0
/VARIABLES=
DSProcesso AUTO
IDSubstancia AUTO
IDTipoUsoSubstancia AUTO
/MAP.
RESTORE.
```

```
CACHE.
EXECUTE.
```

```
*Add metadata to the variables.
VARIABLE LABELS
DSPROCESSO 'ANM process number'
/IDSubstancia 'Substance ID'
/IDTipoUsoSubstancia 'Substance use'.
```

VALUE LABELS
IDSubstancia

```
100100 'ALUMINUM ORE'
100101 'ALUMINUM'
100102 'ALUMINUM LATERITE'
100103 'BAUXITE'
100104 'BOEHMITE'
100105 'GIBBSITE'
100106 'HYDRARGILITE'
100108 'DAILY'
100200 'ANTIMONY ORE'
100201 'ANTIMONY'
100202 'STIBNITE'
100203 'STIBICONITE'
100204 'NATIVE ANTIMONY'
100205 'VALENTINITE'
100206 'BINDERHEIMITE'
100207 'CERVANTITE'
100300 'ARSENIC ORE'
100301 'ARSENE'
100302 'SULFECT ARSENE'
100303 'LOLLINGITE'
100304 'ARSENOPYRITE'
100305 'MISPICHEL'
100306 'TENNANTITE'
100307 'GOLD PKEMMENT'
100308 'ENHANCE'
100309 'SCORODITE'
100310 'ENARGITE'
100400 'BERYLLIUM ORE'
100401 'BERYLLIUM'
100402 'BERYL'
100403 'PHENACITE'
100404 'HELVITA'
100405 'EUCALASSIUM'
100500 'BISMUT ORE'
100501 'BISMUTH'
100502 'BISMUTITA'
100504 'BISMUTINITE'
100505 'TETRADIMITE'
100506 'BISMITE'
100600 'Cadmium Ore'
100601 'CADMIUM'
100602 'GREENOCKITA'
100700 'Cesium ore'
100701 'CESIUM'
100702 'POLICITE'
100703 'AVOGADRITE'
100704 'PEGMATITO'
100800 'LEAD ORE'
100801 'LEAD'
100802 'LEAD SULFETS'
100803 'LEAD CARBONATES'
100804 'LEAD OXIDES'
100805 'GALENA'
100806 'CERUSSITE'
100807 'ANGLESITE'
100808 'PYROMORPHITE'
100812 'MASSIC OT'
100813 'BOURNONITE'
100814 'CROCOITE'
100815 'BOULANGERITE'
100816 'JAMESONITE'
100817 'MIMETITE'
100900 'COPPER ORE'
100901 'COPPER'
100902 'COPPER SULFETS'
100903 'COPPER OXIDES'
100904 'COPPER CARBONATES'
100905 'COPPER SILICATES'
100906 'NATIVE COPPER'
100907 'CALCOPIRITE'
100908 'BORNITE'
100909 'CALCOCITE'
100910 'COVELITE'
100911 'CUBANITE'
100912 'CUPRITE'
100913 'AZURITE'
100914 'MALACHITE'
100915 'CRISOCOLA'
100916 'ANTILERITE'
100921 'TETRAEDRITA'
100923 'TENORITE'
100928 'COPPER PYRITE'
100929 'IDAIT'
101100 'TIN ORE'
101101 'TIN'
101102 'STANIFERING ROCK'
101103 'STANIER ALUVIAO'
101104 'CASSITERITA'
101105 'STANITE'
101106 'TIN PYRITE'
101107 'FRANCHEITA'
101108 'TANK GRAVEL'
101109 'PEGMATITO'
101300 'IRON ORE'
101301 'IRON'
101302 'HEMATITE'
101304 'ITABIRITO'
101305 'CANGA'
101307 'SPECIALARITE'
```

101308 LIMONITE'
 101309 IRON OXIDE'
 101310 JACUTINGA'
 101311 GOETHITA'
 101312 MARTITA'
 101313 MAGNETITE'
 101314 CURLING IRON'
 101318 IRON-SILICON-MANGANESE'
 101321 SIDERITA'
 101322 FERRUGINOSA LATERITA'
 101400 GERMAN ORE'
 101401 GERMANIUM'
 101402 ARGIRODITE'
 101404 GERMANITE'
 101500 HAPHON ORE'
 101501 HAFNIUM'
 101600 INDIAN ORE'
 101601 INDIAN'
 101602 ROQUESITA'
 101700 YIELD ORE'
 101701 YTTRIUM'
 101702 XENOTIMY'
 101703 XENOTIMA'
 101704 GADOLINITE'
 101705 TITROFLUORITE'
 101800 LITHIUM ORE'
 101801 LITHIUM'
 101802 AMBLIGONITE'
 101803 SPODUMEN'
 101804 LEPIDOLITE'
 101805 PETALITA'
 101806 TRIPHYLITE'
 101807 PEGMATITO'
 101900 MAGNESIUM ORE'
 101901 MAGNESIUM'
 101902 MAGNESIUM SALTS'
 101903 BRUCITA'
 102100 MANGANESE ORE'
 102101 MANGANESE'
 102102 MANGANESE OXIDES'
 102103 MANGANESE CARBONATES'
 102105 CRYPTOMELAN'
 102106 MANGANESE IRON'
 102107 MANGANITA'
 102108 PIROLISTITA'
 102109 POLYANITE'
 102110 PSILOMELANO'
 102111 RHODOCROSITE'
 102112 RODOHITE'
 102113 HAUSMANNITA'
 102117 MANGANESE SILICATES'
 102200 MOLYBDENUM ORE'
 102201 MOLYBDENUM'
 102202 MOLIBDENITE'
 102203 FERRIMOLIBDENITA'
 102205 WULPHENITE'
 102206 CHILLAGITA'
 102207 POWELLITA'
 102300 NIOBIO ORE'
 102301 NIOBIUM'
 102302 PIROCHLORO'
 102303 COLUMBITE'
 102304 LOPARITA'
 102305 NIOBITE'
 102306 PEGMATITO'
 102307 TANTALITE-COLUMBITE'
 102400 NICKEL ORE'
 102401 NICKEL'
 102402 NICKEL SULPHETS'
 102403 NICKEL SILICATES'
 102404 NIQUELIFERA LATERITA'
 102407 NIQUELIFERO DUNITO'
 102408 NICOLITE'
 102409 BRAVOITA'
 102410 MILLERITA'
 102411 GARNIERITA'
 102413 PENTLANDITE'
 102414 PYRRHOTITE'
 102424 VOLARITE'
 102500 RADIO ORE'
 102501 RADIO'
 102600 RENIUM ORE'
 102601 RENO'
 102700 RUBY ORE'
 102701 RUBIDIUM'
 102800 SELENEOUS ORE'
 102801 SELENIUM'
 102802 ONOFRITA'
 102900 Thallium ore'
 102901 THALLIUM'
 102902 AVICENITE'
 102903 URBAITE'
 103100 TANTALUM ORE'
 103101 TANTALUM'
 103102 TANTALITE'
 103103 TANTALITE-COLUMBITE'
 103104 MICROLITE'
 103105 DJALMAITA'
 103106 MANGANOTANTALITA'
 103107 PEGMATITO'
 103108 TAPIOLITE'
 103200 TUNGSTEN ORE'
 103201 TUNGSTEN'
 103202 WOLFRAMIUM'
 103203 SCHEELITA'
 103204 WOLFRAMITA'
 103205 FERBERITA'
 103206 HEBNERITA'
 103207 WOLFRAMIUM ORE'
 103208 PEGMATITO'
 103300 ZINC ORE'
 103301 ZINC'
 103302 ZINC OXIDES'
 103303 ZINC SULPHETS'
 103304 ZINC SILICATES'
 103305 BLEND'A'
 103306 SPHALERITE'
 103307 CALAMINE'
 103308 HEMIMORPHITE'
 103309 WILLEMITE'
 103310 SMITHSONITA'
 103312 ZINCITE'
 103313 FRANCKLINITA'
 103314 HYDROZINCITE'
 103315 ZINC CARBONATES'
 103400 VANADIO ORE'
 103401 VANADIUM'
 103402 VANADINITE'
 103403 DECLOSED'
 103404 ROSCOELITA'
 103405 SENGIERITA'
 103500 TITANIUM ORE'
 103501 TITANIUM'
 103502 ILMENITA'
 103503 RUTILO'
 103504 ANATASIO'
 103505 BROOKITA'
 103507 LEUKOXEN'
 103508 ILMENO HEMATITA'
 103509 ILMENO MAGNETITA'
 103510 ILMENITA MAGNESIANA'
 103511 PEROVSKITA'
 103512 SPHERE'
 103513 TITANO MAGNETITA'
 103600 ZIRCON ORE'
 103601 ZIRCONIUM'
 103602 ZIRCON'
 103603 ZIRCONITE'
 103604 BADDELEITA'
 103605 CALDASITO'
 103606 TUDALITA'
 103700 CHROME ORE'

103701 'CHROME'
 103702 'CHROMITE'
 103703 'CHROMITE GRADE METALURG'
 103704 'CHROMITE METALLURGY'
 103705 'CHRISTIAN DUNITO'
 103706 'CHROMITITE'
 103707 'CHROMIUM SPINEL'
 103708 'CHEMICAL GRADE CHROMITE'
 103800 'GALLIUM ORE'
 103801 'GALLIUM'
 103802 'SOHNGEITA'
 103900 'MERCURY ORE'
 103901 'MERCURY'
 103902 'CNABRO'
 103903 'NATIVE MERCURY'
 103904 'AMALGAM'
 104100 'COBALT ORE'
 104101 'COBALT'
 104102 'ENAMEL'
 104104 'COBALTITA'
 104105 'PIRITE COBALT'
 104106 'LINNETA'
 104108 'SAFLORITA'
 104109 'GLAUCODOTO'
 104110 'ERYTHRINE'
 104111 'ASBOLAN'
 104112 'NIQUELIFERO ASBOLANO'
 104113 'SIEGENITE'
 104200 'SCANDIUM ORE'
 104201 'SCANDIUM'
 104202 'THORTVEITA'
 104300 'PLATINUM ORE'
 104301 'PLATINUM'
 104302 'NATIVE PLATINUM'
 104303 'PLATINUM ALUVIONAR'
 104304 'SPERRYLITA'
 104305 'COOPERITA'
 104306 'PLATINIRIDIO'
 104307 'PLATINOIDS'
 104308 'POLYXENE'
 104400 'Palladium ore'
 104401 'PALLADIUM'
 104402 'NATIVE PALADIO'
 104500 'RODEO ORE'
 104501 'RHODIUM'
 104600 'OSMIO ORE'
 104601 'OSMIO'
 104602 'NEWJANSKITA'
 104603 'OSMIRIDIO'
 104700 'IRIDE ORE'
 104701 'IRIDIOUS'
 104702 'OSMIRIDIO'
 104800 'RUTENE ORE'
 104801 'RUTHENIUM'
 104900 'GOLD ORE'
 104901 'GOLD'
 104902 'AURIFER ROCK'
 104903 'AURIFER GRAVEL'
 104904 'AURIFERO ALUVIÃO'
 104906 'SILVANITA'
 104907 'CALAVERITA'
 104908 'NATIVE GOLD'
 105100 'SILVER ORE'
 105101 'SILVER'
 105102 'ARGENTITA'
 105103 'NATIVE SILVER'
 105104 'CERARGIRITA'
 105105 'STEPHANITA'
 105107 'PRARGIRITE'
 105108 'PROKSTITA'
 105109 'SILVANITA'
 105110 'CARNOTITA'
 105300 'CEREAL ORE'
 105301 'CERIUM'
 105302 'CERITA'
 105303 'LOPARITA'
 105304 'POLYCRASITE'
 105305 'MONAZITE'
 105306 'ALLANITA'
 105307 'DISPROSY'
 105308 'ERBIO'
 105309 'EUROPIO'
 105310 'GADOLINIUM'
 105311 'HOLMIO'
 105312 'YTTERBIUM'
 105313 'KNOPITA'
 105314 'LANTHANUM'
 105315 'LUTÉCIO'
 105316 'NEODYME'
 105317 'PARISITE'
 105318 'PRASEODYMIUM'
 105319 'PROMETHIUM'
 105320 'RABDOFANITA'
 105321 'RNKOLITA'
 105322 'SAMARIUM'
 105323 'TERBIUM'
 105324 'RARE LANDS'
 105325 'THULIUM'
 105327 'MONAZYTIC SAND'
 105328 'BASTNAESITA'
 105500 'TELÚRIO ORE'
 105501 'TELLURIUM'
 106000 'TORIO ORE'
 106001 'THORIANITE'
 106002 'THORIUM'
 106003 'TORITA'
 107000 'URANIUM ORE'
 107001 'AUTUNTA'
 107002 'CARNOTITA'
 107003 'EUXENITE'
 107004 'PITCHBLENDE'
 107005 'URANINITE'
 107006 'URANIUM'
 107007 'URANOPHAN'
 107008 'URANOTALITE'
 108000 'SILICON ORE'
 200100 'SLATE'
 200101 'STONE SÃO TOMÉ'
 200200 'SAND'
 200201 'SAND ALUVIONAR'
 200202 'COMMON SAND'
 200203 'BARRANCO SAND'
 200204 'THIN SAND'
 200205 'FLUVIAL SAND'
 200206 'SAND IN NATURA'
 200207 'WASHED SAND'
 200208 'SANDSTONE'
 200300 'CLAY'
 200301 'COMMON CLAY'
 200302 'CLAY P / CER. RED'
 200303 'RED CLAY'
 200304 'SHEET'
 200305 'CLAY LEAF'
 200306 'TAGUA'
 200400 'BASALT'
 200401 'BASALT FOR COATING'
 200402 'DIABÁSIO'
 200403 'DIABÁSIO FOR COATING'
 200500 'PEGMATITO'
 200600 'GRAVEL'
 200601 'BOULDER'
 200602 'PEBBLES'
 200603 'ROLLED PEBBLES'
 200700 'DOLOMITE'
 200701 'DOLOMITICAL LIMESTONE'
 200800 'QUARTZ'
 200801 'QUARTZ STONE'
 200900 'SAIBRO'
 200901 'LEARN MORE'
 201200 'CONGLOMERATE'
 300101 'PHOSPHATE'
 300102 'APATITE'

300103 'PHOSPHORITE (OY'
 300104 'PHOSPHORUS BAUXITE'
 300105 'PHOSPHORUS LIMESTONE'
 300107 'COLOPHAN'
 300108 'COLOPHANITE'
 300109 'PHOSPHATE FERTILIZER'
 300110 'CARBONATITE'
 300111 'FLUOR-A'
 300112 'PHOSPHATIC ROCK'
 300113 'SENEGALITE'
 300201 'ORGANIC FERTILIZERS'
 300206 'GUANO'
 300313 'POTASSIUM SALTS'
 300314 'EVAPORITE'
 300315 'SILVITA'
 300317 'SILVINITA'
 300318 'CARNALITA'
 300319 'KAINIT A'
 300320 'POLIALITE'
 300400 'SALITRE'
 300401 'CALICHE'
 300402 'POTASSIUM NITRATE'
 300403 'SODIUM NITRATE'
 300404 'NITRATES'
 300405 'NITRO'
 300500 'POTASSIC ROCK'
 400101 'ANTHRACITE'
 400102 'BITUMINOUS COAL'
 400103 'COAL'
 400104 'SUB-BITUMINOUS COAL'
 400108 'ANTHRACITE COAL'
 400109 'MINERAL COAL'
 400200 'LIGNITE'
 400201 'CARBON LINES'
 400300 'SAPROPEL'
 400301 'SAPROPELITO'
 400400 'PEAT'
 400401 'PURPLE'
 400402 'MARAUIT'
 500101 'ASPHALT'
 500102 'BITUMINOUS ROCK'
 500103 'BITUMINOUS LEAF'
 500105 'BITUMINOUS SANDSTONE'
 500106 'BITUMINOUS LIMESTONE'
 500110 'BITUMEN'
 500111 'OIL LEAF'
 500112 'BITUMINOUS SHALE'
 500113 'OLEIGEN SHALE'
 500200 'PIROBETUMINOUS A ROCK'
 500201 'PIROBETUMINO SHEET'
 500202 'PIROBETUMINOSIS SHALE'
 500203 'PIROBETUMINOS SANDSTONE'
 500204 'PIROBETUMINOUS LIMESTONE'
 601000 'EGG YOLK'
 601001 'GREEN BERILE'
 601002 'COLORED STONE'
 601003 'GEMSTONE'
 601004 'PEGMATITO'
 601005 'SEA WATER'
 601006 'ALEXANDRIT A'
 601007 'ALMANDINA'
 601008 'GRENADINE'
 601009 'AMAZONITE'
 601010 'AMETHYST'
 601011 'ANDRADITA'
 601012 'BERYL'
 601013 'RED BERILE'
 601014 'BRASILIANITA'
 601015 'CITRUS'
 601016 'CITRINO RIO GRANDE'
 601017 'CRISOBERILO'
 601018 'CRISOPRASIO'
 601019 'DIAMOND'
 601020 'DIAMOND CONGLOMERATE'
 601021 'DIAMOND ROCK'
 601022 'DJALMAITA'
 601023 'SPHERE'
 601024 'TITANITE'
 601025 'EMERALD'
 601026 'SPODUMEN'
 601027 'STAUROLITE'
 601028 'HELIOBORO'
 601029 'JADE'
 601030 'JASPER'
 601031 'KUNZITE'
 601032 'PENCIL LAZULI'
 601033 'LAZULITE'
 601034 'OBSIDIAN'
 601035 'CAT EYE'
 601036 'OLIVINE'
 601037 'PERIDOT'
 601038 'ONYX'
 601039 'PERISTERITE'
 601040 'ROCK CRYSTAL'
 601041 'OPAL'
 601042 'MORION'
 601043 'QUARTZ MORION'
 601044 'BICOLOR QUARTZ'
 601045 'QUARTZ'
 601046 'HYALINE QUARTZ'
 601047 'QUARTZ WITH INCLUSIONS'
 601048 'SMOKE QUARTZ'
 601049 'PINK QUARTZ'
 601050 'GREEN QUARTZ'
 601051 'RUBY'
 601052 'SAPPHIRE'
 601053 'SADDLE'
 601054 'SIBERITA'
 601055 'SILLIMANITA'
 601056 'TOPAZ'
 601057 'IMPERIAL TOPAZ'
 601058 'TOURMALINE'
 601059 'AFRISITA'
 601060 'RUBELITE'
 601061 'BICOLOR TOURMALINE'
 601062 'GREEN TOURMALINE'
 601063 'PINK TOURMALINE'
 601064 'BLUE TOURMALINE'
 601065 'TURQUOISE'
 601066 'UVAROVITA'
 601067 'VARISCITA'
 601068 'ZIRCON'
 601069 'ZIRCONITE'
 601070 'SPINEL RUBY'
 601071 'MORGANITA'
 601072 'CRISOLITE'
 601073 'DIOPSIDE'
 601074 'CORDIERITA'
 602000 'ORNAMENTAL STONE'
 602001 'AGATE'
 602002 'AMBER'
 602003 'CHALCEDONY'
 602004 'STATIC'
 602005 'SOAP STONE'
 602006 'MALACHITE'
 602007 'SEPIOLITE'
 602008 'SODALITE'
 602009 'HIDDENITE'
 602010 'CORAL'
 602011 'JADE'
 700101 'ASBESTOS'
 700102 'ASBESTOS'
 700200 'AGALMATOLITE'
 700201 'LARDITO'
 700202 'PAGODITO'
 700228 'LAND OF SIENA'
 700229 'PERLITE'
 700300 'ANDALUSIAN'
 700301 'INDUSTRIAL ANDALUSIAN'
 700400 'ANDESITE'
 700500 'AMFIBOLITE'
 700501 'ACTINOLITE'

700502 'AMPHIBOLITE'
 700503 'GLAUCOPHANE'
 700600 'ANHYDRITE'
 700700 'ANORTOSITO'
 700800 'ANTOPHILITE'
 700900 'SLATE'
 700901 'ARDOSIAN LEAF'
 701100 'CASTING SAND'
 701201 'SAND FOR GLASS'
 701202 'QUARTZ SAND'
 701203 'SILICO SAND'
 701204 'SANDSTONE'
 701205 'INDUSTRIAL SAND'
 701206 'SAND FOR FILTERS'
 701207 'SAND FOR BLASTING'
 701208 'DRILLING SAND'
 701209 'INDUSTRIAL SANDSTONE'
 701300 'SANDSTONE'
 701400 'CLAY'
 701401 'WHITE CLAY'
 701402 'FERRUGINOSA CLAY'
 701403 'ATAPULGITA'
 701404 'TAUÁ'
 701500 'SHEET'
 701501 'CLAY LEAF'
 701502 'TABATINGA'
 701503 'TAGUA'
 701504 'VARVITO'
 701505 'BARITA'
 701600 'SILTITO'
 701700 'REFRACTORY CLAY'
 701701 'ALUMINUM CLAY'
 701702 'BAUXITIC CLAY'
 701703 'CAULINIC CLAY'
 701704 'LEUCITIC CLAY'
 701705 'HALLOYSITA'
 701800 'ARGILITE'
 701801 'BARIUM'
 701802 'BARITINA'
 701803 'WITHERITA'
 701900 'BASALTO P / BRITA'
 701901 'DIABÁSIO P / BRITA'
 701902 'BASALT'
 702100 'BAUXITE'
 702101 'STUDENT'
 702102 'HALOTRIQUITA'
 702200 'BENTONITE'
 702201 'BENTONITIC CLAY'
 702202 'SMILE'
 702203 'MONTMORILONITA'
 702204 'TERRA FULLER'
 702300 'BORATOS'
 702301 'BORAX (TINCAL)'
 702302 'COLEMANITE'
 702303 'SZAIBELLYITA'
 702304 'TINCAL'
 702305 'ULEXITE'
 702400 'LIMESTONE'
 702401 'CALCITIC LIMESTONE'
 702402 'INDUSTRIAL LIMESTONE'
 702403 'MAGNESIAN LIMESTONE'
 702404 'LIMESTONE FOR CRUSH'
 702405 'SEDIMENTARY LIMESTONE'
 702406 'SILICO LIMESTONE'
 702407 'LIMESTONE'
 702408 'LIMESTONE ROCK'
 702409 'CARBONATIC ROCK'
 702410 'MARGA'
 702500 'CORALINE LIMESTONE'
 702501 'LIME SEAWEEP'
 702600 'DOLOMITICAL LIMESTONE'
 702700 'CALCITE'
 702701 'BREAK'
 702702 'OPTICAL CALCITE'
 702800 'CATACLASITE'
 702900 'KAOLIN'
 702901 'CLAY KAOLIN'
 702902 'Kaolinite'
 703001 'VOLCANIC TUFO'
 703100 'CELESTITA'
 703200 'CHARNOQUITO'
 703201 'GREEN GRANITE UBATUBA'
 703302 'ADDRESS'
 703300 'KYANITE'
 703301 'DISTENE'
 703400 'LIME SHELLS'
 703401 'CALCITIC SHELLS'
 703402 'CONCHIPHERAL LIMESTONE'
 703403 'COQUINA'
 703404 'NATURAL SHELL'
 703600 'CORUNDUM'
 703700 'CHRYSOITILE'
 703800 'CHROMITE'
 703801 'REFRACTORY CHROME'
 703900 'DACTO'
 704100 'INDUSTRIAL DIAMOND'
 704101 'DIAMOND HALLOWEEN'
 704102 'CARBONATE'
 704103 'CARBONATE'
 704104 'DIAMOND GRAVEL'
 704105 'DIAMOND'
 704106 'LAVRITA'
 704107 'DIAMOND CONGLOMERATE'
 704200 'DIATOMITE'
 704201 'DIATOMITE'
 704300 'DIORITO'
 704301 'INDUSTRIAL DIORITE'
 704302 'ORNAMENTAL DIORITE'
 704303 'DIORITO P / BRITA'
 704304 'DIORITO P / COATING'
 704305 'HORNBLEND DIORITO'
 704400 'DOLomite'
 704500 'DUMORTIERITA'
 704600 'DUNITO'
 704700 'SULFUR'
 704701 'NATIVE SULFUR'
 704800 'STATIC'
 704801 'SOAP STONE'
 704900 'STRONCIANITE'
 704901 'STRONTIUM'
 704902 'GOYAZITA'
 705100 'FELDSPAR'
 705101 'ORTOCLÁSIO'
 705102 'PEGMATITO'
 705200 'FILITO'
 705300 'FLUORITE'
 705301 'FLUORINE'
 705302 'FLUORITE ACID GRADE'
 705303 'CERAMIC FLUORITE'
 705304 'METALLURG GRADE FLUORITE'
 705305 'CHEMICAL GRADE FLUORITE'
 705400 'Phonolith'
 705401 'FOIAITO'
 705402 'NEFELINA FONÓLITO'
 705403 'TINGUAITO'
 705500 'GABRO'
 705501 'NORITO'
 705600 'GYPSUM'
 705601 'GYPSUM'
 705602 'PLASTER'
 705700 'GNAISSE'
 705701 'AUGEN GNAISSE'
 705702 'GNAISSE FACOIDAL'
 705703 'GRANITIC GNAISSE'
 705704 'INDUSTRIAL GNAISSE'
 705705 'ORNAMENTAL GNAISSE'
 705706 'GNAISSE FOR COATING'
 705707 'GNAISSE FOR BRITA'
 705708 'SIENITIC GNAISSE'
 705709 'KINZIGITO'
 705800 'GRAPHITE'
 705900 'GRENADE'

705901 'ALMANDINA'
 705902 'ANDRADITA'
 705903 'SPESSARTITE'
 705904 'GRENADA ALUVIONAR'
 705905 'INDUSTRIAL GRENADE'
 705906 'GROSSULARY'
 705907 'PIROPO'
 706100 'GRANITE'
 706101 'ALASKITO'
 706102 'APPLY'
 706103 'GRANITE BIOTITE'
 706104 'GRANITE GRAVEL'
 706105 'YELLOW GRANITE'
 706106 'GNÁSSICO GRANITE'
 706107 'ORNAMENTAL GRANITE'
 706108 'GRANITE FOR COATING'
 706109 'GRANITE FOR BRITAIN'
 706110 'GRANITE HORNBLEND'
 706111 'MONZOGGRANITE'
 706112 'SIENO GRANITO'
 707100 'GRANODIORITE'
 707102 'INDUSTRIAL GRANODIORITE'
 707103 'GRANODIORITE FOR GRAVEL'
 707104 'GRANODIORITE FOR COATING'
 707701 'GRANODIORITE BIOTITE'
 708100 'GRANULITE'
 708101 'EPIDOLITE'
 709100 'HYDRARGILITE'
 709101 'GIBBSITE'
 710100 'LATERITA'
 710200 'LEUCITA'
 710300 'LEUKOPHYLITE'
 710400 'MAGNESITA'
 710500 'MARBLE'
 710501 'DOLOMITIC MARBLE'
 710502 'INDUSTRIAL MARBLE'
 710503 'MARBLE FOR COATING'
 710600 'MICA'
 710601 'FLOGOPIT A'
 710602 'FUCHSITE'
 710603 'JACKET'
 710604 'MOSCOW'
 710605 'MUSCOVITA'
 710606 'PEGMATITO'
 710607 'BIOTITA'
 710608 'SERICITA'
 710700 'MIGMATITO'
 710701 'DIATXIT'
 710702 'EMBRICHITO'
 710703 'DIADISITO'
 710704 'ORNAMENTAL MIGMATITE'
 710705 'MIGMATITO P / BRITA'
 710706 'MIGMATITO FOR COATING'
 710707 'MIGMATITO INDUSTRIAL'
 710800 'MONZONITE'
 710801 'ADAMELITE'
 710802 'ALCALI MONZONITO'
 710803 'INDUSTRIAL MONZONITE'
 710804 'ORNAMENTAL MONZONITE'
 710805 'MONZONITE FOR BRITA'
 710806 'MONZONITE FOR COATING'
 710807 'MONZONITE QUARTZ'
 710900 'OCHER'
 710901 'IRON Ocher'
 711100 'PERIDOTITE'
 711200 'PERLITE'
 711300 'PINGUITA'
 711301 'NONTRONITE'
 711400 'PYRITE'
 711500 'PROPHYLYTE'
 711600 'PIROXENITE'
 711700 'QUARTZ'
 711701 'DUMORTIERITE QUARTZITE'
 711702 'COLD QUARTZITE'
 711703 'INDUSTRIAL QUARTZITE'
 711704 'QUARTZITE MICACEO'
 711705 'QUARTZITE FOR COATING'
 711706 'PINK QUARTZ'
 711707 'SERCITIC QUARTZ'
 711708 'GREEN QUARTZ'
 711800 'QUARTZ'
 711801 'SILICOO GRAVEL'
 711802 'ROCK CRYSTAL'
 711803 'PEGMATITO'
 711804 'FOUNDING QUARTZ'
 711805 'INDUSTRIAL QUARTZ'
 711806 'MILKY QUARTZ'
 711807 'SILICA'
 711808 'SILICON'
 711900 'RIOLITH'
 712100 'BROMO SALTS'
 712101 'BROMO'
 712200 'IODINE SALTS'
 712201 'IODINE'
 712300 'ROCK SALT'
 712301 'HALITE'
 712302 'SODIUM SALTS'
 712400 'SAPONITO'
 712401 'SAPONITE'
 712500 'SERPENTINITE'
 712600 'SYENITE'
 712601 'NEFELINA SIENITO'
 712602 'INDUSTRIAL SIENITE'
 712603 'ORNAMENTAL SIENITE'
 712604 'SIENITO P / BRITA'
 712605 'SIENITO P / COATING'
 712606 'SIENITE SODALITE'
 712607 'NEFELINA'
 712700 'FLINT'
 712701 'CHERT'
 712702 'SILEXITO'
 712800 'SILLMANITA'
 713100 'BABY POWDER'
 713101 'TALCO SHISTO'
 713102 'TALCIFERO SHALE'
 713200 'TONALITE'
 713201 'TONALITE PYROXENE'
 713202 'TRONDIEMITO'
 713300 'TRAQUITO'
 713301 'ALKALINE TRAQUITO'
 713302 'INDUSTRIAL TRAQUITO'
 713303 'ORNAMENTAL TRAQUITO'
 713400 'TREMOLITE'
 713401 'TREMOLITITE'
 713500 'TRIPOLITE'
 713501 'TRIPOL'
 713600 'TRONA'
 713700 'VERMICULITE'
 713800 'WOLLASTONITA'
 713900 'ARCOSIO'
 714100 'SCHIST'
 714101 'MICAXISTO'
 714102 'CLAYY SHALE'
 715100 'TUFO'
 716200 'METACONGLOMERATE'
 800101 'MINERAL WATER'
 800102 'MINERAL WATER ALC. BIC'
 800103 'MINERAL WATER ALC. TO HAVE. CALCL'
 800104 'MINERAL WATER ALC. TO HAVE. MAGNE'
 800105 'MINERAL WATER SULFATAD'
 800106 'MINERAL WATER SULFURES'
 800107 'NITRATAD MINERAL WATER'
 800108 'CHORETAD MINERAL WATER'
 800109 'FERRUGIN MINERAL WATER'
 800110 'CARBOGAS MINERAL WATER'
 800111 'MINERAL WATER RADIFERA'
 800112 'MINERAL WATER TORIO-AT'
 800113 'MINERAL WATER RAD. FON'
 800114 'MINERAL WATER LITINATED'
 800116 'MINERAL WATER ALC. TO HAVE'
 800118 'WATER MINERAL TERM'
 800200 'OLIGOMINERAL WATERS'

800300 'TABLE DRINKING WATER'
 800400 'THERMAL WATERS'
 800500 'GAS WATER'

/IDTipoUsoSubstancia
 1 'Construction'
 2 'Alloy manufacturing'
 3 'Jewelry'
 4 'Soil amendment'
 5 'Cement manufacturing'
 6 'Lime manufacturing'
 7 'Ceramic Tiles'
 8 'Metallurgy'
 9 'Gravel'
 10 'Fertilizers'
 11 'Pigment'
 12 'Glass manufacturing'
 13 'Red pottery'
 14 'Cut stone'
 15 'Mineral crafts'
 16 'Collection Stone'
 17 'Decorative stone'
 18 'Energetic'
 19 'Balneotherapy'
 20 'Bottling'
 21 'Industrial'
 22 'Gem'
 23 'Abrasive'
 24 'Agricultural input'
 99 'Not informed'
 9999 'Not informed'.

*Sort cases by main ID.

SORT CASES BY DSProcesso.

*Save mining process substance dataset.

SAVE OUTFILE ='E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessSubstance.sav'.

EXECUTE.

*Get data from the person SSN dataset.

PRESERVE.

SET DECIMAL COMMA.

GET DATA /TYPE=TXT

/FILE="E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\Pessoa.txt"

/ENCODING='LOCALE'

/DELCASE=LINE

/DELIMITERS=";"

/ARRANGEMENT=DELIMITED

/FIRSTCASE=2

/DATATYPEMIN PERCENTAGE=95.0

/VARIABLES=

IDPessoa AUTO

NRCPF CNPJ AUTO

TPPessoa AUTO

NMPessoa AUTO

/MAP.

RESTORE.

CACHE.

EXECUTE.

*Add metadata.

```
VARIABLE LABELS
  IDPessoa 'Person ID'
  /NRCPCNPJ 'Person SSN'
  /TPPessoa 'Person type'
  /NMPessoa 'Person name'.
```

*Sort cases by main ID.

```
SORT CASES BY IDPessoa.
```

*Save person SSN dataset.

```
SAVE OUTFILE ='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonID.sav'.
EXECUTE.
```

*Get data from the person dataset.

```
PRESERVE.
SET DECIMAL COMMA.
```

```
GET DATA /TYPE=TEXT
  /FILE="E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessoPessoa.txt"
  /ENCODING='LOCALE'
  /DELCASE=LINE
  /DELIMITERS=";"
  /ARRANGEMENT=DELIMITED
  /FIRSTCASE=2
  /DATATYPEMIN PERCENTAGE=95.0
  /VARIABLES=
  DSProcesso A12
  IDPessoa AUTO
  IDTipoRelacao AUTO
  IDTipoResponsabilidadeTecnica AUTO
  IDTipoRepresentacao AUTO
  DTPrazoArrendamento AUTO
  DTInicioVigencia SDATE10
  DTFimVigencia SDATE10
  /MAP.
RESTORE.
```

```
CACHE.
```

```
EXECUTE.
```

*Add metadata.

```
VARIABLE LABELS
  DSProcesso 'ANM process number'
  /IDPessoa 'Person ID'
  /IDTipoRelacao 'Process Relation Type'.
```

```
VALUE LABELS IDTipoRelacao
```

```
1 'Holder \ Applicant'
2 'Tenant'
3 'Descriptive Memorial Technical Manager'
4 'Legal Representative'
5 'Mining Company Partner'
6 'Board Member'
7 'Project Executor'
8 'Aerial Photo Executor'
9 'Technical Manager'
10 'Assignee'
```

11 'First Buyer'.

*Sort cases by main ID.

SORT CASES BY IDPessoa.

*Save mining person dataset.

SAVE OUTFILE ='E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPerson.sav'

/DROP

IDTipoResponsabilidadeTecnica

IDTipoRepresentacao

DTPrazoArrendamento.

EXECUTE.

*Get data from the process dataset.

PRESERVE.

SET DECIMAL COMMA.

GET DATA /TYPE=TEXT

/FILE="E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\Processo.txt"

/ENCODING='Locale'

/DELCASE=LINE

/DELIMITERS=";"

/ARRANGEMENT=DELIMITED

/FIRSTCASE=2

/DATATYPEMIN PERCENTAGE=95.0

/VARIABLES=

DSProcesso A36

NRProcesso F6

NRAnoProcesso F4

BTAtivo A3

NRNUP A60

IDTipoRequerimento F2

IDFaseProcesso F2

IDUnidadeAdministrativaRegional F2

IDUnidadeProtocolizadora F5

DTProtocolo YMDHMS19

DTPrioridade YMDHMS19

QTAraHA F7.2

/MAP.

RESTORE.

CACHE.

EXECUTE.

*Correct invalid area values.

IF QTAraHA<0 QTAraHA=QTAraHA*-1.

EXECUTE.

*convert BTAtivo to numeric.

IF BTAtivo='N' active=0.

IF BTAtivo='S' active=1.

EXECUTE.

*Format variables.

FORMATS

DSProcesso (A12)

BTAtivo (A1)

active (F1).

VARIABLE LABELS

IDTipoRequerimento 'Mining process type'

IDFaseProcesso 'Mining process last known stage '

Active 'Process currently active'

QTAreaHA 'Declared area in hectare'.

VALUE LABELS

IDTipoRequerimento

1 'Requerimento de Autorização de Pesquisa'

2 'Requerimento de Lavra Garimpeira'

3 'Requerimento de Grupamento Mineiro'

4 'Requerimento de Consórcio de Mineração'

5 'Requerimento de Registro de Licença'

6 'Requerimento de Reconhecimento Geológico'

7 'Requerimento de Registro de Extração'

8 'Requerimento de Manifesto de Mina'

9 'Desconhecido'

10 'Ficha Cadastral'

11 'Requerimento de Disponibilidade para pesquisa'

12 'Requerimento de Disponibilidade para lavra'

13 'Requerimento de Englobamento de áreas'

14 'Requerimento de Cessão total'

15 'Requerimento de Cessão parcial'

16 'Requerimento de Lavra'

17 'Requerimento de Arrendamento Total'

18 'Requerimento de Arrendamento Parcial'

19 'Requerimento de Redução de Área'

20 'Requerimento de Desmembramento'

22 'Requerimento de Mudança de Regime para Aut. de Pesquisa'

23 'Requerimento de Mudança de Regime para Licenciamento'

24 'Requerimento de Mudança de Regime para PLG'

25 'Requerimento de Disponibilidade para Lavra Garimpeira'

31 'Requerimento de Área de Servidão'

32 'Requerimento de Disponibilidade para Pesquisa - Cumprimento Exigência'

33 'Requerimento de Disponibilidade para Lavra - Cumprimento Exigência'

34 'Requerimento de Disponibilidade Lavra Garimpeira - Cumprimento Exigência'

35 'Requerimento de Pesquisa - Oferta Pública '

36 'Requerimento de Pesquisa - Leilão'

37 'Requerimento de Lavra Garimpeira - Oferta Pública'

38 'Requerimento de Lavra Garimpeira - Leilão'

39 'Requerimento de Lavra - Oferta Pública'

40 'Requerimento de Lavra - Leilão'

/IDFaseProcesso

0 'Reconhecimento Geológico'

1 'Requerimento de Pesquisa'

2 'Autorização de Pesquisa'

3 'Requerimento de Lavra'

4 'Concessão de Lavra'

5 'Requerimento de Lavra Garimpeira'

6 'Lavra Garimpeira'

7 'Licenciamento'

8 'Disponibilidade'

9 'Manifesto de Mina'

10 'Manifesto de Jazida'

11 'Requerimento de Registro de Extração'

12 'Registro de Extração'

```

13 'Requerimento de Licenciamento'
14 'Direito de Requerer a Lavra'
15 'Apto para Disponibilidade'
/active
1 'Yes'
0MATCH FILES /FILE=*
/TABLE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'
/RENAME (event_count fine_sum fine_sum_2003 fine_sum_2004 fine_sum_2005 fine_sum_2006
fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010 fine_sum_2011 fine_sum_2012
fine_sum_2013
fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017 fine_sum_2018 fine_sum_2019
fine_sum_2020
fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003 auto_sum_2004 auto_sum_2005
auto_sum_2006
auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010 auto_sum_2011 auto_sum_2012
auto_sum_2013
auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017 auto_sum_2018 auto_sum_2019
auto_sum_2020
auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17
d18 d19
d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42)
/BY DSProcesso
/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
d24
d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42.
EXECUTE.
GET FILE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'.
DATASET NAME DataSet13.
DATASET ACTIVATE ProcessTitle.
SORT CASES BY DSProcesso.
DATASET ACTIVATE DataSet13.
SORT CASES BY DSProcesso.
DATASET ACTIVATE ProcessTitle.
MATCH FILES /FILE=*
/TABLE='DataSet13'
/RENAME (event_count fine_sum fine_sum_2003 fine_sum_2004 fine_sum_2005 fine_sum_2006
fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010 fine_sum_2011 fine_sum_2012
fine_sum_2013
fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017 fine_sum_2018 fine_sum_2019
fine_sum_2020
fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003 auto_sum_2004 auto_sum_2005
auto_sum_2006
auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010 auto_sum_2011 auto_sum_2012
auto_sum_2013
auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017 auto_sum_2018 auto_sum_2019
auto_sum_2020
auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17
d18 d19
d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42)
/BY DSProcesso
/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
d24
d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42.
EXECUTE.
GET FILE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'.
DATASET NAME DataSet14.
DATASET ACTIVATE ProcessTitle.

```

```

SORT CASES BY DSProcesso.
DATASET ACTIVATE DataSet14.
SORT CASES BY DSProcesso.
DATASET ACTIVATE ProcessTitle.
MATCH FILES /FILE=*
  /TABLE='DataSet14'
/RENAME (event_count fine_sum fine_sum_2003 fine_sum_2004 fine_sum_2005 fine_sum_2006
  fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010 fine_sum_2011 fine_sum_2012
fine_sum_2013
  fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017 fine_sum_2018 fine_sum_2019
fine_sum_2020
  fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003 auto_sum_2004 auto_sum_2005
auto_sum_2006
  auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010 auto_sum_2011 auto_sum_2012
auto_sum_2013
  auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017 auto_sum_2018 auto_sum_2019
auto_sum_2020
  auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17
d18 d19
  d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42)
/BY DSProcesso
/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
d24
  d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42.
EXECUTE.
GET FILE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'.
DATASET NAME DataSet15.
DATASET ACTIVATE ProcessTitle.
SORT CASES BY DSProcesso.
DATASET ACTIVATE DataSet15.
SORT CASES BY DSProcesso.
DATASET ACTIVATE ProcessTitle.
MATCH FILES /FILE=*
  /TABLE='DataSet15'
/RENAME (event_count fine_sum fine_sum_2003 fine_sum_2004 fine_sum_2005 fine_sum_2006
  fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010 fine_sum_2011 fine_sum_2012
fine_sum_2013
  fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017 fine_sum_2018 fine_sum_2019
fine_sum_2020
  fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003 auto_sum_2004 auto_sum_2005
auto_sum_2006
  auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010 auto_sum_2011 auto_sum_2012
auto_sum_2013
  auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017 auto_sum_2018 auto_sum_2019
auto_sum_2020
  auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17
d18 d19
  d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42)
/BY DSProcesso
/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
d24
  d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42.
EXECUTE.
GET FILE='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'.
DATASET NAME DataSet16.
DATASET ACTIVATE ProcessTitle.
SORT CASES BY DSProcesso.
DATASET ACTIVATE DataSet16.

```

```

SORT CASES BY DSProcesso.
DATASET ACTIVATE ProcessTitle.
MATCH FILES /FILE=*
  /TABLE='DataSet16'
  /RENAME (event_count fine_sum fine_sum_2003 fine_sum_2004 fine_sum_2005 fine_sum_2006
    fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010 fine_sum_2011 fine_sum_2012
    fine_sum_2013
    fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017 fine_sum_2018 fine_sum_2019
    fine_sum_2020
    fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003 auto_sum_2004 auto_sum_2005
    auto_sum_2006
    auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010 auto_sum_2011 auto_sum_2012
    auto_sum_2013
    auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017 auto_sum_2018 auto_sum_2019
    auto_sum_2020
    auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17
    d18 d19
    d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42)
  /BY DSProcesso
  /DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
  d24
    d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42.
EXECUTE.
'No'.

*Declare IDFaseProcesso missing values.
MISSING VALUES IDFaseProcesso (97,98,99)
  QTAreaHA (0).

*Sort cases.
SORT CASES BY DSProcesso.

*Save mining person dataset.
SAVE OUTFILE ='E:\OneDrive\Acadêmica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\Process.sav'
  /DROP BTAtoivo NRNUP IDUnidadeProtocolizadora IDUnidadeAdministrativaRegional DTProtocolo
  DTPrioridade.

```

ANM – SPSS - WORKFLOW

Events

* Encoding: UTF-8.

*Get Process Event dataset.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent.sav'.

DATASET NAME ProcessEvent_sc WINDOW=FRONT.

*Format variables.

FORMATS

DSProcesso (A12).

*@Create a dummy variable to flag if fines were applied.

IF

IDEvento=224 OR

IDEvento=225 OR

IDEvento=226 OR

IDEvento=459 OR

IDEvento=460 OR

IDEvento=576 OR

IDEvento=577 OR

IDEvento=773 OR

IDEvento=811 OR

IDEvento=1078 OR

IDEvento=1080 OR

IDEvento=1180 OR

IDEvento=1842 OR

IDEvento=1843 OR

IDEvento=2179 OR

IDEvento=2182 OR

IDEvento=2184 OR

IDEvento=2186 OR

IDEvento=2285 OR

IDEvento=2414 OR

IDEvento=2415 OR

IDEvento=2416 OR

IDEvento=2417 OR

IDEvento=2907 OR

IDEvento=2908

fine=1.

*@Create dummy variables to flag processes that have been fined, year by year, since 2003.

DO IF

(

(event_dt<=DATE.DMY(31,12,2003) AND event_dt>=DATE.DMY(1,1,2003))

AND

(IDEvento=224 OR

IDEvento=225 OR

IDEvento=226 OR

IDEvento=459 OR

IDEvento=460 OR

IDEvento=576 OR

IDEvento=577 OR

IDEvento=773 OR

IDEvento=811 OR

IDEvento=1078 OR

IDEvento=1080 OR

IDEvento=1180 OR

IDEvento=1842 OR

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IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2003=1.
ELSE.
COMPUTE fine_2003=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2004) AND event_dt>=DATE.DMY(1,1,2004))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2004=1.
ELSE.
COMPUTE fine_2004=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2005) AND event_dt>=DATE.DMY(1,1,2005))
AND
(IDEvento=224 OR

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IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2005=1.
ELSE.
COMPUTE fine_2005=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2006) AND event_dt>=DATE.DMY(1,1,2006))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)

```

```

)
.
COMPUTE fine_2006=1.
ELSE.
COMPUTE fine_2006=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2007) AND event_dt>=DATE.DMY(1,1,2007))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2007=1.
ELSE.
COMPUTE fine_2007=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2008) AND event_dt>=DATE.DMY(1,1,2008))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR

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IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2008=1.
ELSE.
COMPUTE fine_2008=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2009) AND event_dt>=DATE.DMY(1,1,2009))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2009=1.
ELSE.
COMPUTE fine_2009=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2010) AND event_dt>=DATE.DMY(1,1,2010))
AND
(IDEvento=224 OR

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IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2010=1.
ELSE.
COMPUTE fine_2010=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2011) AND event_dt>=DATE.DMY(1,1,2011))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)

```

```

.
COMPUTE fine_2011=1.
ELSE.
COMPUTE fine_2011=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2012) AND event_dt>=DATE.DMY(1,1,2012))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2012=1.
ELSE.
COMPUTE fine_2012=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2013) AND event_dt>=DATE.DMY(1,1,2013))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR

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IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2013=1.
ELSE.
COMPUTE fine_2013=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2014) AND event_dt>=DATE.DMY(1,1,2014))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2014=1.
ELSE.
COMPUTE fine_2014=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2015) AND event_dt>=DATE.DMY(1,1,2015))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR

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IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2015=1.
ELSE.
COMPUTE fine_2015=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2016) AND event_dt>=DATE.DMY(1,1,2016))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2016=1.
ELSE.
COMPUTE fine_2016=0.

```

```

END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2017) AND event_dt>=DATE.DMY(1,1,2017))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2017=1.
ELSE.
COMPUTE fine_2017=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2018) AND event_dt>=DATE.DMY(1,1,2018))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR

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IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2018=1.
ELSE.
COMPUTE fine_2018=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2019) AND event_dt>=DATE.DMY(1,1,2019))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2019=1.
ELSE.
COMPUTE fine_2019=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2020) AND event_dt>=DATE.DMY(1,1,2020))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR

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IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2020=1.
ELSE.
COMPUTE fine_2020=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2021) AND event_dt>=DATE.DMY(1,1,2021))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2021=1.
ELSE.
COMPUTE fine_2021=0.
END IF.

DO IF
(

```

```

(event_dt<=DATE.DMY(31,12,2022) AND event_dt>=DATE.DMY(1,1,2022))
AND
(IDEvento=224 OR
IDEvento=225 OR
IDEvento=226 OR
IDEvento=459 OR
IDEvento=460 OR
IDEvento=576 OR
IDEvento=577 OR
IDEvento=773 OR
IDEvento=811 OR
IDEvento=1078 OR
IDEvento=1080 OR
IDEvento=1180 OR
IDEvento=1842 OR
IDEvento=1843 OR
IDEvento=2179 OR
IDEvento=2182 OR
IDEvento=2184 OR
IDEvento=2186 OR
IDEvento=2285 OR
IDEvento=2414 OR
IDEvento=2415 OR
IDEvento=2416 OR
IDEvento=2417 OR
IDEvento=2907 OR
IDEvento=2908)
)
.
COMPUTE fine_2022=1.
ELSE.
COMPUTE fine_2022=0.
END IF.
* EXECUTE.

```

*@Create a dummy variable to flag administrative infractions.

```

IF
IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR

```

IDEvento=2567
 auto=1.

*@Create dummy variables to flag processes that have committed an administrative infraction, year by year,
 since 2003.

```
DO IF
(
(event_dt<=DATE.DMY(31,12,2003) AND event_dt>=DATE.DMY(1,1,2003))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2003=1.
ELSE.
COMPUTE auto_2003=0.
END IF.
```

```
DO IF
(
(event_dt<=DATE.DMY(31,12,2004) AND event_dt>=DATE.DMY(1,1,2004))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
```

```

IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2004=1.
ELSE.
COMPUTE auto_2004=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2005) AND event_dt>=DATE.DMY(1,1,2005))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2005=1.
ELSE.
COMPUTE auto_2005=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2006) AND event_dt>=DATE.DMY(1,1,2006))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR

```

```

IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2006=1.
ELSE.
COMPUTE auto_2006=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2007) AND event_dt>=DATE.DMY(1,1,2007))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2007=1.
ELSE.
COMPUTE auto_2007=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2008) AND event_dt>=DATE.DMY(1,1,2008))
AND

```

```

(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2008=1.
ELSE.
COMPUTE auto_2008=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2009) AND event_dt>=DATE.DMY(1,1,2009))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2009=1.

```

```

ELSE.
COMPUTE auto_2009=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2010) AND event_dt>=DATE.DMY(1,1,2010))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2010=1.
ELSE.
COMPUTE auto_2010=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2011) AND event_dt>=DATE.DMY(1,1,2011))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR

```



```

IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2011=1.
ELSE.
COMPUTE auto_2011=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2012) AND event_dt>=DATE.DMY(1,1,2012))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2012=1.
ELSE.
COMPUTE auto_2012=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2013) AND event_dt>=DATE.DMY(1,1,2013))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR

```

```

IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2013=1.
ELSE.
COMPUTE auto_2013=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2014) AND event_dt>=DATE.DMY(1,1,2014))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2014=1.
ELSE.
COMPUTE auto_2014=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2015) AND event_dt>=DATE.DMY(1,1,2015))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR

```

```

IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2015=1.
ELSE.
COMPUTE auto_2015=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2016) AND event_dt>=DATE.DMY(1,1,2016))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2016=1.
ELSE.
COMPUTE auto_2016=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2017) AND event_dt>=DATE.DMY(1,1,2017))
AND

```

```

        (IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
    )
.
    COMPUTE auto_2017=1.
    ELSE.
    COMPUTE auto_2017=0.
    END IF.
    DO IF
    (
        (event_dt<=DATE.DMY(31,12,2018) AND event_dt>=DATE.DMY(1,1,2018))
        AND
        (IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
    )
.
    COMPUTE auto_2018=1.
    ELSE.

```

```

COMPUTE auto_2018=0.
END IF.
DO IF
(
(event_dt<=DATE.DMY(31,12,2019) AND event_dt>=DATE.DMY(1,1,2019))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2019=1.
ELSE.
COMPUTE auto_2019=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2020) AND event_dt>=DATE.DMY(1,1,2020))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR

```

```

IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2020=1.
ELSE.
COMPUTE auto_2020=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2021) AND event_dt>=DATE.DMY(1,1,2021))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR
IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2021=1.
ELSE.
COMPUTE auto_2021=0.
END IF.

DO IF
(
(event_dt<=DATE.DMY(31,12,2022) AND event_dt>=DATE.DMY(1,1,2022))
AND
(IDEvento=761 OR
IDEvento=1693 OR
IDEvento=1694 OR
IDEvento=1695 OR
IDEvento=806 OR
IDEvento=221 OR
IDEvento=1179 OR
IDEvento=2394 OR
IDEvento=1691 OR
IDEvento=1077 OR
IDEvento=1692 OR
IDEvento=2395 OR

```

```

IDEvento=2284 OR
IDEvento=2145 OR
IDEvento=1233 OR
IDEvento=2396 OR
IDEvento=2397 OR
IDEvento=2539 OR
IDEvento=2178 OR
IDEvento=2180 OR
IDEvento=2183 OR
IDEvento=2185 OR
IDEvento=2567)
)
.
COMPUTE auto_2022=1.
ELSE.
COMPUTE auto_2022=0.
END IF.

```

*Aggregate variables per process per year (2003-2022).

```

AGGREGATE
/OUTFILE=* MODE=ADDVARIABLES OVERWRITE=YES
/BREAK=DSProcesso
/event_count=NU(DSProcesso)
/fine_sum=SUM(fine)
/fine_sum_2003=SUM(fine_2003)
/fine_sum_2004=SUM(fine_2004)
/fine_sum_2005=SUM(fine_2005)
/fine_sum_2006=SUM(fine_2006)
/fine_sum_2007=SUM(fine_2007)
/fine_sum_2008=SUM(fine_2008)
/fine_sum_2009=SUM(fine_2009)
/fine_sum_2010=SUM(fine_2010)
/fine_sum_2011=SUM(fine_2011)
/fine_sum_2012=SUM(fine_2012)
/fine_sum_2013=SUM(fine_2013)
/fine_sum_2014=SUM(fine_2014)
/fine_sum_2015=SUM(fine_2015)
/fine_sum_2016=SUM(fine_2016)
/fine_sum_2017=SUM(fine_2017)
/fine_sum_2018=SUM(fine_2018)
/fine_sum_2019=SUM(fine_2019)
/fine_sum_2020=SUM(fine_2020)
/fine_sum_2021=SUM(fine_2021)
/fine_sum_2022=SUM(fine_2022)
/auto_sum=SUM(auto)
/auto_sum_2003=SUM(auto_2003)
/auto_sum_2004=SUM(auto_2004)
/auto_sum_2005=SUM(auto_2005)
/auto_sum_2006=SUM(auto_2006)
/auto_sum_2007=SUM(auto_2007)
/auto_sum_2008=SUM(auto_2008)
/auto_sum_2009=SUM(auto_2009)
/auto_sum_2010=SUM(auto_2010)
/auto_sum_2011=SUM(auto_2011)
/auto_sum_2012=SUM(auto_2012)
/auto_sum_2013=SUM(auto_2013)
/auto_sum_2014=SUM(auto_2014)
/auto_sum_2015=SUM(auto_2015)

```

```

/auto_sum_2016=SUM(auto_2016)
/auto_sum_2017=SUM(auto_2017)
/auto_sum_2018=SUM(auto_2018)
/auto_sum_2019=SUM(auto_2019)
/auto_sum_2020=SUM(auto_2020)
/auto_sum_2021=SUM(auto_2021)
/auto_sum_2022=SUM(auto_2022).

```

```

FORMATS fine to auto_2022 (F4.2)
/event_count(F7.2)
/ fine_sum to auto_sum_2022 (F5.2).

```

*Add metadata to the new variables.

VARIABLE LABELS

```

fine "Dummy for fine"
fine_2003 "Fines applied in 2003"
fine_2004 "Fines applied in 2004"
fine_2005 "Fines applied in 2005"
fine_2006 "Fines applied in 2006"
fine_2007 "Fines applied in 2007"
fine_2008 "Fines applied in 2008"
fine_2009 "Fines applied in 2009"
fine_2010 "Fines applied in 2010"
fine_2011 "Fines applied in 2011"
fine_2012 "Fines applied in 2012"
fine_2013 "Fines applied in 2013"
fine_2014 "Fines applied in 2014"
fine_2015 "Fines applied in 2015"
fine_2016 "Fines applied in 2016"
fine_2017 "Fines applied in 2017"
fine_2018 "Fines applied in 2018"
fine_2019 "Fines applied in 2019"
fine_2020 "Fines applied in 2020"
fine_2021 "Fines applied in 2021"
fine_2022 "Fines applied in 2022"
fine_sum "Number of fines applied per process (all time)"
fine_sum_2003 "Number of fines per process in 2003"
fine_sum_2004 "Number of fines per process in 2004"
fine_sum_2005 "Number of fines per process in 2005"
fine_sum_2006 "Number of fines per process in 2006"
fine_sum_2007 "Number of fines per process in 2007"
fine_sum_2008 "Number of fines per process in 2008"
fine_sum_2009 "Number of fines per process in 2009"
fine_sum_2010 "Number of fines per process in 2010"
fine_sum_2011 "Number of fines per process in 2011"
fine_sum_2012 "Number of fines per process in 2012"
fine_sum_2013 "Number of fines per process in 2013"
fine_sum_2014 "Number of fines per process in 2014"
fine_sum_2015 "Number of fines per process in 2015"
fine_sum_2016 "Number of fines per process in 2016"
fine_sum_2017 "Number of fines per process in 2017"
fine_sum_2018 "Number of fines per process in 2018"
fine_sum_2019 "Number of fines per process in 2019"
fine_sum_2020 "Number of fines per process in 2020"
fine_sum_2021 "Number of fines per process in 2021"
fine_sum_2022 "Number of fines per process in 2022"
auto "Dummy for administrative infraction"
auto_2003 "Administrative infractions in 2003"
auto_2004 "Administrative infractions in 2004"
auto_2005 "Administrative infractions in 2005"

```



```

auto_2006 "Administrative infractions in 2006"
auto_2007 "Administrative infractions in 2007"
auto_2008 "Administrative infractions in 2008"
auto_2009 "Administrative infractions in 2009"
auto_2010 "Administrative infractions in 2010"
auto_2011 "Administrative infractions in 2011"
auto_2012 "Administrative infractions in 2012"
auto_2013 "Administrative infractions in 2013"
auto_2014 "Administrative infractions in 2014"
auto_2015 "Administrative infractions in 2015"
auto_2016 "Administrative infractions in 2016"
auto_2017 "Administrative infractions in 2017"
auto_2018 "Administrative infractions in 2018"
auto_2019 "Administrative infractions in 2019"
auto_2020 "Administrative infractions in 2020"
auto_2021 "Administrative infractions in 2021"
auto_2022 "Administrative infractions in 2022"
auto_sum "Number of administrative infractions per process (all time)"
auto_sum_2003 "Number of administrative infractions per process in 2003"
auto_sum_2004 "Number of administrative infractions per process in 2004"
auto_sum_2005 "Number of administrative infractions per process in 2005"
auto_sum_2006 "Number of administrative infractions per process in 2006"
auto_sum_2007 "Number of administrative infractions per process in 2007"
auto_sum_2008 "Number of administrative infractions per process in 2008"
auto_sum_2009 "Number of administrative infractions per process in 2009"
auto_sum_2010 "Number of administrative infractions per process in 2010"
auto_sum_2011 "Number of administrative infractions per process in 2011"
auto_sum_2012 "Number of administrative infractions per process in 2012"
auto_sum_2013 "Number of administrative infractions per process in 2013"
auto_sum_2014 "Number of administrative infractions per process in 2014"
auto_sum_2015 "Number of administrative infractions per process in 2015"
auto_sum_2016 "Number of administrative infractions per process in 2016"
auto_sum_2017 "Number of administrative infractions per process in 2017"
auto_sum_2018 "Number of administrative infractions per process in 2018"
auto_sum_2019 "Number of administrative infractions per process in 2019"
auto_sum_2020 "Number of administrative infractions per process in 2020"
auto_sum_2021 "Number of administrative infractions per process in 2021"
auto_sum_2022 "Number of administrative infractions per process in 2022"
event_count "Number of events per process (all time)".

```

*Adjust missing values.

```

DO REPEAT x=fine to auto_sum_2022.
IF SYSMIS(x) x=0.
END REPEAT.
EXECUTE.

```

*Save dataset as SPSS .sav file.

```

SORT CASES BY DSProcesso(A).
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent_count.sav'.

```

* Delete Duplicate Cases.

```

MATCH FILES
/FILE=*
/BY DSProcesso
/LAST=PrimaryLast.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
SELECT IF PrimaryLast=1.

```

EXECUTE.

Show n.

*913.775

*Save single case fines dataset as SPSS .sav file.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'

/DROP IDEvento DTEvento event_dt PrimaryLast fine fine_2003 to fine_2022 auto auto_2003 to auto_2022.

*Create a variable describing the year that the tenement became inactive.

*Hence, if ANY inactivation event id is found, the variable "inactive" will present the value extracted from the year of that event.

* TEMPORARY.

* SELECT IF ANY(IDEvento,155,279,410,951,1039,1147,1678,2289).

* FREQUENCIES IDEvento.

* *n=83609.

*Open process events original dataset.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent.sav'.

DATASET NAME ProcessEvent WINDOW=FRONT.

DATASET CLOSE processevent_sc.

*create inactive variable.

IF ANY(IDEvento,155,279,410,951,1039,1147,1678,2289) inactive=event_dt.

EXECUTE.

*Filter inactivated tenements.

SELECT IF inactive<>0.

EXECUTE.

*SHOW the number of active cases.

SHOW N.

*Number of cases in the working data file 83609.

FORMATS inactive(SDATE10).

VARIABLE LABELS inactive "Inactivation year".

* Identify Duplicate Cases.

SORT CASES BY DSProcesso(A) inactive(A).

MATCH FILES

/FILE=*

/BY DSProcesso

/FIRST=PrimaryFirst

/LAST=PrimaryLast.

DO IF (PrimaryFirst).

COMPUTE MatchSequence=1-PrimaryLast.

ELSE.

COMPUTE MatchSequence=MatchSequence+1.

END IF.

LEAVE MatchSequence.

FORMATS MatchSequence (f7).

COMPUTE InDupGrp=MatchSequence>0.

SORT CASES InDupGrp(D).

MATCH FILES

/FILE=*

/DROP=PrimaryFirst InDupGrp.

VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary' MatchSequence 'Sequential count of matching cases'.

```

VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL) /MatchSequence (SCALE).
FREQUENCIES VARIABLES=PrimaryLast MatchSequence.
EXECUTE.

```

```

*Select only last inactivation events.
SELECT IF PrimaryLast=1.
EXECUTE.

```

```

*Save single case active processes dataset as SPSS .sav file.
SORT CASES DSProcesso.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent_sorted_single_case_inactive.sav'
/keep DSProcesso inactive.

```

```

*Flag inactive processes merging with ANM mining tenements dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all.sav'.
DATASET NAME ANM_all WINDOW=FRONT.
DATASET CLOSE ProcessEvent.
MATCH FILES /FILE = *
/TABLE ='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent_sorted_single_case_inactive.sav'
/BY DSProcesso.
EXECUTE.

```

```

*Save ANM mining tenements dataset as SPSS .sav file.
SORT CASES BY DSProcesso.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_inactive.sav'.

```

* Create a variable with the date of processes' last event .

```

*Open process events original dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent.sav'.
DATASET NAME ProcessEvent WINDOW=FRONT.
DATASET CLOSE ANM_all.

```

*Flag last events.

* Identify Duplicate Cases.

```

SORT CASES BY DSProcesso(A) event_dt(A).
MATCH FILES
/FILE=*
/BY DSProcesso
/FIRST=PrimaryFirst
/LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
/FILE=*
/DROP=PrimaryFirst InDupGrp.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary' MatchSequence

```

```

'Sequential count of matching cases'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL) /MatchSequence (SCALE).
FREQUENCIES VARIABLES=PrimaryLast MatchSequence.
EXECUTE.

*Create last event variable.
IF PrimaryLast=1 last_event=event_dt.
EXECUTE.

*Filter inactivated tenements.
SELECT IF last_event<>0.
EXECUTE.

*SHOW the number of active cases.
SHOW N.
*Number of cases in the working data file 913,775.
FORMATS last_event(SDATE10).
VARIABLE LABELS last_event "Process last event".

*Save last event dataset as SPSS .sav file.
SORT CASES BY DSProcesso.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent_sorted_single_case_last_event.sav'
/keep DSProcesso last_event.

*Flag last event merging with ANM mining tenements dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_inactive.sav'.
DATASET NAME ANM_all WINDOW=FRONT.
DATASET CLOSE ProcessEvent.
MATCH FILES /FILE = *
/TABLE ='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessEvent_sorted_single_case_last_event.sav'
/BY DSProcesso.
EXECUTE.

*Create a variable to flag processes that had an event after 2009.
DO IF last_event>DATE.DMY(31,12,2009).
COMPUTE event=1.
ELSE.
COMPUTE event=0.
END IF.
EXECUTE.

*Add metadata.
FORMATS event(F1).
VARIABLE LABELS event 'Processes that were active after 2009'.
VALUE LABELS event 1 'Yes' 0 'No'.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_event.sav'.

*Add variables from process dataset.
DATASET ACTIVATE ANM_all.
MATCH FILES /FILE=*
/TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\Process.sav'

```

```

/RENAME (NRProcesso IDTipoRequerimento IDFaseProcesso = d0 d1 d2)
/BY DSProcesso
/DROP= d0 d1 d2.
EXECUTE.

```

```

*Save ANM mining tenements dataset as SPSS .sav file.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_active.sav'.

```

```

**Correct expiration dates

```

```

*GET mining process titles dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle.sav'.
DATASET NAME ProcessTitle WINDOW=FRONT.
DATASET CLOSE ANM_all.
*Format variables.
FORMATS
DSProcesso (A12).

```

```

*SHOW the number of active cases.
SHOW N.
*Number of cases in the working data file 620,082

```

```

*Check valid expiration dates.
FREQUENCIES DTVencimento /FORMAT NOTABLE.
* N Valid 444213
Missing175869

```

```

*Add variables from other datasets to help determining missing expiration dates.

```

```

*process dataset.
DATASET ACTIVATE ProcessTitle.
MATCH FILES /FILE=*
/TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\Process.sav'
/RENAME (IDTipoRequerimento IDFaseProcesso = d0 d1)
/BY DSProcesso
/DROP= d0 d1.
EXECUTE.

```

```

*anm all dataset.
MATCH FILES /FILE=*
/TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_active.sav'
/RENAME (QTAreaHA NRAnoProcesso active event_count fine_sum fine_sum_2003 fine_sum_2004
fine_sum_2005 fine_sum_2006 fine_sum_2007 fine_sum_2008 fine_sum_2009 fine_sum_2010
fine_sum_2011
fine_sum_2012 fine_sum_2013 fine_sum_2014 fine_sum_2015 fine_sum_2016 fine_sum_2017
fine_sum_2018
fine_sum_2019 fine_sum_2020 fine_sum_2021 fine_sum_2022 auto_sum auto_sum_2003
auto_sum_2004
auto_sum_2005 auto_sum_2006 auto_sum_2007 auto_sum_2008 auto_sum_2009 auto_sum_2010
auto_sum_2011
auto_sum_2012 auto_sum_2013 auto_sum_2014 auto_sum_2015 auto_sum_2016 auto_sum_2017
auto_sum_2018
auto_sum_2019 auto_sum_2020 auto_sum_2021 auto_sum_2022 = d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10
d11 d12
d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23 d24 d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35
d36 d37

```

```

d38 d39 d40 d41 d42 d43 d44 d45)
/BY DSProcesso
/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23
d24
d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42 d43 d44 d45.
EXECUTE.

```

```

*Save titles_complete dataset as SPSS .sav file.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\titles_complete.sav'.

```

```

*Check invalid expiration dates.
* TEMPORARY.
* SELECT IF SYSMIS(DTVencimento).
* FREQUENCIES IDTipoDocumentoLegal /FORMAT DFREQ.

```

```

* IDTipoDocumentoLegal Title type
FrequencyPercent Valid Percent Cumulative Percent
Valid 1 Research Permit 107383 61,1 61,1 61,1
99 *** 33352 19,0 19,0 80,0
4 Mining Concession 19295 11,0 11,0 91,0
3 License Registration 13029 7,4 7,4 98,4
2 Artisanal Mining Permit 1636 0,9 0,9 99,3
6 Mine Manifest 771 0,4 0,4 99,8
7 Mining Group Registration 307 0,2 0,2 99,9
5 Deposit Manifest 620,0 0,0 100,0
11 Extraction Log 210,0 0,0 100,0
8 Permission for Geological Recognition 120,0 0,0 100,0
10 Aggregation 1 0,0 0,0 100,0
Total 175869 100,0 100,0

```

*Delete canceled, null, expired/no effect/repealed and suspended titles.

```

* TEMPORARY.
* SELECT IF (ANY(IDSituacaoDocumentoLegal, 5,6,7,8,9)).
* FREQUENCIES IDTipoDocumentoLegal /FORMAT DFREQ.
* IDTipoDocumentoLegal Title type
FrequencyPercent Valid Percent Cumulative Percent
Valid 4 Mining Concession 1761 95,2 95,2 95,2
1 Research Permit 824,4 4,4 99,7
11 Extraction Log 3 0,2 0,2 99,8
6 Mine Manifest 1 0,1 0,1 99,9
7 Mining Group Registration 1 0,1 0,1 99,9
99 *** 1 0,1 0,1 100,0
Total 1849 100,0 100,0

```

```

IF (ANY(IDSituacaoDocumentoLegal, 5,6,7,8,9)) delete=1.
SELECT IF (SYSMIS(delete)).
EXECUTE.
DELETE VARIABLES delete.

```

*@Delete titles that signal the end of the process (disponibility, null, incorporated, revoked).

```

* temporary.
* SELECT IF any(IDDocumentoLegal,301,302,328,305,306,310,2135).
* FREQUENCIES IDTipoDocumentoLegal.
* IDTipoDocumentoLegal Title type
FrequencyPercent Valid Percent Cumulative Percent
Valid 3 License Registration 1 0,0 0,0 0,0
10 Aggregation 1 0,0 0,0 0,0
99 *** 22100 100,0 100,0 100,0

```

Total22102 100,0 100,0

```
IF any(IDDocumentoLegal, 301,302,304,328,305,306,310,2135) delete=1.
SELECT IF (SYSMIS(delete)).
EXECUTE.
DELETE VARIABLES delete.
```

```
*@Correct missing IDTipoDocumentoLegal.
IF
ANY(IDDocumentoLegal,101,102,176,201,202,203,204,205,206,303,304,321,322,323,324,325,326,964)
IDTipoDocumentoLegal=1.
IF ANY(IDDocumentoLegal,701,914) IDTipoDocumentoLegal=3.
IF (IDDocumentoLegal=104) IDTipoDocumentoLegal=7.
EXECUTE
```

```
.
*@ correct 1 year-titles expiration dates.
IF (any(IDDocumentoLegal, 204,321,324,901,906) AND SYSMIS(DTVencimento))
DTVencimento=DATESUM(DTPublicacao, 1, "years","rollover").
EXECUTE.
```

```
*@ correct 2 year-titles expiration dates.
IF (any(IDDocumentoLegal, 205,322,325,902,907) AND SYSMIS(DTVencimento))
DTVencimento=DATESUM(DTPublicacao, 2, "years","rollover").
EXECUTE.
```

```
*@ correct 3 year-titles expiration dates.
IF (any(IDDocumentoLegal, 206,323,326,903,908) AND SYSMIS(DTVencimento))
DTVencimento=DATESUM(DTPublicacao, 3, "years","rollover").
EXECUTE.
```

```
*@ correct 4 year-titles expiration dates.
IF (any(IDDocumentoLegal, 904,909,964,965) AND SYSMIS(DTVencimento))
DTVencimento=DATESUM(DTPublicacao, 4, "years","rollover").
EXECUTE.
```

```
*@ correct 5 year-titles expiration dates.
IF (any(IDDocumentoLegal, 905,910,915) AND SYSMIS(DTVencimento))
DTVencimento=DATESUM(DTPublicacao, 5, "years","rollover").
EXECUTE.
```

```
*Correct missing expiration dates from mining tenements legal titles to one year after last event.
IF SYSMIS(DTVencimento) DTVencimento=DATESUM(last_event, 1, "years","rollover").
EXECUTE.
```

```
*Delete cases of permission for geological recognition because they don't represent legal clearance to
mining.
IF IDTipoDocumentoLegal=8 delete=1.
SELECT IF (SYSMIS(delete)).
EXECUTE.
DELETE VARIABLES delete.
```

*Create a variable to flag processes that had a valid title after 2009.

```
IF DTVencimento>DATE.DMY(31,12,2009) event_title=1.
IF DTVencimento>last_event last_event=DTVencimento.
IF last_event>inactive inactive=last_event.
EXECUTE.
```

```
*@correct inactive date.
IF active=0 and SYSMIS(inactive) inactive=last_event.
```

EXECUTE.

```
*Create variables to count number of titles - all time.
* Identify Duplicate Cases.
SORT CASES BY DSProcesso(A) title_n(A).
MATCH FILES
  /FILE=*
  /BY DSProcesso title_n
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
  COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
  COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryLast InDupGrp MatchSequence.
EXECUTE.
SORT CASES BY DSProcesso.
AGGREGATE
  /OUTFILE=* MODE=ADDVARIABLES OVERWRITE=YES
  /PRESORTED
  /BREAK=DSProcesso
  /dtitlect_all 'Distinct titles - All time'=SUM(PrimaryFirst)
  /titlect_all 'Number of times a title was given, renewed, extended - All time'=N.
```

```
FORMATS
event_title (F1)
dtitlect_all (F4.2)
titlect_all (F5.2).
```

```
VARIABLE LABELS
event_title 'Dummy for either event or expiration date after 2009'
NRProcesso 'Process number'
NRAnoProcesso 'Process start year'.
```

```
DELETE VARIABLES
PrimaryFirst.
```

```
*@Save dataset with titles with expiration dates after 2009 as SPSS .sav file.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\titles_complete_last_event.sav'.
```

```
SELECT IF event_title=1.
EXECUTE.
show n.
*N 343,677.
```

```
*Exclude processes created after 31/12/2020.
SELECT IF NRAnoProcesso<2021.
EXECUTE.
```

```
*Exclude processes with expiration dates after 31/12/2020.
SELECT IF DTPublicacao<DATE.DMY(1,1,2021).
EXECUTE.
```


show n.

*N 278,319.

*Sort cases by process number.

SORT CASES BY DSProcesso.

*@Save dataset with titles with expiration dates after 2009 as SPSS .sav file.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\active_titles.sav'.

*Create variables to count number of titles between 2010 and 2020.

* Identify Duplicate Cases.

SORT CASES BY DSProcesso(A) title_n(A).

MATCH FILES

/FILE=*

/BY DSProcesso title_n

/FIRST=PrimaryFirst

/LAST=PrimaryLast.

DO IF (PrimaryFirst).

COMPUTE MatchSequence=1-PrimaryLast.

ELSE.

COMPUTE MatchSequence=MatchSequence+1.

END IF.

LEAVE MatchSequence.

FORMATS MatchSequence (f7).

COMPUTE InDupGrp=MatchSequence>0.

SORT CASES InDupGrp(D).

MATCH FILES

/FILE=*

/DROP=PrimaryLast InDupGrp MatchSequence.

EXECUTE.

SORT CASES BY DSProcesso.

AGGREGATE

/OUTFILE=* MODE=ADDVARIABLES OVERWRITE=YES

/PRESORTED

/BREAK=DSProcesso

/dtitlect 'Distinct titles - 2010/2020'=SUM(PrimaryFirst)

/titlect 'Number of times a title was given, renewed, extended - 2010/2020'=N.

FORMATS

dtitlect (F4.2)

titlect (F5.2).

DELETE VARIABLES

PrimaryFirst.

*rename variables.

RENAME VARIABLES NRAnoProcesso=year_process.

VARIABLE LABELS year_process 'Process start year'.

*Create a variable to help correct wrong expiration dates.

COMPUTE diff=DATEDIFF(DTVencimento, DTPublicacao,"days").

EXECUTE.

VARIABLE LABELS diff 'Process expiration and publication difference in days'.

*Correct expiration dates with negative values.

IF diff<=0 AND ANY(IDDDocumentoLegal,176, 201,202,405,701,914,2481) DTVencimento=last_event.

```

IF diff<=0 AND ANY(IDDocumentoLegal,324,901) DTVencimento= DATESUM(DTPublicacao, 1,
"years","rollover").
IF diff<=0 AND ANY(IDDocumentoLegal,322,325,902) DTVencimento= DATESUM(DTPublicacao, 2,
"years","rollover").
IF diff<=0 AND ANY(IDDocumentoLegal,323,326,903) DTVencimento= DATESUM(DTPublicacao, 3,
"years","rollover").
IF diff<=0 AND ANY(IDDocumentoLegal,904) DTVencimento= DATESUM(DTPublicacao, 4,
"years","rollover").
IF diff<=0 AND ANY(IDDocumentoLegal,910,915) DTVencimento= DATESUM(DTPublicacao, 5,
"years","rollover").
EXECUTE.
COMPUTE diff=DATEDIFF(DTVencimento, DTPublicacao,"days").
EXECUTE.
*Correct remaining wrong expiration dates, with problems on last event date.
IF diff<=0 DTVencimento= DATESUM(DTPublicacao, 1, "years","rollover").
COMPUTE diff=DATEDIFF(DTVencimento, DTPublicacao,"days").
EXECUTE.

*correct last event dates based on new expiration dates.
IF last_event<DTVencimento last_event=DTVencimento.
EXECUTE.

```

*Create variables to calculate the number of authorized mining days per year.

```

DO IF year_process<=2003 AND (DTPublicacao<DATE.DMY(1,1,2003) AND
DTVencimento>DATE.DMY(31,12,2003)).
COMPUTE legal_2003=365.
ELSE IF year_process<=2003 AND((DTPublicacao>=DATE.DMY(1,1,2003) AND
DTPublicacao<=DATE.DMY(31,12,2003)) AND DTVencimento>DATE.DMY(31,12,2003)).
COMPUTE legal_2003= DATEDIFF(DATE.DMY(31,12,2003), DTPublicacao,"days").
ELSE IF year_process<=2003 AND (DTPublicacao<DATE.DMY(1,1,2003) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2003) AND DTVENCIMENTO<=DATE.DMY(31,12,2003))).
COMPUTE legal_2003= DATEDIFF(DTVencimento,DATE.DMY(1,1,2003),"days").
ELSE IF year_process<=2003 AND (DTPublicacao>=DATE.DMY(1,1,2003) AND
DTPublicacao<=DATE.DMY(31,12,2003)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2003) AND
DTVENCIMENTO<=DATE.DMY(31,12,2003)).
COMPUTE legal_2003=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2003=0.
END IF.
DO IF year_process<=2004 AND (DTPublicacao<DATE.DMY(1,1,2004) AND
DTVencimento>DATE.DMY(31,12,2004)).
COMPUTE legal_2004=365.
ELSE IF year_process<=2004 AND((DTPublicacao>=DATE.DMY(1,1,2004) AND
DTPublicacao<=DATE.DMY(31,12,2004)) AND DTVencimento>DATE.DMY(31,12,2004)).
COMPUTE legal_2004= DATEDIFF(DATE.DMY(31,12,2004), DTPublicacao,"days").
ELSE IF year_process<=2004 AND (DTPublicacao<DATE.DMY(1,1,2004) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2004) AND DTVENCIMENTO<=DATE.DMY(31,12,2004))).
COMPUTE legal_2004= DATEDIFF(DTVencimento,DATE.DMY(1,1,2004),"days").
ELSE IF year_process<=2004 AND (DTPublicacao>=DATE.DMY(1,1,2004) AND
DTPublicacao<=DATE.DMY(31,12,2004)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2004) AND
DTVENCIMENTO<=DATE.DMY(31,12,2004)).
COMPUTE legal_2004=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2004=0.
END IF.
DO IF year_process<=2005 AND (DTPublicacao<DATE.DMY(1,1,2005) AND
DTVencimento>DATE.DMY(31,12,2005)).
COMPUTE legal_2005=365.

```

```

ELSE IF year_process<=2005 AND((DTPublicacao>=DATE.DMY(1,1,2005) AND
DTPublicacao<=DATE.DMY(31,12,2005)) AND DTVencimento>DATE.DMY(31,12,2005)).
COMPUTE legal_2005= DATEDIFF(DATE.DMY(31,12,2005), DTPublicacao,"days").
ELSE IF year_process<=2005 AND (DTPublicacao<DATE.DMY(1,1,2005) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2005) AND DTVENCIMENTO<=DATE.DMY(31,12,2005))).
COMPUTE legal_2005= DATEDIFF(DTVencimento,DATE.DMY(1,1,2005),"days").
ELSE IF year_process<=2005 AND (DTPublicacao>=DATE.DMY(1,1,2005) AND
DTPublicacao<=DATE.DMY(31,12,2005)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2005) AND
DTVENCIMENTO<=DATE.DMY(31,12,2005)).
COMPUTE legal_2005=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2005=0.
END IF.
DO IF year_process<=2006 AND (DTPublicacao<DATE.DMY(1,1,2006) AND
DTVencimento>DATE.DMY(31,12,2006)).
COMPUTE legal_2006=365.
ELSE IF year_process<=2006 AND((DTPublicacao>=DATE.DMY(1,1,2006) AND
DTPublicacao<=DATE.DMY(31,12,2006)) AND DTVencimento>DATE.DMY(31,12,2006)).
COMPUTE legal_2006= DATEDIFF(DATE.DMY(31,12,2006), DTPublicacao,"days").
ELSE IF year_process<=2006 AND (DTPublicacao<DATE.DMY(1,1,2006) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2006) AND DTVENCIMENTO<=DATE.DMY(31,12,2006))).
COMPUTE legal_2006= DATEDIFF(DTVencimento,DATE.DMY(1,1,2006),"days").
ELSE IF year_process<=2006 AND (DTPublicacao>=DATE.DMY(1,1,2006) AND
DTPublicacao<=DATE.DMY(31,12,2006)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2006) AND
DTVENCIMENTO<=DATE.DMY(31,12,2006)).
COMPUTE legal_2006=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2006=0.
END IF.
DO IF year_process<=2007 AND (DTPublicacao<DATE.DMY(1,1,2007) AND
DTVencimento>DATE.DMY(31,12,2007)).
COMPUTE legal_2007=365.
ELSE IF year_process<=2007 AND((DTPublicacao>=DATE.DMY(1,1,2007) AND
DTPublicacao<=DATE.DMY(31,12,2007)) AND DTVencimento>DATE.DMY(31,12,2007)).
COMPUTE legal_2007= DATEDIFF(DATE.DMY(31,12,2007), DTPublicacao,"days").
ELSE IF year_process<=2007 AND (DTPublicacao<DATE.DMY(1,1,2007) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2007) AND DTVENCIMENTO<=DATE.DMY(31,12,2007))).
COMPUTE legal_2007= DATEDIFF(DTVencimento,DATE.DMY(1,1,2007),"days").
ELSE IF year_process<=2007 AND (DTPublicacao>=DATE.DMY(1,1,2007) AND
DTPublicacao<=DATE.DMY(31,12,2007)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2007) AND
DTVENCIMENTO<=DATE.DMY(31,12,2007)).
COMPUTE legal_2007=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2007=0.
END IF.
DO IF year_process<=2008 AND (DTPublicacao<DATE.DMY(1,1,2008) AND
DTVencimento>DATE.DMY(31,12,2008)).
COMPUTE legal_2008=365.
ELSE IF year_process<=2008 AND((DTPublicacao>=DATE.DMY(1,1,2008) AND
DTPublicacao<=DATE.DMY(31,12,2008)) AND DTVencimento>DATE.DMY(31,12,2008)).
COMPUTE legal_2008= DATEDIFF(DATE.DMY(31,12,2008), DTPublicacao,"days").
ELSE IF year_process<=2008 AND (DTPublicacao<DATE.DMY(1,1,2008) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2008) AND DTVENCIMENTO<=DATE.DMY(31,12,2008))).
COMPUTE legal_2008= DATEDIFF(DTVencimento,DATE.DMY(1,1,2008),"days").
ELSE IF year_process<=2008 AND (DTPublicacao>=DATE.DMY(1,1,2008) AND
DTPublicacao<=DATE.DMY(31,12,2008)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2008) AND
DTVENCIMENTO<=DATE.DMY(31,12,2008)).
COMPUTE legal_2008=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2008=0.

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```

END IF.
DO IF year_process<=2009 AND (DTPublicacao<DATE.DMY(1,1,2009) AND
DTVencimento>DATE.DMY(31,12,2009)).
COMPUTE legal_2009=365.
ELSE IF year_process<=2009 AND((DTPublicacao>=DATE.DMY(1,1,2009) AND
DTPublicacao<=DATE.DMY(31,12,2009)) AND DTVencimento>DATE.DMY(31,12,2009)).
COMPUTE legal_2009= DATEDIFF(DATE.DMY(31,12,2009), DTPublicacao,"days").
ELSE IF year_process<=2009 AND (DTPublicacao<DATE.DMY(1,1,2009) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2009) AND DTVENCIMENTO<=DATE.DMY(31,12,2009))).
COMPUTE legal_2009= DATEDIFF(DTVencimento,DATE.DMY(1,1,2009),"days").
ELSE IF year_process<=2009 AND (DTPublicacao>=DATE.DMY(1,1,2009) AND
DTPublicacao<=DATE.DMY(31,12,2009)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2009) AND
DTVENCIMENTO<=DATE.DMY(31,12,2009)).
COMPUTE legal_2009=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2009=0.
END IF.
DO IF year_process<=2010 AND (DTPublicacao<DATE.DMY(1,1,2010) AND
DTVencimento>DATE.DMY(31,12,2010)).
COMPUTE legal_2010=365.
ELSE IF year_process<=2010 AND((DTPublicacao>=DATE.DMY(1,1,2010) AND
DTPublicacao<=DATE.DMY(31,12,2010)) AND DTVencimento>DATE.DMY(31,12,2010)).
COMPUTE legal_2010= DATEDIFF(DATE.DMY(31,12,2010), DTPublicacao,"days").
ELSE IF year_process<=2010 AND (DTPublicacao<DATE.DMY(1,1,2010) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2010) AND DTVENCIMENTO<=DATE.DMY(31,12,2010))).
COMPUTE legal_2010= DATEDIFF(DTVencimento,DATE.DMY(1,1,2010),"days").
ELSE IF year_process<=2010 AND (DTPublicacao>=DATE.DMY(1,1,2010) AND
DTPublicacao<=DATE.DMY(31,12,2010)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2010) AND
DTVENCIMENTO<=DATE.DMY(31,12,2010)).
COMPUTE legal_2010=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2010=0.
END IF.
DO IF year_process<=2011 AND (DTPublicacao<DATE.DMY(1,1,2011) AND
DTVencimento>DATE.DMY(31,12,2011)).
COMPUTE legal_2011=365.
ELSE IF year_process<=2011 AND((DTPublicacao>=DATE.DMY(1,1,2011) AND
DTPublicacao<=DATE.DMY(31,12,2011)) AND DTVencimento>DATE.DMY(31,12,2011)).
COMPUTE legal_2011= DATEDIFF(DATE.DMY(31,12,2011), DTPublicacao,"days").
ELSE IF year_process<=2011 AND (DTPublicacao<DATE.DMY(1,1,2011) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2011) AND DTVENCIMENTO<=DATE.DMY(31,12,2011))).
COMPUTE legal_2011= DATEDIFF(DTVencimento,DATE.DMY(1,1,2011),"days").
ELSE IF year_process<=2011 AND (DTPublicacao>=DATE.DMY(1,1,2011) AND
DTPublicacao<=DATE.DMY(31,12,2011)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2011) AND
DTVENCIMENTO<=DATE.DMY(31,12,2011)).
COMPUTE legal_2011=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2011=0.
END IF.
DO IF year_process<=2012 AND (DTPublicacao<DATE.DMY(1,1,2012) AND
DTVencimento>DATE.DMY(31,12,2012)).
COMPUTE legal_2012=365.
ELSE IF year_process<=2012 AND((DTPublicacao>=DATE.DMY(1,1,2012) AND
DTPublicacao<=DATE.DMY(31,12,2012)) AND DTVencimento>DATE.DMY(31,12,2012)).
COMPUTE legal_2012= DATEDIFF(DATE.DMY(31,12,2012), DTPublicacao,"days").
ELSE IF year_process<=2012 AND (DTPublicacao<DATE.DMY(1,1,2012) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2012) AND DTVENCIMENTO<=DATE.DMY(31,12,2012))).
COMPUTE legal_2012= DATEDIFF(DTVencimento,DATE.DMY(1,1,2012),"days").

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ELSE IF year_process<=2012 AND (DTPublicacao>=DATE.DMY(1,1,2012) AND
DTPublicacao<=DATE.DMY(31,12,2012)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2012) AND
DTVENCIMENTO<=DATE.DMY(31,12,2012)).
COMPUTE legal_2012=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2012=0.
END IF.
DO IF year_process<=2013 AND (DTPublicacao<DATE.DMY(1,1,2013) AND
DTVencimento>DATE.DMY(31,12,2013)).
COMPUTE legal_2013=365.
ELSE IF year_process<=2013 AND((DTPublicacao>=DATE.DMY(1,1,2013) AND
DTPublicacao<=DATE.DMY(31,12,2013)) AND DTVencimento>DATE.DMY(31,12,2013)).
COMPUTE legal_2013= DATEDIFF(DATE.DMY(31,12,2013), DTPublicacao,"days").
ELSE IF year_process<=2013 AND (DTPublicacao<DATE.DMY(1,1,2013) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2013) AND DTVENCIMENTO<=DATE.DMY(31,12,2013))).
COMPUTE legal_2013= DATEDIFF(DTVencimento,DATE.DMY(1,1,2013),"days").
ELSE IF year_process<=2013 AND (DTPublicacao>=DATE.DMY(1,1,2013) AND
DTPublicacao<=DATE.DMY(31,12,2013)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2013) AND
DTVENCIMENTO<=DATE.DMY(31,12,2013)).
COMPUTE legal_2013=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2013=0.
END IF.
DO IF year_process<=2014 AND (DTPublicacao<DATE.DMY(1,1,2014) AND
DTVencimento>DATE.DMY(31,12,2014)).
COMPUTE legal_2014=365.
ELSE IF year_process<=2014 AND((DTPublicacao>=DATE.DMY(1,1,2014) AND
DTPublicacao<=DATE.DMY(31,12,2014)) AND DTVencimento>DATE.DMY(31,12,2014)).
COMPUTE legal_2014= DATEDIFF(DATE.DMY(31,12,2014), DTPublicacao,"days").
ELSE IF year_process<=2014 AND (DTPublicacao<DATE.DMY(1,1,2014) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2014) AND DTVENCIMENTO<=DATE.DMY(31,12,2014))).
COMPUTE legal_2014= DATEDIFF(DTVencimento,DATE.DMY(1,1,2014),"days").
ELSE IF year_process<=2014 AND (DTPublicacao>=DATE.DMY(1,1,2014) AND
DTPublicacao<=DATE.DMY(31,12,2014)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2014) AND
DTVENCIMENTO<=DATE.DMY(31,12,2014)).
COMPUTE legal_2014=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2014=0.
END IF.
DO IF year_process<=2015 AND (DTPublicacao<DATE.DMY(1,1,2015) AND
DTVencimento>DATE.DMY(31,12,2015)).
COMPUTE legal_2015=365.
ELSE IF year_process<=2015 AND((DTPublicacao>=DATE.DMY(1,1,2015) AND
DTPublicacao<=DATE.DMY(31,12,2015)) AND DTVencimento>DATE.DMY(31,12,2015)).
COMPUTE legal_2015= DATEDIFF(DATE.DMY(31,12,2015), DTPublicacao,"days").
ELSE IF year_process<=2015 AND (DTPublicacao<DATE.DMY(1,1,2015) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2015) AND DTVENCIMENTO<=DATE.DMY(31,12,2015))).
COMPUTE legal_2015= DATEDIFF(DTVencimento,DATE.DMY(1,1,2015),"days").
ELSE IF year_process<=2015 AND (DTPublicacao>=DATE.DMY(1,1,2015) AND
DTPublicacao<=DATE.DMY(31,12,2015)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2015) AND
DTVENCIMENTO<=DATE.DMY(31,12,2015)).
COMPUTE legal_2015=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2015=0.
END IF.
DO IF year_process<=2016 AND (DTPublicacao<DATE.DMY(1,1,2016) AND
DTVencimento>DATE.DMY(31,12,2016)).
COMPUTE legal_2016=365.
ELSE IF year_process<=2016 AND((DTPublicacao>=DATE.DMY(1,1,2016) AND
DTPublicacao<=DATE.DMY(31,12,2016)) AND DTVencimento>DATE.DMY(31,12,2016)).

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COMPUTE legal_2016= DATEDIFF(DATE.DMY(31,12,2016), DTPublicacao,"days").
ELSE IF year_process<=2016 AND (DTPublicacao<DATE.DMY(1,1,2016) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2016) AND DTVENCIMENTO<=DATE.DMY(31,12,2016))).
COMPUTE legal_2016= DATEDIFF(DTVencimento,DATE.DMY(1,1,2016),"days").
ELSE IF year_process<=2016 AND (DTPublicacao>=DATE.DMY(1,1,2016) AND
DTPublicacao<=DATE.DMY(31,12,2016)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2016) AND
DTVENCIMENTO<=DATE.DMY(31,12,2016)).
COMPUTE legal_2016=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2016=0.
END IF.
DO IF year_process<=2017 AND (DTPublicacao<DATE.DMY(1,1,2017) AND
DTVencimento>DATE.DMY(31,12,2017)).
COMPUTE legal_2017=365.
ELSE IF year_process<=2017 AND((DTPublicacao>=DATE.DMY(1,1,2017) AND
DTPublicacao<=DATE.DMY(31,12,2017)) AND DTVencimento>DATE.DMY(31,12,2017)).
COMPUTE legal_2017= DATEDIFF(DATE.DMY(31,12,2017), DTPublicacao,"days").
ELSE IF year_process<=2017 AND (DTPublicacao<DATE.DMY(1,1,2017) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2017) AND DTVENCIMENTO<=DATE.DMY(31,12,2017))).
COMPUTE legal_2017= DATEDIFF(DTVencimento,DATE.DMY(1,1,2017),"days").
ELSE IF year_process<=2017 AND (DTPublicacao>=DATE.DMY(1,1,2017) AND
DTPublicacao<=DATE.DMY(31,12,2017)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2017) AND
DTVENCIMENTO<=DATE.DMY(31,12,2017)).
COMPUTE legal_2017=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2017=0.
END IF.
DO IF year_process<=2018 AND (DTPublicacao<DATE.DMY(1,1,2018) AND
DTVencimento>DATE.DMY(31,12,2018)).
COMPUTE legal_2018=365.
ELSE IF year_process<=2018 AND((DTPublicacao>=DATE.DMY(1,1,2018) AND
DTPublicacao<=DATE.DMY(31,12,2018)) AND DTVencimento>DATE.DMY(31,12,2018)).
COMPUTE legal_2018= DATEDIFF(DATE.DMY(31,12,2018), DTPublicacao,"days").
ELSE IF year_process<=2018 AND (DTPublicacao<DATE.DMY(1,1,2018) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2018) AND DTVENCIMENTO<=DATE.DMY(31,12,2018))).
COMPUTE legal_2018= DATEDIFF(DTVencimento,DATE.DMY(1,1,2018),"days").
ELSE IF year_process<=2018 AND (DTPublicacao>=DATE.DMY(1,1,2018) AND
DTPublicacao<=DATE.DMY(31,12,2018)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2018) AND
DTVENCIMENTO<=DATE.DMY(31,12,2018)).
COMPUTE legal_2018=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2018=0.
END IF.
DO IF year_process<=2019 AND (DTPublicacao<DATE.DMY(1,1,2019) AND
DTVencimento>DATE.DMY(31,12,2019)).
COMPUTE legal_2019=365.
ELSE IF year_process<=2019 AND((DTPublicacao>=DATE.DMY(1,1,2019) AND
DTPublicacao<=DATE.DMY(31,12,2019)) AND DTVencimento>DATE.DMY(31,12,2019)).
COMPUTE legal_2019= DATEDIFF(DATE.DMY(31,12,2019), DTPublicacao,"days").
ELSE IF year_process<=2019 AND (DTPublicacao<DATE.DMY(1,1,2019) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2019) AND DTVENCIMENTO<=DATE.DMY(31,12,2019))).
COMPUTE legal_2019= DATEDIFF(DTVencimento,DATE.DMY(1,1,2019),"days").
ELSE IF year_process<=2019 AND (DTPublicacao>=DATE.DMY(1,1,2019) AND
DTPublicacao<=DATE.DMY(31,12,2019)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2019) AND
DTVENCIMENTO<=DATE.DMY(31,12,2019)).
COMPUTE legal_2019=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2019=0.
END IF.

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DO IF year_process<=2020 AND (DTPublicacao<DATE.DMY(1,1,2020) AND
DTVencimento>DATE.DMY(31,12,2020)).
COMPUTE legal_2020=365.
ELSE IF year_process<=2020 AND((DTPublicacao>=DATE.DMY(1,1,2020) AND
DTPublicacao<=DATE.DMY(31,12,2020)) AND DTVencimento>DATE.DMY(31,12,2020)).
COMPUTE legal_2020= DATEDIFF(DATE.DMY(31,12,2020), DTPublicacao,"days").
ELSE IF year_process<=2020 AND (DTPublicacao<DATE.DMY(1,1,2020) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2020) AND DTVENCIMENTO<=DATE.DMY(31,12,2020))).
COMPUTE legal_2020= DATEDIFF(DTVencimento,DATE.DMY(1,1,2020),"days").
ELSE IF year_process<=2020 AND (DTPublicacao>=DATE.DMY(1,1,2020) AND
DTPublicacao<=DATE.DMY(31,12,2020)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2020) AND
DTVENCIMENTO<=DATE.DMY(31,12,2020)).
COMPUTE legal_2020=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2020=0.
END IF.
DO IF year_process<=2021 AND (DTPublicacao<DATE.DMY(1,1,2021) AND
DTVencimento>DATE.DMY(31,12,2021)).
COMPUTE legal_2021=365.
ELSE IF year_process<=2021 AND((DTPublicacao>=DATE.DMY(1,1,2021) AND
DTPublicacao<=DATE.DMY(31,12,2021)) AND DTVencimento>DATE.DMY(31,12,2021)).
COMPUTE legal_2021= DATEDIFF(DATE.DMY(31,12,2021), DTPublicacao,"days").
ELSE IF year_process<=2021 AND (DTPublicacao<DATE.DMY(1,1,2021) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2021) AND DTVENCIMENTO<=DATE.DMY(31,12,2021))).
COMPUTE legal_2021= DATEDIFF(DTVencimento,DATE.DMY(1,1,2021),"days").
ELSE IF year_process<=2021 AND (DTPublicacao>=DATE.DMY(1,1,2021) AND
DTPublicacao<=DATE.DMY(31,12,2021)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2021) AND
DTVENCIMENTO<=DATE.DMY(31,12,2021)).
COMPUTE legal_2021=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2021=0.
END IF.
DO IF year_process<=2022 AND (DTPublicacao<DATE.DMY(1,1,2022) AND
DTVencimento>DATE.DMY(31,12,2022)).
COMPUTE legal_2022=365.
ELSE IF year_process<=2022 AND((DTPublicacao>=DATE.DMY(1,1,2022) AND
DTPublicacao<=DATE.DMY(31,12,2022)) AND DTVencimento>DATE.DMY(31,12,2022)).
COMPUTE legal_2022= DATEDIFF(DATE.DMY(31,12,2022), DTPublicacao,"days").
ELSE IF year_process<=2022 AND (DTPublicacao<DATE.DMY(1,1,2022) AND
(DTVENCIMENTO>=DATE.DMY(1,1,2022) AND DTVENCIMENTO<=DATE.DMY(31,12,2022))).
COMPUTE legal_2022= DATEDIFF(DTVencimento,DATE.DMY(1,1,2022),"days").
ELSE IF year_process<=2022 AND (DTPublicacao>=DATE.DMY(1,1,2022) AND
DTPublicacao<=DATE.DMY(31,12,2022)) AND (DTVENCIMENTO>=DATE.DMY(1,1,2022) AND
DTVENCIMENTO<=DATE.DMY(31,12,2022)).
COMPUTE legal_2022=DATEDIFF(DTVencimento,DTPublicacao,"days").
ELSE.
COMPUTE legal_2022=0.
END IF.
EXECUTE.

```

*Format new variables.

FORMATS legal_2003 to legal_2022(F6.2).

*Add metadata to the new variables.

VARIABLE LABELS

```

legal_2003 'Number of legal mining days in 2003'
legal_2004 'Number of legal mining days in 2004'
legal_2005 'Number of legal mining days in 2005'
legal_2006 'Number of legal mining days in 2006'
legal_2007 'Number of legal mining days in 2007'
legal_2008 'Number of legal mining days in 2008'

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legal_2009 'Number of legal mining days in 2009'
legal_2010 'Number of legal mining days in 2010'
legal_2011 'Number of legal mining days in 2011'
legal_2012 'Number of legal mining days in 2012'
legal_2013 'Number of legal mining days in 2013'
legal_2014 'Number of legal mining days in 2014'
legal_2015 'Number of legal mining days in 2015'
legal_2016 'Number of legal mining days in 2016'
legal_2017 'Number of legal mining days in 2017'
legal_2018 'Number of legal mining days in 2018'
legal_2019 'Number of legal mining days in 2019'
legal_2020 'Number of legal mining days in 2020'
legal_2021 'Number of legal mining days in 2021'
legal_2022 'Number of legal mining days in 2022'.

```

```

*Save cleaned mining process with legal title year by year dataset (multiple cases).
SORT CASES BY DSProcesso DTPublicacao DTVencimento.
SAVE OUTFILE ='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle_cleaned_sorted_2003-2022.sav'
/DROP diff.

```

```

SORT CASES BY DSProcesso NRProcesso year_process QTAreaHA active inactive last_event event
event_title dtitlect_all titlect_all dtitlect titlect.

```

```

AGGREGATE

```

```

/OUTFILE='E:\OneDrive\Academica\1-Doutorado '+'
'UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle_cleaned_sorted_2003-2022_sc.sav'
/PRESORTED
/BREAK=DSProcesso NRProcesso year_process active event event_title
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/legal_2004 'Number of legal mining days in 2004'=SUM(legal_2004)
/legal_2005 'Number of legal mining days in 2005'=SUM(legal_2005)
/legal_2006 'Number of legal mining days in 2006'=SUM(legal_2006)
/legal_2007 'Number of legal mining days in 2007'=SUM(legal_2007)
/legal_2008 'Number of legal mining days in 2008'=SUM(legal_2008)
/legal_2009 'Number of legal mining days in 2009'=SUM(legal_2009)
/legal_2010 'Number of legal mining days in 2010'=SUM(legal_2010)
/legal_2011 'Number of legal mining days in 2011'=SUM(legal_2011)
/legal_2012 'Number of legal mining days in 2012'=SUM(legal_2012)
/legal_2013 'Number of legal mining days in 2013'=SUM(legal_2013)
/legal_2014 'Number of legal mining days in 2014'=SUM(legal_2014)
/legal_2015 'Number of legal mining days in 2015'=SUM(legal_2015)
/legal_2016 'Number of legal mining days in 2016'=SUM(legal_2016)
/legal_2017 'Number of legal mining days in 2017'=SUM(legal_2017)
/legal_2018 'Number of legal mining days in 2018'=SUM(legal_2018)
/legal_2019 'Number of legal mining days in 2019'=SUM(legal_2019)
/legal_2020 'Number of legal mining days in 2020'=SUM(legal_2020)
/legal_2021 'Number of legal mining days in 2021'=SUM(legal_2021)
/legal_2022 'Number of legal mining days in 2022'=SUM(legal_2022)
/last_event=max(last_event)
/QTAreaHA=max(QTAreaHA)
/inactive=max(inactive).

```

```

GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle_cleaned_sorted_2003-2022_sc.sav'.
DATASET NAME titles_sc WINDOW=FRONT.
DATASET CLOSE ProcessTitle.
*Format variables.
FORMATS legal_2003 to legal_2022(F6.2).

```



```
DO REPEAT
X=legal_2003 to legal_2022.
IF X>365 X=365.
END REPEAT.
EXECUTE.
```

*Create a variable to compute the number of legal mining days granted to a polygon between 2010 and 2020.

```
COMPUTE ledays=sum(legal_2010 to legal_2020).
EXECUTE.
VARIABLE LABELS ledays 'Number of legal mining days between 2010 and 2020'.
```

*Save the final legal title 2003-2022 dataset (single case).

```
SORT CASES BY DSProcesso.
SAVE OUTFILE ='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle_cleaned_sorted_2003-2022_sc.sav'
/RENAME inactive=inactive_t last_event=last_event_t event=event_t QTAraHA=QTAraHA_t
active=active_t
/DROP year_process NRProcesso.
```

*Merge active processes dataset with legal title dataset.

```
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_active.sav'.
DATASET NAME anm WINDOW=FRONT.
DATASET CLOSE titles_sc.
DATASET ACTIVATE anm.
MATCH FILES /FILE=*
/TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessTitle_cleaned_sorted_2003-2022_sc.sav'
/BY DSProcesso.
EXECUTE.
```

*adjust data from new merged variables.

```
IF active_t<>active active=active_t.
IF event_t<>event event=event_t.
IF last_event_t<>last_event last_event=last_event_t.
IF QTAraHA_t<>QTAraHA QTAraHA=QTAraHA_t.
IF inactive_t<>inactive inactive=inactive_t.
EXECUTE.
DELETE VARIABLES active_t event_t last_event_t QTAraHA_t inactive_t.
IF SYSMIS(event_title) event_title=event.
EXECUTE.
```

*Adjust missing values from legal_title_number.

```
DO REPEAT
X=dtlect_all TO ledays.
IF SYSMIS(X) X=0.
END REPEAT.
EXECUTE.
```

*Rename process year variable.

```
RENAME VARIABLES NRAnoProcesso=year_process.
FORMATS year_process(F4).
VARIABLE LABELS year_process 'Process start year'.
```

*Show number of Active cases.

```
show n.
*N 913,775.
```

*Save final ANM dataset without substances .

SORT CASES BY DSProcesso.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_title.sav'

/keep

DSProcesso

year_process

QTAraHA

last_event

active

inactive

event

event_count

event_title

dttitlect_all

titlect_all

dttitlect

titlect

fine_sum

fine_sum_2003 to fine_sum_2022

auto_sum

auto_sum_2003 to auto_sum_2022

ledays

legal_2003 to legal_2022.

*Get the substance dataset.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessSubstance.sav'.

DATASET NAME ProcessSubstance WINDOW=FRONT.

DATASET CLOSE anm.

*Format variables.

FORMATS

DSProcesso (A12).

*Check the use of substances frequency.

* CROSSTABS

/TABLES=IDSubstancia BY IDTipoUsoSubstancia

/FORMAT=AVALUE TABLES

/CELLS=COUNT

/COUNT ROUND CELL.

*Create a variable to adjust missing use values to the most common uses of substances (suse).

IF ANY(IDSubstancia,101322, 104902, 200200, 200201, 200202, 200203, 200204, 200205, 200206, 200207, 200208, 200301, 200303, 200400, 200600, 200601, 200602, 200603, 200801, 200900, 200901, 700400, 701204, 701300, 701900, 701901, 702407, 702408, 702409, 705600, 705702, 705703, 705707, 706103, 706104, 710100, 710607, 710705, 711707, 711801, 712604, 714101) suse=1.

IF ANY(IDSubstancia,100307, 601000, 601001, 601003, 601014, 601045, 601057) suse=3.

IF ANY(IDSubstancia,200701, 702410, 702600, 710501) suse=4.

IF ANY(IDSubstancia,101308, 701402, 702400, 702401) suse=5.

IF ANY(IDSubstancia,103107, 200100, 200500, 200800, 201200, 601049, 602000, 700502, 700700, 700900, 701504, 703200, 703900, 704300, 704600, 705500, 705706,

706100, 706105, 706107, 706108, 707100, 707104, 710500, 710704, 710706, 710800, 711100, 711600, 711700, 711703, 711708, 711803, 711900, 713200, 713300, 714100) suse=7.

IF ANY(IDSubstancia,100600, 100906, 102301, 102305, 103101, 103202, 104307, 105300, 601002) suse=8.

IF ANY(IDSubstancia,200402, 701902, 705700, 705709, 706106, 706109, 708100, 710606, 710700) suse=9.

IF ANY(IDSubstancia,300101, 300102, 300103, 300110, 300112, 300400, 702501, 702800) suse=10.

```

IF ANY(IDSubstancia,601068, 702901) suse=12.
IF ANY(IDSubstancia,200300, 200302, 710300) suse=13.
IF ANY(IDSubstancia,601050, 602003, 602005, 602008, 711802) suse=15.
IF ANY(IDSubstancia,602001, 702700) suse=16.
IF ANY(IDSubstancia,100704, 601030) suse=17.
IF ANY(IDSubstancia,400103, 500102, 500105, 500200) suse=18.
IF ANY(IDSubstancia,800118, 800400) suse=19.
IF ANY(IDSubstancia,800101, 800300, 800500) suse=20.
IF ANY(IDSubstancia,100100, 100101, 100103, 100300, 100304, 100400, 100401, 100402, 100500,
100501, 100601, 100800, 100801, 100802, 100805, 100900, 100901, 100907,
101100, 101101, 101104, 101109, 101300, 101301, 101302, 101313, 101700, 101800, 101802, 101803,
101804, 101805, 101900, 101901, 101902, 102100, 102101, 102200,
102201, 102202, 102300, 102302, 102307, 102400, 102401, 102402, 102700, 102901, 103100, 103103,
103200, 103201, 103203, 103204, 103207, 103300, 103301, 103400,
103401, 103500, 103501, 103502, 103503, 103509, 103600, 103601, 103602, 103603, 103700, 103701,
103702, 103900, 103902, 104100, 104101, 104300, 104301, 104400,
104401, 104601, 104900, 104901, 104903, 104908, 105100, 105101, 105305, 105324, 105327, 105501,
106002, 107000, 108000, 200304, 200305, 200401, 200403, 200700,
300104, 300313, 300317, 300402, 300500, 400109, 400200, 500103, 601008, 601009, 601019, 601040,
601046, 601069, 602002, 602004, 700101, 700102, 700200, 700500,
700501, 700800, 701100, 701201, 701202, 701203, 701205, 701209, 701400, 701401, 701403, 701500,
701501, 701505, 701600, 701700, 701701, 701703, 701800, 701802,
702100, 702200, 702201, 702203, 702300, 702402, 702404, 702500, 702702, 702900, 702902, 703001,
703300, 703400, 703600, 703700, 703800, 704100, 704102, 704105,
704200, 704201, 704302, 704400, 704500, 704700, 704800, 704801, 705100, 705102, 705200, 705300,
705305, 705400, 705401, 705403, 705601, 705701, 705704, 705705,
705800, 705905, 710200, 710400, 710502, 710503, 710600, 710601, 710602, 710604, 710605, 710900,
711400, 711702, 711705, 711800, 711804, 711805, 711806, 711808,
712300, 712400, 712500, 712600, 712601, 712602, 712603, 712605, 712606, 712607, 712700, 712702,
712800, 713100, 713400, 713700, 713800, 713900, 716200) suse=21.
IF ANY(IDSubstancia,102303, 103102, 601005, 601006, 601010, 601012, 601015, 601017, 601018,
601024, 601025, 601028, 601029, 601031, 601036, 601041, 601051,
601052, 601056, 601058, 601065, 601071, 601073, 601074, 602009, 700300, 705900) suse=22.
IF ANY(IDSubstancia,400301, 400400) suse=24.
IF SYSMIS(suse) suse=99.
EXECUTE.

```

*Recode suse according to frequency.

```

EXECUTE.
RECODE suse
(21=1)
(1=2)
(7=3)
(5=4)
(9=5)
(10=6)
(22=7)
(20=8)
(13=9)
(24=10)
(18=11)
(3=12)
(8=13)
(4=14)
(16=15)
(15=16)
(19=17)
(12=18)
(17=19).
EXECUTE.

```

```

*Create metadata.
VARIABLE LABELS suse 'Substance general use'.
FORMATS suse (F2).
VALUE LABELS suse
1 'Industrial'
2 'Construction'
3 'Wall Cladding'
4 'Cement manufacturing'
5 'Gravel'
6 'Fertilizers'
7 'Gem'
8 'Bottling'
9 'Red pottery'
10 'Agricultural input'
11 'Energetic'
12 'Jewelery'
13 'Metallurgy'
14 'Soil amendment'
15 'Collection Stone'
16 'Mineral crafts'
17 'Balneotherapy'
18 'Glass manufacturing'
19 'Decorative stone'
99 'Others'.

show n.
* n 1077573.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessSubstance_suse_all.sav'.

*Transpose to a wide dataset.
SORT CASES BY DSProcesso.
CASESTOVARS
  /ID=DSProcesso
  /GROUPBY=Index
  /COUNT=subs_count "Number of substances per process".

*Save substance dataset single case.
SORT CASES BY DSProcesso.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessSubstance_sc.sav'.

*Add substance variables to the main dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_title.sav'.
DATASET NAME ANM_all_title WINDOW=FRONT.
DATASET CLOSE ProcessSubstance.
MATCH FILES /FILE = *
  /TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessSubstance_sc.sav'
  /BY DSProcesso.
EXECUTE.

*Save ANM dataset.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_subs.sav'
  /DROP year_process.

```



```

DO IF p_type=0.
COMPUTE n_ssn=(REPLACE(ssn,'*',')).
ELSE.
COMPUTE n_ssn=ssn.
END IF.
EXECUTE.

STRING anm_f_key (A20).
DO IF p_type=0.
COMPUTE anm_f_key=CONCAT(n_ssn,(char.substr(nm_person,1,15))).
ELSE.
COMPUTE anm_f_key=n_ssn.
END IF.
EXECUTE.

*Save person SSN dataset.
SORT CASES BY IDPessoa.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonID_clean.sav'.

*Add type of person variables to the person dataset.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPerson.sav'.
DATASET NAME ProcessPerson WINDOW=FRONT.
DATASET CLOSE ProcessPersonID.
*Format variables.
FORMATS
DSProcesso (A12).

SORT CASES BY IDPessoa.
MATCH FILES /FILE = *
/TABLE ='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonID_clean.sav'
/BY IDPessoa.
EXECUTE.

* Select only holder/applicant cases.
SELECT IF IDTipoRelacao=1.
EXECUTE.

*Select only holder/applicant that started operating before 01/01/2021.
SELECT IF DTInicioVigencia<=DATE.DMY(01,01,2023).
EXECUTE.

*Substitute DTFinVigencia missing dates for today.
IF SYSMIS(DTFinVigencia) DTFinVigencia=DATE.DMY(31,12,2022).
EXECUTE.

*Create variable to control for juridical person across the years.

SORT CASES BY DSProcesso DTFinVigencia.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2003) AND
(DTFinVigencia>=DATE.DMY(1,1,2003)).
COMPUTE jp_2003=1.
ELSE.
COMPUTE jp_2003=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2004) AND
(DTFinVigencia>=DATE.DMY(1,1,2004)).

```

```

COMPUTE jp_2004=1.
ELSE.
COMPUTE jp_2004=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2005) AND
(DTFimVigencia>=DATE.DMY(1,1,2005)).
COMPUTE jp_2005=1.
ELSE.
COMPUTE jp_2005=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2006) AND
(DTFimVigencia>=DATE.DMY(1,1,2006)).
COMPUTE jp_2006=1.
ELSE.
COMPUTE jp_2006=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2007) AND
(DTFimVigencia>=DATE.DMY(1,1,2007)).
COMPUTE jp_2007=1.
ELSE.
COMPUTE jp_2007=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2008) AND
(DTFimVigencia>=DATE.DMY(1,1,2008)).
COMPUTE jp_2008=1.
ELSE.
COMPUTE jp_2008=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2009) AND
(DTFimVigencia>=DATE.DMY(1,1,2009)).
COMPUTE jp_2009=1.
ELSE.
COMPUTE jp_2009=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2010) AND
(DTFimVigencia>=DATE.DMY(1,1,2010)).
COMPUTE jp_2010=1.
ELSE.
COMPUTE jp_2010=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2011) AND
(DTFimVigencia>=DATE.DMY(1,1,2011)).
COMPUTE jp_2011=1.
ELSE.
COMPUTE jp_2011=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2012) AND
(DTFimVigencia>=DATE.DMY(1,1,2012)).
COMPUTE jp_2012=1.
ELSE.
COMPUTE jp_2012=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2013) AND
(DTFimVigencia>=DATE.DMY(1,1,2013)).
COMPUTE jp_2013=1.
ELSE.
COMPUTE jp_2013=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2014) AND
(DTFimVigencia>=DATE.DMY(1,1,2014)).

```

```

COMPUTE jp_2014=1.
ELSE.
COMPUTE jp_2014=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2015) AND
(DTFimVigencia>=DATE.DMY(1,1,2015)).
COMPUTE jp_2015=1.
ELSE.
COMPUTE jp_2015=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2016) AND
(DTFimVigencia>=DATE.DMY(1,1,2016)).
COMPUTE jp_2016=1.
ELSE.
COMPUTE jp_2016=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2017) AND
(DTFimVigencia>=DATE.DMY(1,1,2017)).
COMPUTE jp_2017=1.
ELSE.
COMPUTE jp_2017=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2018) AND
(DTFimVigencia>=DATE.DMY(1,1,2018)).
COMPUTE jp_2018=1.
ELSE.
COMPUTE jp_2018=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2019) AND
(DTFimVigencia>=DATE.DMY(1,1,2019)).
COMPUTE jp_2019=1.
ELSE.
COMPUTE jp_2019=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2020) AND
(DTFimVigencia>=DATE.DMY(1,1,2020)).
COMPUTE jp_2020=1.
ELSE.
COMPUTE jp_2020=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2021) AND
(DTFimVigencia>=DATE.DMY(1,1,2021)).
COMPUTE jp_2021=1.
ELSE.
COMPUTE jp_2021=0.
END IF.
DO IF p_type=1 AND DTInicioVigencia<=DATE.DMY(31,12,2022) AND
(DTFimVigencia>=DATE.DMY(1,1,2022)).
COMPUTE jp_2022=1.
ELSE.
COMPUTE jp_2022=0.
END IF.
EXECUTE.

```

*Create an SSN dataset containing the sum of juridical persons that were responsible for the polygon in an specific year.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonSSN_aggregated.sav'

/PRESORTED


```

/BREAK=DSProcesso
/jp_2003_s=SUM(jp_2003)
/jp_2004_s=SUM(jp_2004)
/jp_2005_s=SUM(jp_2005)
/jp_2006_s=SUM(jp_2006)
/jp_2007_s=SUM(jp_2007)
/jp_2008_s=SUM(jp_2008)
/jp_2009_s=SUM(jp_2009)
/jp_2010_s=SUM(jp_2010)
/jp_2011_s=SUM(jp_2011)
/jp_2012_s=SUM(jp_2012)
/jp_2013_s=SUM(jp_2013)
/jp_2014_s=SUM(jp_2014)
/jp_2015_s=SUM(jp_2015)
/jp_2016_s=SUM(jp_2016)
/jp_2017_s=SUM(jp_2017)
/jp_2018_s=SUM(jp_2018)
/jp_2019_s=SUM(jp_2019)
/jp_2020_s=SUM(jp_2020)
/jp_2021_s=SUM(jp_2021)
/jp_2022_s=SUM(jp_2022).

```

* Identify Duplicate Cases.

DATASET ACTIVATE ProcessPerson.

SORT CASES BY DSProcesso(A) DTFimVigencia.

MATCH FILES

/FILE=*

/BY DSProcesso

/FIRST=PrimaryFirst

/LAST=PrimaryLast.

DO IF (PrimaryFirst).

COMPUTE MatchSequence=1-PrimaryLast.

ELSE.

COMPUTE MatchSequence=MatchSequence+1.

END IF.

LEAVE MatchSequence.

FORMATS MatchSequence (f7).

MATCH FILES

/FILE=*

/DROP=PrimaryFirst.

VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary' MatchSequence
'Sequential count of matching cases'.

VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.

VARIABLE LEVEL PrimaryLast (ORDINAL) /MatchSequence (SCALE).

FREQUENCIES VARIABLES=PrimaryLast MatchSequence.

EXECUTE.

***Even if only 7% of the polygons had more than one responsible along the years, I've decided to control for the presence of a different juridical person responsible for a polygon in an specific year (variables jp_YEAR)**

and keep only SSN that correspond to the responsible for the polygon in 12/31/2022.

SELECT IF primarylast=1.

EXECUTE.

*Add variable labels.

VARIABLE LABELS

nm_person 'Holder/Applicant name in 12/31/2020 without special characters and spaces'

n_ssn 'Social Security Number without *'

anm_f_key 'Foreign key'.

*Merge aggregated file with main SSN file.

MATCH FILES /FILE = *

/TABLE ='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonSSN_aggregated.sav'

/BY DSPProcesso.

EXECUTE.

*Save final person SSN dataset.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonSSN.sav'.

*Add final person SSN variables to Final ANM dataset.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_ALL_subs.sav'.

DATASET NAME ANM_all_subs WINDOW=FRONT.

DATASET CLOSE ProcessPerson.

MATCH FILES /FILE=*

/TABLE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ProcessPersonSSN.sav'

/RENAME (IDPessoa IDTipoRelacao DTInicioVigencia DTFimVigencia TPPessoa nm_person n_ssn
jp_2003

jp_2004 jp_2005 jp_2006 jp_2007 jp_2008 jp_2009 jp_2010 jp_2011 jp_2012 jp_2013 jp_2014

jp_2015

jp_2016 jp_2017 jp_2018 jp_2019 jp_2020 jp_2021 jp_2022 PrimaryLast MatchSequence jp_2003_s

jp_2004_s jp_2005_s jp_2006_s jp_2007_s jp_2008_s jp_2009_s jp_2010_s jp_2011_s jp_2012_s

jp_2013_s

jp_2014_s jp_2015_s jp_2016_s jp_2017_s jp_2018_s jp_2019_s jp_2020_s jp_2021_s jp_2022_s =

d0 d1

d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23 d24 d25 d26 d27

d28

d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42 d43 d44 d45 d46 d47 d48)

/BY DSPProcesso

/DROP= d0 d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d16 d17 d18 d19 d20 d21 d22 d23

d24

d25 d26 d27 d28 d29 d30 d31 d32 d33 d34 d35 d36 d37 d38 d39 d40 d41 d42 d43 d44 d45 d46 d47

d48.

EXECUTE.

*Create a new process year variable.

STRING year_process(A4).

COMPUTE #spaceLoc=CHAR.INDEX(DSPProcesso, "/").

COMPUTE year_process=CHAR.SUBSTR(DSPProcesso, (#spaceLoc+1)).

EXECUTE.

ALTER TYPE year_process to year_process(F4).

*Add metadata.

VARIABLE LABELS year_process 'Year in which the process started'.

FORMATS QTAreaHA(F10.2).

*Save Final ANM dataset.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_ssn.sav'.

**Clean cfem data.

*import cfem csv dataset.

*PRESERVE.

*SET DECIMAL COMMA.

```
*Create an id to allow merging with IBGE's municipality id.  
*Create a new variable to remove accents from the names of the municipalities where materials were  
cfem occurred.  
String cfem_mu_recoded (A33).  
compute cfem_mu_recoded=  
(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replac  
e(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace  
(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replac  
e(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace  
(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replac  
e(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace  
(Município  
, 'Š','S'),'š','s'),'Ž','Z'),'ž','z'),'À','A'),'Á','A'),'Â','A'),'Ã','A'),'Ä','A'),'Å','A'),'Æ','A'),'Ç','C'),'È','E'),'É','E'),'Ê','E'  
)  
, 'Ě','E'),'İ','I'),'Í','I'),'Î','I'),'Ï','I'),'Ñ','N'),'Ò','O'),'Ó','O'),'Ô','O'),'Õ','O'),'Ö','O'),'Ø','O'),'Ù','U'),'Ú','U'),'Û','U')  
, 'Ů','U')  
, 'Ý','Y'),'P','B'),'ß','B'),'à','a'),'á','a'),'â','a'),'ã','a'),'ä','a'),'å','a'),'æ','a'),'ç','c'),'è','e'),'é','e'),'ê','e'),'ë','e'),'ì','i')  
, 'í','i'),'î','i'),'ï','i'),'ð','o'),'ñ','n'),'ò','o'),'ó','o'),'ô','o'),'õ','o'),'ø','o'),'ù','u'),'ú','u'),'û','u'),'ý','y'),'ÿ','y'),'þ','b'),'  
'ÿ','y'),'?o','ao'),'?O','AO'))).  
EXECUTE.
```


show n.

*n 3,815

*Adjust missing values.

DO REPEAT x=cfem.2002 to cfem.2023.

IF SYSMIS(x) x=0.

END REPEAT.

EXECUTE.

*Save cfem dataset.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem_mun_id_all_wide.sav'.

*Delete variables outside the scope of the project.

DELETE VARIABLES cfem.2002 to cfem.2009 cfem.2021 TO cfem.2023.

*Create variable to sum all cfem paid between 2010-2020.

COMPUTE cfem=SUM(cfem.2010 to cfem.2020).

EXECUTE.

*Save cfem dataset 2010-2020.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem_2010-2020_wide.sav'.

DATASET NAME cfem_2010_2020.

SAVE TRANSLATE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem_2010-2020_wide.xlsx'

/TYPE=XLS

/VERSION=12

/MAP

/FIELDNAMES VALUE=NAMES

/CELLS=VALUES

/REPLACE.

Create a dataset of cfem paid per process.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\CFEM\CFEM.sav'.

DATASET NAME CFEM WINDOW=FRONT.

*Create process variable to serve as foreign key.

STRING process_string(A6).

COMPUTE process_string=STRING(Processo,F6.0).

COMPUTE process_string= REPLACE (process_string, ".", "").

IF (Processo<>0) process_string= (CHAR.LPAD(LTRIM(process_string), 6, "0")).

STRING ano_string(A4).

COMPUTE ano_string=STRING(AnoDoProcesso,F4.0).

COMPUTE ano_string= REPLACE (ano_string, ".", "").

STRING process(A12).

IF (Processo<>0) process=CONCAT(char.substr(process_string,1,3), ".", char.substr(process_string,4,3),

"/",ano_string).

EXECUTE.

*Aggregate mining tenements CFEM per year.

SORT CASES BY process Ano.

AGGREGATE

/OUTFILE='E:\OneDrive\Acadêmica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem.sav'

/PRESORTED

/BREAK=process Ano

```
/cfem=SUM(ValorRecolhido).
```

```
*restructure data to wide.
SORT CASES BY process Ano.
CASESTOVARS
  /ID=process
  /INDEX= Ano
  /GROUPBY=INDEX.
```

```
show n.
*n 40.913
```

```
*Save cfem dataset.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem_all_wide.sav'.
*Merge cfem data with anm general data.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_all_ssn.sav'.
DATASET NAME ANM_all_ssn WINDOW=FRONT.
*Rename DSProcesso.
RENAME VARIABLES DSProcesso=process.
FORMATS process(A12).
DATASET CLOSE cfem_2010_2020.
MATCH FILES /FILE=*
  /TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\CFEM\Last\cfem_wide.sav'
  /BY process.
EXECUTE.
```

```
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_cfem.sav'.
```

```
*Create variable to control for TAH payment
*Import TAH data.
* GET DATA
  /TYPE=XLSX
  /FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\ANM\TAH\tah.xlsx'
  /SHEET=name 'Sheet1'
  /CELLRANGE=FULL
  /READNAMES=ON
  /DATATYPEMIN PERCENTAGE=95.0
  /HIDDEN IGNORE=YES.
* EXECUTE.
* DATASET NAME tah WINDOW=FRONT.
* DATASET CLOSE ANM_no_CFEM.
```

```
* SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\TAH\tah.sav'.
```

```
*Create process variable to serve as foreign key.
* STRING process_string(A6).
* COMPUTE process_string=STRING(Processo,F6.0).
* COMPUTE process_string= REPLACE (process_string, ".", "").
* IF (Processo<>0) process_string= (CHAR.LPAD(LTRIM(process_string), 6, "0")).
* STRING ano_string(A4).
* COMPUTE ano_string=STRING(AnodoProcesso,F4.0).
* COMPUTE ano_string= REPLACE (ano_string, ".", "").
* STRING process(A12).
* IF (Processo<>0) process=CONCAT(char.substr(process_string,1,3), ".",
char.substr(process_string,4,3), "/",ano_string).
```

* EXECUTE.

*Agregate mining tenements CFEM per year.

* SORT CASES BY process.

* AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\TAH\Last\tah_sc.sav'

/PRESORTED

/BREAK=process

/tah=SUM(ValorPago).

*Merge tah data with anm general data.

GET FILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_cfem.sav'.

DATASET NAME ANM_cfem WINDOW=FRONT.

* DATASET CLOSE tah.

MATCH FILES /FILE=*

/TABLE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\TAH\Last\tah_sc.sav'

/BY process.

EXECUTE.

*Adjust missing values.

DO REPEAT x=cfem.2003 to tah.

IF SYSMIS(x) x=0.

END REPEAT.

EXECUTE.

*Add metadata.

VARIABLE LABELS

cfem.2003 'Mining compensation tax per mining tenement -2003 '

cfem.2004 'Mining compensation tax per mining tenement -2004 '

cfem.2005 'Mining compensation tax per mining tenement -2005 '

cfem.2006 'Mining compensation tax per mining tenement -2006 '

cfem.2007 'Mining compensation tax per mining tenement -2007 '

cfem.2008 'Mining compensation tax per mining tenement -2008 '

cfem.2009 'Mining compensation tax per mining tenement -2009 '

cfem.2010 'Mining compensation tax per mining tenement -2010 '

cfem.2011 'Mining compensation tax per mining tenement -2011 '

cfem.2012 'Mining compensation tax per mining tenement -2012 '

cfem.2013 'Mining compensation tax per mining tenement -2013 '

cfem.2014 'Mining compensation tax per mining tenement -2014 '

cfem.2015 'Mining compensation tax per mining tenement -2015 '

cfem.2016 'Mining compensation tax per mining tenement -2016 '

cfem.2017 'Mining compensation tax per mining tenement -2017 '

cfem.2018 'Mining compensation tax per mining tenement -2018 '

cfem.2019 'Mining compensation tax per mining tenement -2019 '

cfem.2020 'Mining compensation tax per mining tenement -2020 '

cfem.2021 'Mining compensation tax per mining tenement -2021 '

cfem.2022 'Mining compensation tax per mining tenement -2022 '

cfem 'Mining compensation tax per mining tenement -Sum 2002/2022 '

tah 'Fee paid per hectare due to mining or research'.

SHOW n.

*n 913,775.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_tah.sav'.

*Import utilization permit dataset.

```

* PRESERVE.
* SET DECIMAL COMMA.

* GET DATA /TYPE=TXT
/FILE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\Guia_de_utilizacao\Guia_de_Utilizacao_Autorizada_UTF.csv"
/ENCODING='UTF8'
/DELIMITERS=","
/QUALIFIER=""
/ARRANGEMENT=DELIMITED
/FIRSTCASE=2
/DATATYPEMIN PERCENTAGE=95.0
/VARIABLES=
Superintendência AUTO
Processo AUTO
Tipoderequerimento AUTO
FaseAtual AUTO
CPF CNPJ do titular AUTO
Titular AUTO
Municipios AUTO
Substâncias AUTO
Tipos de Uso AUTO
Situação AUTO
/MAP.
* RESTORE.
* CACHE.
* EXECUTE.
* DATASET NAME GU WINDOW=FRONT.

* SAVE OUTFILE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\Guia_de_utilizacao\gu.sav".

* GET FILE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\Guia_de_utilizacao\gu.sav".
* DATASET NAME GU WINDOW=FRONT.
* Identify Duplicate Cases.
* SORT CASES BY Processo(A).
* MATCH FILES
/FILE=*
/BY Processo
/LAST=PrimaryLast.
* VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
* VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
* VARIABLE LEVEL PrimaryLast (ORDINAL).
* FREQUENCIES VARIABLES=PrimaryLast.
* EXECUTE.

*Delete duplicated cases.
* SELECT IF PrimaryLast=1.
* EXECUTE.

*Create a dummy for GU.
* COMPUTE ut_per=1.
* EXECUTE.

* STRING process(A12).
* COMPUTE process=CONCAT(char.substr(Processo,1,3), ".", char.substr(Processo,4,9)).
* EXECUTE.

* EXECUTE.

```



```

*Add metadata.
* VARIABLE LABELS
ut_per 'Utilization permit'.
* FORMATS ut_per(F1).

* SORT CASES by process.
* SAVE OUTFILE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\Guia_de_utilizacao\gu_dummy.sav"
/KEEP process ut_per.

```

```

*Merge tah data with anm general data.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\API_SCM\ANM_tah.sav'.
DATASET NAME ANM_tah WINDOW=FRONT.
* DATASET CLOSE GU.
MATCH FILES /FILE=*
/TABLE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\Guia_de_utilizacao\gu_dummy.sav"
/BY process.
EXECUTE.

```

```

*Adjust missing.
IF SYSMIS(ut_per) ut_per=0.
EXECUTE.

```

```

*Add metadata.
VALUE LABELS ut_per 1 'Yes' 0 'No'.

```

```

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_all.sav'.

```

```

RENAME VARIABLES
IDSubstancia.1=subs
suse.1=suse.

```

```

*Categorize substances.
IF ANY(subs, 101300, 101301) subs=1.
IF ANY(subs, 706100, 706107, 706109, 706108, 706104, 706103, 706106) subs=2.
IF ANY(subs, 200200, 701100, 701202, 200204, 200201, 200202, 701205, 200207, 701201) subs=3.
IF ANY(subs, 104900, 104901) subs=4.
IF ANY(subs, 711700, 200800, 711703, 711708, 711701, 711705) subs=5.
IF ANY(subs, 702400, 702401, 702600, 702402, 200701, 702404) subs=6.
IF ANY(subs, 100900, 100901) subs=7.
IF ANY(subs, 102100, 102101) subs=8.
IF ANY(subs, 701400, 200300, 701700, 200302, 200303, 702201, 701401, 701703, 701402, 200301) subs=9.
IF ANY(subs, 300101) subs=10.
EXECUTE.

```

```

*Label substances names

```

```

VALUE LABELS
subs
1 'Iron'
2 'Granite'
3 'Sand'
4 'Gold'
5 'Quartzite'
6 'Limestone'
7 'Copper'
8 'Manganese'

```

9 'Clay'
10 'Phosphate'.

*Select only mining tenements exploring only one substance.

```
SELECT IF subs_count=1.  
EXECUTE.
```

```
SHOW n.  
*n 771,632.
```

*Select only mining tenements exploring the ten most explored substances in Brazil.

```
SELECT IF ANY(subs,1,2,3,4,5,6,7,8,9,10).  
EXECUTE.
```

```
SHOW n.  
*n 482,851.
```

*Drop >2020 cases.

```
SELECT IF year_process<2021.  
EXECUTE.
```

```
show n.  
*N 467,628.
```

*Select cases that had an event or a valid title between 2010 and 2020.

```
SELECT IF event_title=1.  
EXECUTE.
```

*Show number of Active cases.

```
show n.  
*N 217,685.
```

*drop unused variables.

```
DELETE VARIABLES subs_count IDTipoUsoSubstancia.1 IDSubstancia.2 to suse.23.
```

*Rename Variables bigger then 8 char.

```
RENAME VARIABLES  
last_event=last_eve  
event_count=event_ct  
event_title=event_ti  
dtitlect_all=dtitlecta  
titlect_all=titlecta  
NMPessoa=name  
fine_sum=afs_sum  
fine_sum_2003=afs_2003  
fine_sum_2004=afs_2004  
fine_sum_2005=afs_2005  
fine_sum_2006=afs_2006  
fine_sum_2007=afs_2007  
fine_sum_2008=afs_2008  
fine_sum_2009=afs_2009  
fine_sum_2010=afs_2010  
fine_sum_2011=afs_2011  
fine_sum_2012=afs_2012  
fine_sum_2013=afs_2013  
fine_sum_2014=afs_2014
```

```

fine_sum_2015= afs_2015
fine_sum_2016= afs_2016
fine_sum_2017= afs_2017
fine_sum_2018= afs_2018
fine_sum_2019= afs_2019
fine_sum_2020= afs_2020
fine_sum_2021= afs_2021
fine_sum_2022= afs_2022
auto_sum_2003= aa_2003
auto_sum_2004= aa_2004
auto_sum_2005= aa_2005
auto_sum_2006= aa_2006
auto_sum_2007= aa_2007
auto_sum_2008= aa_2008
auto_sum_2009= aa_2009
auto_sum_2010= aa_2010
auto_sum_2011= aa_2011
auto_sum_2012= aa_2012
auto_sum_2013= aa_2013
auto_sum_2014= aa_2014
auto_sum_2015= aa_2015
auto_sum_2016= aa_2016
auto_sum_2017= aa_2017
auto_sum_2018= aa_2018
auto_sum_2019= aa_2019
auto_sum_2020= aa_2020
auto_sum_2021= aa_2021
auto_sum_2022= aa_2022
ledays=ledsum
legal_2003= led_2003
legal_2004= led_2004
legal_2005= led_2005
legal_2006= led_2006
legal_2007= led_2007
legal_2008= led_2008
legal_2009= led_2009
legal_2010= led_2010
legal_2011= led_2011
legal_2012= led_2012
legal_2013= led_2013
legal_2014= led_2014
legal_2015= led_2015
legal_2016= led_2016
legal_2017= led_2017
legal_2018= led_2018
legal_2019= led_2019
legal_2020= led_2020
legal_2021= led_2021
legal_2022= led_2022
anm_f_key= anm_key
year_process= year_pro
cfem.2003= cfem2003
cfem.2004= cfem2004
cfem.2005= cfem2005
cfem.2006= cfem2006
cfem.2007= cfem2007
cfem.2008= cfem2008
cfem.2009= cfem2009
cfem.2010= cfem2010
cfem.2011= cfem2011

```

```
cfem.2012= cfem2012
cfem.2013= cfem2013
cfem.2014= cfem2014
cfem.2015= cfem2015
cfem.2016= cfem2016
cfem.2017= cfem2017
cfem.2018= cfem2018
cfem.2019= cfem2019
cfem.2020= cfem2020
cfem.2021= cfem2021
cfem.2022= cfem2022.
```

```
DO REPEAT
X=cfem2003 to tah.
FORMATS X(F14.2).
END REPEAT.
EXECUTE.
```

```
*Create a variable to control for the number of years.
COUNT op_year=cfem2010 cfem2011 cfem2012
cfem2013 cfem2014 cfem2015 cfem2016 cfem2017 cfem2018 cfem2019 cfem2020 (0.15 THRU HI).
EXECUTE.
```

```
*Add metadata.
VARIABLE LABELS
subs 'Substance ID'
suse 'Substance general use'
op_year 'Number of years that CFEM was paid - 2010/2020'.
```

```
*Save Final ANM dataset.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM.sav'
/keep
process
QTAreaHA
subs
suse
ssn
name
p_type
anm_key
year_pro
last_eve
active
inactive
event
event_ct
event_ti
dtitleca
titlecta
dtitlect
titlect
afs_sum
afs_2003 to afs_2022
auto_sum
aau_2003 to aau_2022
ledsum
led_2003 to led_2022
cfem2003 to cfem2022
cfem
```

op_year
ut_per
tah.

FORMATS cfem2003 TO cfem (F14.2) tah(F10.2).

*Create a dataset to be used on GIS.

```
SAVE TRANSLATE
  /OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM.dbf'
  /TYPE=DB4
  /REPLACE.
```

*Create a dummy to flag chosen processes on the main dataset.

```
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM.sav'.
DATASET NAME final_anm WINDOW=FRONT.
COMPUTE select=1.
EXECUTE.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_selected.sav'
  /keep
  process select.
```

```
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_all.sav'.
DATASET NAME final_anm_all WINDOW=FRONT.
MATCH FILES /FILE=*
  /TABLE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_selected.sav'
  /BY process.
EXECUTE.
```

*adjust metadata.

```
IF SYSMIS(select) select=0.
EXECUTE.
VARIABLE LABELS select 'Sample mining tenements'.
```

RENAME VARIABLES

```
last_event=last_eve
event_count=event_ct
event_title=event_ti
dtlect_all=dtlecta
titlect_all=titlecta
NMPessoa=name
fine_sum=afs_sum
fine_sum_2003=afs_2003
fine_sum_2004=afs_2004
fine_sum_2005=afs_2005
fine_sum_2006=afs_2006
fine_sum_2007=afs_2007
fine_sum_2008=afs_2008
fine_sum_2009=afs_2009
fine_sum_2010=afs_2010
fine_sum_2011=afs_2011
fine_sum_2012=afs_2012
fine_sum_2013=afs_2013
fine_sum_2014=afs_2014
fine_sum_2015=afs_2015
fine_sum_2016=afs_2016
```

```

fine_sum_2017= afs_2017
fine_sum_2018= afs_2018
fine_sum_2019= afs_2019
fine_sum_2020= afs_2020
fine_sum_2021= afs_2021
fine_sum_2022= afs_2022
auto_sum_2003= aa_2003
auto_sum_2004= aa_2004
auto_sum_2005= aa_2005
auto_sum_2006= aa_2006
auto_sum_2007= aa_2007
auto_sum_2008= aa_2008
auto_sum_2009= aa_2009
auto_sum_2010= aa_2010
auto_sum_2011= aa_2011
auto_sum_2012= aa_2012
auto_sum_2013= aa_2013
auto_sum_2014= aa_2014
auto_sum_2015= aa_2015
auto_sum_2016= aa_2016
auto_sum_2017= aa_2017
auto_sum_2018= aa_2018
auto_sum_2019= aa_2019
auto_sum_2020= aa_2020
auto_sum_2021= aa_2021
auto_sum_2022= aa_2022
ledays=ledsum
legal_2003= led_2003
legal_2004= led_2004
legal_2005= led_2005
legal_2006= led_2006
legal_2007= led_2007
legal_2008= led_2008
legal_2009= led_2009
legal_2010= led_2010
legal_2011= led_2011
legal_2012= led_2012
legal_2013= led_2013
legal_2014= led_2014
legal_2015= led_2015
legal_2016= led_2016
legal_2017= led_2017
legal_2018= led_2018
legal_2019= led_2019
legal_2020= led_2020
legal_2021= led_2021
legal_2022= led_2022
anm_f_key= anm_key
year_process= year_pro
cfem.2003= cfem2003
cfem.2004= cfem2004
cfem.2005= cfem2005
cfem.2006= cfem2006
cfem.2007= cfem2007
cfem.2008= cfem2008
cfem.2009= cfem2009
cfem.2010= cfem2010
cfem.2011= cfem2011
cfem.2012= cfem2012
cfem.2013= cfem2013

```

cfem.2014= cfem2014
cfem.2015= cfem2015
cfem.2016= cfem2016
cfem.2017= cfem2017
cfem.2018= cfem2018
cfem.2019= cfem2019
cfem.2020= cfem2020
cfem.2021= cfem2021
cfem.2022= cfem2022
subs_count=subs_cnt
IDSubstancia.1=IDSbs1
IDSubstancia.2=IDSbs2
IDSubstancia.3=IDSbs3
IDSubstancia.4=IDSbs4
IDSubstancia.5=IDSbs5
IDSubstancia.6=IDSbs6
IDSubstancia.7=IDSbs7
IDSubstancia.8=IDSbs8
IDSubstancia.9=IDSbs9
IDSubstancia.10=IDSbs10
IDSubstancia.11=IDSbs11
IDSubstancia.12=IDSbs12
IDSubstancia.13=IDSbs13
IDSubstancia.14=IDSbs14
IDSubstancia.15=IDSbs15
IDSubstancia.16=IDSbs16
IDSubstancia.17=IDSbs17
IDSubstancia.18=IDSbs18
IDSubstancia.19=IDSbs19
IDSubstancia.20=IDSbs20
IDSubstancia.21=IDSbs21
IDSubstancia.22=IDSbs22
IDSubstancia.23=IDSbs23
IDTipoUsoSubstancia.1=use_1
IDTipoUsoSubstancia.2=use_2
IDTipoUsoSubstancia.3=use_3
IDTipoUsoSubstancia.4=use_4
IDTipoUsoSubstancia.5=use_5
IDTipoUsoSubstancia.6=use_6
IDTipoUsoSubstancia.7=use_7
IDTipoUsoSubstancia.8=use_8
IDTipoUsoSubstancia.9=use_9
IDTipoUsoSubstancia.10=use_10
IDTipoUsoSubstancia.11=use_11
IDTipoUsoSubstancia.12=use_12
IDTipoUsoSubstancia.13=use_13
IDTipoUsoSubstancia.14=use_14
IDTipoUsoSubstancia.15=use_15
IDTipoUsoSubstancia.16=use_16
IDTipoUsoSubstancia.17=use_17
IDTipoUsoSubstancia.18=use_18
IDTipoUsoSubstancia.19=use_19
IDTipoUsoSubstancia.20=use_20
IDTipoUsoSubstancia.21=use_21
IDTipoUsoSubstancia.22=use_22
IDTipoUsoSubstancia.23=use_23
suse.1=suse_1
suse.2=suse_2
suse.3=suse_3
suse.4=suse_4

```

suse.5=suse_5
suse.6=suse_6
suse.7=suse_7
suse.8=suse_8
suse.9=suse_9
suse.10=suse_10
suse.11=suse_11
suse.12=suse_12
suse.13=suse_13
suse.14=suse_14
suse.15=suse_15
suse.16=suse_16
suse.17=suse_17
suse.18=suse_18
suse.19=suse_19
suse.20=suse_20
suse.21=suse_21
suse.22=suse_22
suse.23=suse_23.

```

```

DO REPEAT
X=cfem2003 to tah.
FORMATS X(F14.2).
END REPEAT.
EXECUTE.

```

```

FORMATS QTAreaHA(F11.2).

```

```

*Create a variable to control for the number of years.
COUNT op_year=cfem2010 cfem2011 cfem2012
      cfem2013 cfem2014 cfem2015 cfem2016 cfem2017 cfem2018 cfem2019 cfem2020 (0.15 THRU HI).
EXECUTE.

```

```

*Add metadata.
VARIABLE LABELS
  op_year 'Number of years that CFEM was paid - 2010/2020'.

```

```

*Create a complete dataset to be used on GIS.
SAVE TRANSLATE
  /OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_all.dbf'
  /TYPE=DB4
  /REPLACE.

```


ANM Mining Area inside municipalities completely within Caatinga

Create layer with all active and inactive mining polygons in municipalities completely inside Caatinga biome

Load:

active mining polygons shapefile (Brasil.shp, available in

https://app.anm.gov.br/dadosabertos/SIGMINE/PROCESSOS_MINERARIOS/BRASIL.zip)

inactive mining polygons shapefile

(https://app.anm.gov.br/dadosabertos/SIGMINE/PROCESSOS_MINERARIOS/BRASIL_INATIVOS.zip)

IBGE biomes limits shapefile

(ftp://geoftp.ibge.gov.br/informacoes_ambientais/estudos_ambientais/biomas/vetores/Biomas_5000mil.zip)

Brazilian municipalities from IBGE

(https://geoftp.ibge.gov.br/organizacao_do_territorio/malhas_territoriais/malhas_municipais/municipio_2020/Brasil/BR/BR_Municipios_2020.zip)

Create a layer with municipalities completely inside Caatinga biome.

Due to divergences between biome and political boundaries, which would exclude coastal municipalities if a "completely within" selection was performed, it was necessary to make a double selection: one to include municipalities that intersect with the Caatinga biome, other to exclude from the previous selection municipalities that intersect with other biomes (Mata Atlântica e Cerrado).

Select and copy layer creating feature containing municipalities completely within Caatinga

"municipalities_within_caatinga_wgs" (adjusted projection using Environments/Output Coordinates/GCS_WGS_1984)

```
arcpy.SelectLayerByLocation_management(in_layer="BR_Municipios_2020", overlap_type="INTERSECT", select_features="E:/OneDrive/GIS/IBGE/caatinga.shp", search_distance="", selection_type="NEW_SELECTION", invert_spatial_relationship="NOT_INVERT")

arcpy.SelectLayerByLocation_management(in_layer="BR_Municipios_2020", overlap_type="INTERSECT", select_features="mata_atlantica_cerrado", search_distance="", selection_type="REMOVE_FROM_SELECTION", invert_spatial_relationship="NOT_INVERT")

arcpy.CopyFeatures_management(in_features="BR_Municipios_2020", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/municipalities_within_caatinga_wgs", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

Create a layer with all ANM polygons within "municipalities_within_caatinga_wgs"

Import to file geodatabase active and inactive ANM mining tenements

```
arcpy.conversion.FeatureClassToGeodatabase(

    Input_Features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/Data/ANM/GIS/BRASIL/BRASIL.shp;E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/Data/ANM/GIS/BRASIL_INATIVOS/BRASIL_INATIVOS.shp",

    Output_Geodatabase="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb"

)
```

Inactive

Select and copy layer creating "Inativos_ANM_Nacional_caatinga_wgs"

```
arcpy.SelectLayerByLocation_management(in_layer="BRASIL_INATIVOS", overlap_type="COMPLETELY_WITHIN", select_features="municipalities_within_caatinga_wgs", search_distance="", selection_type="NEW_SELECTION", invert_spatial_relationship="NOT_INVERT")

arcpy.CopyFeatures_management(in_features="BRASIL_INATIVOS", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/inativos_ANM_Nacional_caatinga_wgs", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

Rename DSProcesso to process and delete other variables

```
arcpy.AlterField_management(in_table="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/inativos_ANM_Nacional_caatinga_wgs", field="DSProcesso", new_field_name="PROCESS", new_field_alias="", field_type="TEXT", field_length="12", field_is_nullable="NULLABLE", clear_field_alias="true")

arcpy.management.DeleteField(

    in_table="inativos_ANM_Nacional_caatinga_wgs",

    drop_field="PROCESSO;NUMERO;ANO;AREA_HA;ID",

    method="DELETE_FIELDS"

)
```

Active

Select and copy layer creating "Ativos_ANM_Nacional_caatinga_wgs"

```
arcpy.SelectLayerByLocation_management(in_layer="BRASIL", overlap_type="COMPLETELY_WITHIN", select_features="municipalities_within_caatinga_wgs", search_distance="", selection_type="NEW_SELECTION", invert_spatial_relationship="NOT_INVERT")

arcpy.CopyFeatures_management(in_features="BRASIL", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/ativos_ANM_Nacional_caatinga_wgs", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

Rename DSProcesso to process and delete other variables

```
arcpy.AlterField_management(in_table="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/Ativos_ANM_Nacional_caatinga_wgs", field="DSProcesso", new_field_name="PROCESS", new_field_alias="", field_type="TEXT", field_length=12, field_is_nullable="NULLABLE", clear_field_alias="true")
```

```
arcpy.management.DeleteField(
```

```
in_table="Ativos_ANM_Nacional_caatinga_wgs",
```

```
drop_field="PROCESSO;NUMERO;ANO;AREA_HA;ID;FASE;ULT_EVENTO;NOME;SUBS;USO;UF",
```

```
method="DELETE_FIELDS"
```

Merge both layers creating "ANM_all_caatinga_municipalities_wgs"

```
arcpy.management.Merge
```

```
inputs="Ativos_ANM_Nacional_caatinga_wgs;Inativos_ANM_Nacional_caatinga_wgs",
```

```
output="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\ANM_all_caatinga_municipalities_wgs"
```

```
field_mappings="PROCESS" "PROCESS" true true false 12 Text 0,0,First,Ativos_ANM_Nacional_catatinga_wgs,PROCESS,0,12,Inativos_ANM_Nacional_catatinga_wgs,PROCESS,0,12,Shape_Length "Shape_Length" false true true 8 Double 0,0,First,Ativos_ANM_Nacional_catatinga_wgs,Shape_Length,-1,-1,Inativos_ANM_Nacional_catatinga_wgs,Shape_Length,-1,-1,Shape_Area "Shape_Area" false true true 8 Double 0,0,First,Ativos_ANM_Nacional_catatinga_wgs,Shape_Area,-1,-1,Inativos_ANM_Nacional_catatinga_wgs,Shape_Area,-1,-1,
```

```
add_source="NO_SOURCE_INFO"
```

Add SPSS data to the ANM layer:

Import Final_ANM from SPSS.

Import SPSS Final ANM dataset to ANM geodatabase

```
arcpy.conversion.TableToTable(
```

```
in_rows=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\ANM\done\Final_ANM.dbf"
```

```
out_path=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"
```

```
out_name="Final_ANM_SPSS_data",
```

```
where_clause=""
```

[illegible]

```
Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2011,-1,-1;CFEM2012 "CFEM2012" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2012,-1,-1;CFEM2013 "CFEM2013" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2013,-1,-1;CFEM2014 "CFEM2014" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2014,-1,-1;CFEM2015 "CFEM2015" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2015,-1,-1;CFEM2016 "CFEM2016" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2016,-1,-1;CFEM2017 "CFEM2017" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2017,-1,-1;CFEM2018 "CFEM2018" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2018,-1,-1;CFEM2019 "CFEM2019" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2019,-1,-1;CFEM2020 "CFEM2020" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2020,-1,-1;CFEM2021 "CFEM2021" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2021,-1,-1;CFEM2022 "CFEM2022" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM2022,-1,-1;CFEM "CFEM" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,CFEM,-1,-1;OP_YEAR "OP_YEAR" true true false 8 Float 2 7,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,OP_YEAR,-1,-1;UT_PER "UT_PER" true true false 1 Short 0 1,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,UT_PER,-1,-1;TAH "TAH" true true false 14 Double 2 13,First,#{E:\OneDrive\Academica\1-Doutorado UFRN(Tese\1_research\Data\ANM\done\Final_ANM.dbf,TAH,-1,-1,
```

```
config_keyword=""
```

```
)
```

Perform a Join, adding the SPSS variables into the geospatial layer

```
arcpy.management.JoinField(
```

```
in_data="ANM_all_caatinga_municipalities_wgs",
```

```
in_field="process",
```

```
join_table="Final_ANM_SPSS_data",
```

```
join_field="PROCESS",
```

```
fields="QTAREAHA,SUBS;SUSE;SSN;NAME;P_TYP;ANM_KEY;YEAR_PRO;LAST_EVE;ACTIVE;INACTIVE;EVENT;EVENT_CT;EVENT_T;DTITLECA;TITLECT;DTITLECT;AFS_SUM;AFS_2003;AFS_2004;AFS_2005;AFS_2006;AFS_2007;AFS_2008;AFS_2009;AFS_2010;AFS_2011;AFS_2012;AFS_2013;AFS_2014;AFS_2015;AFS_2016;AFS_2017;AFS_2018;AFS_2019;AFS_2020;AFS_2021;AFS_2022;AUTO_SUM;AAU_2003;AAU_2004;AAU_2005;AAU_2006;AAU_2007;AAU_2008;AAU_2009;AAU_2010;AAU_2011;AAU_2012;AAU_2013;AAU_2014;AAU_2015;AAU_2016;AAU_2017;AAU_2018;AAU_2019;AAU_2020;AAU_2021;AAU_2022;LED;SUM;LED_2003;LED_2004;LED_2005;LED_2006;LED_2007;LED_2008;LED_2009;LED_2010;LED_2011;LED_2012;LED_2013;LED_2014;LED_2015;LED_2016;LED_2017;LED_2018;LED_2019;LED_2020;LED_2021;LED_2022;CFEM2003;CFEM2004;CFEM2005;CFEM2006;CFEM2007;CFEM2008;CFEM2009;CFEM2010;CFEM2011;CFEM2012;CFEM2013;CFEM2014;CFEM2015;CFEM2016;CFEM2017;CFEM2018;CFEM2019;CFEM2020;CFEM2021;CFEM2022;CFEM;OP_YEAR;UT_PER;TAH",
```

```
fm_option="NOT_USE_FM",
```

```
field_mapping=None
```

```
)
```

Delete cases with missing data (n= 59.206), which are outside the scope of the research.

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="subs IS NULL")
```

```
arcpy.DeleteRows_management(in_rows="ANM_all_caatinga_municipalities_wgs")
```

Repair geometries

```
arcpy.RepairGeometry_management(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/ANM_all_caatinga_municipalities_wgs", delete_null="DELETE_NULL")
```

Create layers of legal and illegal mining polygons per year

Create layers with polygons that had a legal title and are older than the year in reference

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2010<=0 AND YEAR_PRO<=2010")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2010", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2011<=0 AND YEAR_PRO<=2011")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2011", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2012<=0 AND YEAR_PRO<=2012")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2012", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2013<=0 AND YEAR_PRO<=2013")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2013", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2014<=0 AND YEAR_PRO<=2014")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2014", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2015<=0 AND YEAR_PRO<=2015")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2015", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_caatinga_municipalities_wgs", selection_type="NEW_SELECTION", where_clause="LED_2016<=0 AND YEAR_PRO<=2016")
```

```
arcpy.CopyFeatures_management(in_features="ANM_all_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/legal_wgs_2016", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
```


Prepare grid to summarize data

Create a 10km² (3,162277660168379km X 3,162277660168379km) fishnet grid covering the region of interest (936 municipalities completely inside Caatinga biome)

```
arcpy.cartography.GridIndexFeatures(
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid",
    in_features="municipalities_within_caatinga_wgs",
    intersect_feature="INTERSECTFEATURE",
    use_page_units="NO_USEPAGEUNIT",
    scale=None,
    polygon_width="3.16227766016838 Kilometers",
    polygon_height="3.16227766016838 Kilometers",
    origin_coord="-44,337327 -16,416413996",
    number_rows=480,
    number_columns=322,
    starting_page_numbers=1,
    label_from_origins="LABELFROMORIGIN"
)
```

Select only cells completely within the area (68,969 of 72,644 polygons selected)

Create outline to select cells inside.

```
arcpy.analysis.PairwiseDissolve(
    in_features="municipalities_within_caatinga_wgs",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs_outline",
    dissolve_field=None,
    statistics_fields=None,
    multi_part="SINGLE_PART",
    concatenation_separator=""
)
```

Select and delete cells not completely inside the outline

```
arcpy.management.SelectLayerByLocation(
    in_layer="grid",
    overlap_type="COMPLETELY_WITHIN",
    select_features="municipalities_within_caatinga_wgs_outline",

    search_distance=None,
    selection_type="NEW_SELECTION",
    invert_spatial_relationship="INVERT"
)
arcpy.management.DeleteRows(
    in_rows="grid"
)
```

Summarize ANM

Create a new grid with only cells with mining tenements:

```
arcpy.conversion.ExportFeatures(
    in_features="ANM_grid",
    out_features=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net",
    where_clause="",
    use_field_alias_as_name="NOT_USE_ALIAS",
    field_mapping="OID \"OID\" true true false 4 Long 0 0,First,#,ANM_grid,OID,-1,-1",
    sort_field=None
)
```

Split mining tenements using the pairwise intersect tool to preserve absolute variables such as cfem and number of legal mining days.

```
arcpy.analysis.PairwiseIntersect(
    in_features="ANM_all_caatinga_municipalities_wgs\grid_net",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\ANM_all_caatin_PairwiseInter",
    join_attributes="ALL",
    cluster_tolerance=None,
    output_type="INPUT"
)
```

Select existing mining tenements year by year and summarize the results using the following logic:

AAU_{year_str}	Number of ANM administrative infractions	SUM
AFS_{year_str}	Number of ANM fines	SUM
CFEM{year_str}	Mining tax paid	SUM
LED_{year_str}	Number of legal mining days	MEAN
ptp_{year_str}	Type of person (human/corporation)	MEAN
myp_{year_str}	Average year in which the mining processes started	MEAN
area_{year_str}	Mining tenement area	SUM
pct_{year_str}	Mining tenement count	SUM

```
import os
import arcpy

# Set the input and output paths
input_polygons = "grid_net"
input_sum_features = "ANM_all_caatin_PairwiseInter"
output_gdb = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"

# Iterate over the years 2010 to 2020
for year in range(2010, 2021):
    # Set the output feature class and group table paths for the current year
    year_str = str(year)
    output_feature_class = f"{output_gdb}\ANM_grid_{year}"
    output_group_table = f"{output_gdb}\ANM_grid_{year}_subs"
    # Set the sum_fields parameter with the fields for the current year
    sum_fields = f"AAU_{year} Sum;AFS_{year} Sum;CFEM{year} Sum;LED_{year} Mean;OP_YEAR Mean;p_TYPE Mean;YEAR_PRO Mean"
```

```
# Select by attribute
arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="ANM_all_catin_PairwiseInter",
    selection_type="NEW_SELECTION",
    where_clause="YEAR_PRO <= {year} And INACTIVE >= timestamp '{year}-12-31 23:59:59' Or YEAR_PRO <= {year} And INACTIVE IS NULL",
    invert_where_clause=None
)

# Execute the SummarizeWithin analysis for the current year
arcpy.analysis.SummarizeWithin(
    in_polygons=input_polygons,
    in_sum_features=input_sum_features,
    out_feature_class=output_feature_class,
    keep_all_polygons="KEEP_ALL",
    sum_fields=sum_fields,
    sum_shape="ADD_SHAPE_SUM",
    shape_unit="HECTARES",
    group_field="SUBS",
    add_min_maj="NO_MIN_MAJ",
    add_group_percent="ADD_PERCENT",
    out_group_table=output_group_table
)
```

Adjust metadata

```
# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    feature_class_name = f"ANM_grid_{year_str}"

# AlterField for count field
arcpy.management.AlterField(
    in_table=feature_class_name,
    field="Polygon_Count",
    new_field_name=f"pct_{year_str}",
    new_field_alias=f"Mining tenement count {year_str}",
    field_type="LONG",
    field_length=4,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)

# AlterField for sum_area_hectares field
arcpy.management.AlterField(
    in_table=feature_class_name,
    field="sum_Area_HECTARES",
    new_field_name=f"area_{year_str}",
    new_field_alias=f"Mining tenement area {year_str}",
    field_type="DOUBLE",
    field_length=8,
    clear_field_alias="DO_NOT_CLEAR"
)

# Alter field for mean_p_type
arcpy.management.AlterField(
    in_table=feature_class_name,
    field="mean_P_TYPE",
    new_field_name=f"ptp_{year_str}",
    new_field_alias=f"Mean of mining corporation operating {year_str}",
    field_type="DOUBLE",
    field_length=8,
    clear_field_alias="DO_NOT_CLEAR"
)

# Alter field for MEAN_YEAR_PRO
arcpy.management.AlterField(
    in_table=feature_class_name,
    field="Mean_YEAR_PRO",
    new_field_name=f"myp_{year_str}",
    new_field_alias=f"Mean of mining tenement start year {year_str}",
    field_type="DOUBLE",
    field_length=8,
    clear_field_alias="DO_NOT_CLEAR"
)
```

Join substances data to the respective grid

Transpose multi-case dataset

```
# Define the geodatabase workspace
arcpy.env.workspace = r'E:\OneDrive\academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"

# Define the field names and their correspondences
field_correspondence = {
    "1": "Iron",
    "2": "Granite",
    "3": "Sand",
    "4": "Gold",
    "5": "Quartzite",
    "6": "Limestone",
    "7": "Copper",
    "8": "Manganese",
    "9": "Clay",
    "10": "Phosphate"
}

# Iterate over the years
for year in range(2010, 2021): # it's 2021 to include 2020
    # Define input and output table names
    input_table = f"ANM_grid_{year}_subs"
    output_table = f"ANM_grid_{year}_subs_single_case_transposed"

    # Define the fields to be transposed
    transposed_fields = [
        f"sum_AAU_{year}", f"sum_AFS_{year}", f"sum_CFEM{year}", f"mean_LED_{year}", "mean_OP_YEAR",
        "mean_P_TYPE", "mean_YEAR_PRO", "sum_Area_HECTARES", "Polygon_Count", "PercentArea"
    ]

    # Get a list of unique SUBS values
    subs_values = list(set(row[0] for row in arcpy.da.SearchCursor(input_table, "SUBS")))

    # Create the output table
    arcpy.management.CreateTable(arcpy.env.workspace, output_table)

    # Add the id field (Join_ID)
    arcpy.management.AddField(output_table, "Join_ID", "LONG")

    # Create a list to store new field names
    new_field_names = []

    # Add fields for each group of variables
    for subs in subs_values:
        for field in transposed_fields:
            field_name = f"{field_correspondence[str(subs)]}_{field}"
            field_type = arcpy.ListFields(input_table, field)[0].type
            arcpy.management.AddField(output_table, field_name, field_type)
            new_field_names.append(field_name)

    # Create an insert cursor for the output table
    insert_cursor = arcpy.da.InsertCursor(output_table, ["Join_ID"] + new_field_names)

    # Group the records by Join_ID and populate the transposed fields
    with arcpy.da.SearchCursor(input_table, ["Join_ID", "SUBS"] + transposed_fields) as search_cursor:
        previous_id = None
        row_values = []
        for row in search_cursor:
            join_id = row[0]
            subs = row[1]
            if join_id != previous_id:
```

```

# Insert the previous row
if row_values:
    insert_cursor.insertRow(row_values)
# Start a new row for the current join_id
row_values = [join_id] + [None] * len(new_field_names)
previous_id = join_id
# Populate the transposed fields for the current row
for i, field_value in enumerate(row(2)):
    field_index = i + (len(transposed_fields) * (subs_values.index(subs)))
    row_values[field_index+1] = field_value

# Insert the last row
if row_values:
    insert_cursor.insertRow(row_values)

# Cleanup
del insert_cursor

```

Rename variables

```

import arcpy

# Define the geodatabase workspace
arcpy.env.workspace = r'E:\OneDrive\Academica\1-Doutorado UFRM\Tese\1_research\GIS\thesis\thesis.gdb'

# Iterate over the years from 2010 to 2020
for year in range(2010, 2021):
    # Define the input table name for the current year
    input_table = f'ANM_grid_{year}_subs_single_case_transposed'

    # Define the field alterations for the current year
    field_alterations = {
        "Iron_mean_P_TYPE": f'Iron_mean_ptp_{year}',
        "Iron_mean_YEAR_PRO": f'Iron_mean_yr_{year}',
        "Iron_sum_Area_HECTARES": f'Iron_area_{year}',
        "Iron_Polygon_Count": f'Iron_pct_{year}',
        "Iron_PercentArea": f'Iron_PercentArea_{year}',
        "Granite_mean_P_TYPE": f'Granite_mean_ptp_{year}',
        "Granite_mean_YEAR_PRO": f'Granite_mean_yr_{year}',
        "Granite_sum_Area_HECTARES": f'Granite_area_{year}',
        "Granite_Polygon_Count": f'Granite_pct_{year}',
        "Granite_PercentArea": f'Granite_PercentArea_{year}',
        "Sand_mean_P_TYPE": f'Sand_mean_ptp_{year}',
        "Sand_mean_YEAR_PRO": f'Sand_mean_yr_{year}',
        "Sand_sum_Area_HECTARES": f'Sand_area_{year}',
        "Sand_Polygon_Count": f'Sand_pct_{year}',
        "Sand_PercentArea": f'Sand_PercentArea_{year}',
        "Gold_mean_P_TYPE": f'Gold_mean_ptp_{year}',
        "Gold_mean_YEAR_PRO": f'Gold_mean_yr_{year}',
        "Gold_sum_Area_HECTARES": f'Gold_area_{year}',
        "Gold_Polygon_Count": f'Gold_pct_{year}',
        "Gold_PercentArea": f'Gold_PercentArea_{year}',
        "Quartzite_mean_P_TYPE": f'Quartzite_mean_ptp_{year}',
        "Quartzite_mean_YEAR_PRO": f'Quartzite_mean_yr_{year}',
        "Quartzite_sum_Area_HECTARES": f'Quartzite_area_{year}',
        "Quartzite_Polygon_Count": f'Quartzite_pct_{year}',
        "Quartzite_PercentArea": f'Quartzite_PercentArea_{year}',
        "Limestone_mean_P_TYPE": f'Limestone_mean_ptp_{year}',
        "Limestone_mean_YEAR_PRO": f'Limestone_mean_yr_{year}',
        "Limestone_sum_Area_HECTARES": f'Limestone_area_{year}',
        "Limestone_Polygon_Count": f'Limestone_pct_{year}',
        "Limestone_PercentArea": f'Limestone_PercentArea_{year}',
        "Copper_mean_P_TYPE": f'Copper_mean_ptp_{year}',
        "Copper_mean_YEAR_PRO": f'Copper_mean_yr_{year}',
        "Copper_sum_Area_HECTARES": f'Copper_area_{year}',
        "Copper_Polygon_Count": f'Copper_pct_{year}',
        "Copper_PercentArea": f'Copper_PercentArea_{year}',
        "Manganese_mean_P_TYPE": f'Manganese_mean_ptp_{year}',
        "Manganese_mean_YEAR_PRO": f'Manganese_mean_yr_{year}',
        "Manganese_sum_Area_HECTARES": f'Manganese_area_{year}',
        "Manganese_Polygon_Count": f'Manganese_pct_{year}',
        "Manganese_PercentArea": f'Manganese_PercentArea_{year}',
        "Clay_mean_P_TYPE": f'Clay_mean_ptp_{year}',
        "Clay_mean_YEAR_PRO": f'Clay_mean_yr_{year}',
        "Clay_sum_Area_HECTARES": f'Clay_area_{year}',
        "Clay_Polygon_Count": f'Clay_pct_{year}',
        "Clay_PercentArea": f'Clay_PercentArea_{year}',
        "Phosphate_mean_P_TYPE": f'Phosphate_mean_ptp_{year}',
        "Phosphate_mean_YEAR_PRO": f'Phosphate_mean_yr_{year}',
        "Phosphate_sum_Area_HECTARES": f'Phosphate_area_{year}',
        "Phosphate_Polygon_Count": f'Phosphate_pct_{year}',
        "Phosphate_PercentArea": f'Phosphate_PercentArea_{year}'
    }

    # Alter the field names for the current year
    for old_field, new_field in field_alterations.items():
        arcpy.management.AlterField(input_table, old_field, new_field)

```

Perform Join

```

import arcpy

# Define the geodatabase workspace
arcpy.env.workspace = r'E:\OneDrive\Academica\1-Doutorado UFRM\Tese\1_research\GIS\thesis\thesis.gdb'

# Iterate over the years from 2010 to 2020
for year in range(2010, 2021):
    # Define the input table and join table names for the current year
    in_data = f'ANM_grid_{year}'
    join_table = f'ANM_grid_{year}_subs_single_case_transposed'

    # Define the fields for the join
    fields = [
        f'Iron_sum_AAU_{year}', f'Iron_sum_AFS_{year}', f'Iron_sum_CFEM_{year}',
        f'Iron_mean_LED_{year}', f'Iron_mean_OP_YEAR', f'Iron_mean_ptp_{year}',
        f'Iron_mean_yr_{year}', f'Iron_area_{year}', f'Iron_pct_{year}',
        f'Iron_PercentArea_{year}', f'Granite_sum_AAU_{year}', f'Granite_sum_AFS_{year}',
        f'Granite_sum_CFEM_{year}', f'Granite_mean_LED_{year}', f'Granite_mean_OP_YEAR',
        f'Granite_mean_ptp_{year}', f'Granite_mean_yr_{year}', f'Granite_area_{year}',
        f'Granite_pct_{year}', f'Granite_PercentArea_{year}', f'Sand_sum_AAU_{year}',
        f'Sand_sum_AFS_{year}', f'Sand_sum_CFEM_{year}', f'Sand_mean_LED_{year}',
        f'Sand_mean_OP_YEAR', f'Sand_mean_ptp_{year}', f'Sand_mean_yr_{year}',
        f'Sand_area_{year}', f'Sand_pct_{year}', f'Sand_PercentArea_{year}',
        f'Gold_sum_AAU_{year}', f'Gold_sum_AFS_{year}', f'Gold_sum_CFEM_{year}',
        f'Gold_mean_LED_{year}', f'Gold_mean_OP_YEAR', f'Gold_mean_ptp_{year}',
        f'Gold_mean_yr_{year}', f'Gold_area_{year}', f'Gold_pct_{year}',
        f'Gold_PercentArea_{year}', f'Quartzite_sum_AAU_{year}', f'Quartzite_sum_AFS_{year}',
        f'Quartzite_sum_CFEM_{year}', f'Quartzite_mean_LED_{year}', f'Quartzite_mean_OP_YEAR',
        f'Quartzite_mean_ptp_{year}', f'Quartzite_mean_yr_{year}', f'Quartzite_area_{year}',
        f'Quartzite_pct_{year}', f'Quartzite_PercentArea_{year}', f'Limestone_sum_AAU_{year}',
        f'Limestone_sum_AFS_{year}', f'Limestone_sum_CFEM_{year}', f'Limestone_mean_LED_{year}',
        f'Limestone_mean_OP_YEAR', f'Limestone_mean_ptp_{year}', f'Limestone_mean_yr_{year}',
        f'Limestone_area_{year}', f'Limestone_pct_{year}', f'Limestone_PercentArea_{year}',
        f'Copper_sum_AAU_{year}', f'Copper_sum_AFS_{year}', f'Copper_sum_CFEM_{year}',
        f'Copper_mean_LED_{year}', f'Copper_mean_OP_YEAR', f'Copper_mean_ptp_{year}',
        f'Copper_mean_yr_{year}', f'Copper_area_{year}', f'Copper_pct_{year}',
        f'Copper_PercentArea_{year}', f'Manganese_sum_AAU_{year}', f'Manganese_sum_AFS_{year}',
        f'Manganese_sum_CFEM_{year}', f'Manganese_mean_LED_{year}', f'Manganese_mean_OP_YEAR',
        f'Manganese_mean_ptp_{year}', f'Manganese_mean_yr_{year}', f'Manganese_area_{year}',
        f'Manganese_pct_{year}', f'Manganese_PercentArea_{year}', f'Clay_sum_AAU_{year}',
        f'Clay_sum_AFS_{year}', f'Clay_sum_CFEM_{year}', f'Clay_mean_LED_{year}',
        f'Clay_mean_OP_YEAR', f'Clay_mean_ptp_{year}', f'Clay_mean_yr_{year}',
        f'Clay_area_{year}', f'Clay_pct_{year}', f'Clay_PercentArea_{year}',
        f'Phosphate_sum_AAU_{year}', f'Phosphate_sum_AFS_{year}', f'Phosphate_sum_CFEM_{year}',
        f'Phosphate_mean_LED_{year}', f'Phosphate_mean_OP_YEAR', f'Phosphate_mean_ptp_{year}',
        f'Phosphate_mean_yr_{year}', f'Phosphate_area_{year}', f'Phosphate_pct_{year}',
        f'Phosphate_PercentArea_{year}'
    ]

    # Join the fields for the current year
    arcpy.management.JoinField(

```


Create a grid

Join all layers to grid using OID as foreign key (took 3h30m).

Summarize CFEM per municipality (data more complete, with less missing, but without link to specific polygon)

Import excel spreadsheet made by spss containing data about cfem per municipality

Create a new feature layer to join spss cfem per municipality data

Join spss data with municipality feature class

Join ANM_grid_year fields to the main layer

```
import arcpy

# Define the base file path for convenience and reusability
base_path = r'E:\OneDrive\Academia\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb'

# Define the input data layer and join table
input_data = "grid_net"

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)

    # Define the join table based on the current year
    join_table = F'(base_path)\VANM_grid_{year_str}'

    # Define the fields to be joined based on the current year
    fields_to_join = [
        F'sum_AAU_{year_str}',
        F'sum_AFS_{year_str}',
        F'sum_CFEH_{year_str}'
    ]
```

```

f'mean_LED_{year_str}',
f'myp_{year_str}',
f'area_{year_str}',
f'pct_{year_str}'
]

# Join the fields
arcpy.management.JoinField(
    in_data=inp_data,
    in_field="OID_1",
    join_table=join_table,
    join_field="OID_1",
    fields=fields_to_join,
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Federal Police Investigations

* Encoding: UTF-8.

Step 1. *Get PF raw data.

GET DATA

/TYPE=ODBC

/CONNECT='DSN=MS Access Database;DBQ=E:\OneDrive\data\PF\PF_DMAPH.accdb;DriverId=25;FIL=MS '+'
'Access;MaxBufferSize=2048;PageTimeout=5;'

/SQL='SELECT Procedimento_ID, Proc_Tipo, Proc_Situacao, Municipio_Crime, Municipio_Crime_UF, '+'
'Proc_Data_Cota, Proc_Data_Decisao, Proc_Data_Encerrado, Proc_Data_Fato, '+'
'Proc_Data_Instauracao, Proc_Data_Relatorio, Proc_Decisao_Tipo, Proc_Duracao_Dias, '+'
'Proc_Nao_Crime, Proc_Lei, Proc_Lei_Artigo_Isolado, Proc_Quantidade_Indiciados, '+'
'Proc_Quantidade_Mandado_Busca, Proc_Quantidade_Mandado_Prisao, Proc_Quantidade_Presos, '+'
'Proc_Quantidade_Presos_Flagrante, Proc_Tem_Preso, Proc_Valor_a_Apurar, Proc_Valor_Apurado, '+'
'Proc_Data_Decisao_Ano, Proc_Data_Fato_Ano, Proc_Data_Instauracao_Ano, '+'
'Proc_Data_Relatorio_Ano, Proc_Teve_Cota, Proc_TC_Quantidade_Autores, Unidade_UF, '+'
'Proc_Delegacia_Instauracao, Lotacao_Sigla, Proc_Autoria_Identificada '+'
"+

'FROM Sheet1'

/ASSUMEDSTRWIDTH=255.

CACHE.

EXECUTE.

ALTER TYPE ALL(A=AMIN).

DATASET NAME PF_DMAPH WINDOW=FRONT.

*Check cases number (129992).

show n.

SAVE OUTFILE='E:\OneDrive\data\PF\PF_DMAPH_raw.sav'
/COMPRESSED.

*GET FILE ='E:\OneDrive\data\PF\PF_DMAPH_raw.sav'.

*DATASET NAME PF_DMAPH WINDOW=FRONT.

*Rename variables.

RENAME VARIABLES

(Procedimento_ID=p_id)

(Proc_Tipo=p_type)

(Proc_Situacao=p_situat)

(Proc_Duracao_Dias=p_durati)

(Municipio_Crime=crime_mu)

(Municipio_Crime_UF=crime_uf)

(Unidade_UF=pol_stat)

(Proc_Delegacia_Instauracao=open_uni)

(Lotacao_Sigla=pol_unit)

(Proc_Data_Fato=crime_dt)

(Proc_Data_Fato_Ano=crime_ye)

(Proc_Data_Decisao=sent_dt)

(Proc_Data_Decisao_Ano=sent_yea)

(Proc_Decisao_Tipo=sent_tp)

(Proc_Data_Relatorio=report_d)

(Proc_Data_Relatorio_Ano=report_y)

(Proc_Data_Encerrado=close_dt)

(Proc_Data_Instauracao=open_dt)

(Proc_Data_Instauracao_Ano=open_yea)

(Proc_Nao_Crime=d_crime)

(Proc_Lei=crim_law)

```
(Proc_Lei_Artigo_Isolado=crim_art)
(Proc_Quantidade_Indiciados=n_indict)
(Proc_Quantidade_Mandado_Busca=n_search)
(Proc_Quantidade_Mandado_Prisao=n_arre_w)
(Proc_Quantidade_Presos=n_arrest)
(Proc_Quantidade_Presos_Flagrante=n_arre_f)
(Proc_Tem_Preso=d_arrest)
(Proc_TC_Quantidade_Autores=n_crimin)
(Proc_Autoria_Identificada=d_author)
(Proc_Valor_a_Apurar=value_es)
(Proc_Valor_Apurado=value_ca)
(Proc_Teve_Cota=d_prosec)
(Proc_Data_Cota=prosec_dt).
```

*Create variable labels.

```
VARIABLE LABELS
p_id 'Investigation ID'
p_type 'Investigation type'
p_situat 'Investigation situation'
p_durati 'Investigation duration in days'
crime_mu 'Municipality where crime occurred'
crime_uf 'State where crime occurred'
pol_stat 'State of police unit that conducted the investigation'
open_uni 'Police Unit that initiated the investigation'
pol_unit 'Police Unit that conducted the investigation'
crime_dt 'Crime occurrence date '
crime_ye 'Crime occurrence year'
sent_dt 'Judicial sentence date'
sent_yea 'Judicial sentence year'
sent_tp 'Judicial sentence type'
report_d 'Police report date'
report_y 'Police report year'
close_dt 'Investigation closure date'
open_dt 'Investigation start date'
open_yea 'Investigation start year'
d_crime 'Dummy for proved crime existence'
crim_law 'Criminal Law'
crim_art 'Law article '
n_indict 'Number of indicted'
n_search 'Number of search warrants'
n_arre_w 'Number of arrest warrants'
n_arrest 'Number of arrests'
n_arre_f 'Number of caught in the act arrests'
d_arrest 'Dummy for arrests'
n_crimin 'Number of criminals involved'
d_author 'Dummy for perpetrator identification'
value_es 'Estimated value'
value_ca 'Calculated value'
d_prosec 'Dummy for public prosecutor demand'
prosec_dt 'Public prosecutor demand date'.
```

*Reorder the data file.

```
MATCH FILES /FILE = *
/KEEP
p_id
p_type
p_situat
p_durati
crime_mu
crime_uf
pol_stat
open_uni
```

```

pol_unit
crime_dt
crime_ye
sent_dt
sent_yea
sent_tp
report_d
report_y
close_dt
open_dt
open_yea
d_crime
crim_law
crim_art
n_indict
n_search
n_arre_w
n_arrest
n_arre_f
d_arrest
n_crimin
d_author
value_es
value_ca
d_prosec
prosec_dt.
EXECUTE.

```

```

SAVE OUTFILE='E:\OneDrive\data\PF\PF_DMAPH_rename.sav'
/COMPRESSED.

```

*Autorecode string variables that can be transformed into numeric with labels.

```
*GET FILE='E:\OneDrive\data\PF\PF_DMAPH_rename.sav'.
```

```
*DATASET NAME PF_DMAPH.
```

```
AUTORECODE VARIABLES=
```

```

p_type
p_situat
sent_tp
/INTO
p_typeR
p_situatR
sent_tpR
/BLANK=MISSING.

```

```
DELETE VARIABLES
```

```

p_type
p_situat
sent_tp.
RENAME VARIABLES
(p_typeR=p_type)
(p_situatR=p_situat)
(sent_tpR=sent_tp).

```

*Adjust missing values.

```
RECODE sent_tp (1,17=99) (ELSE=COPY)
```

```
/p_situat (3=99) (ELSE=COPY).
```

```
EXECUTE.
```

```
MISSING VALUES sent_tp(99) p_situat(99).
```

*Translate labels of recently created variables.

```
VALUE LABELS
```

```
p_type
```

```
1 "Caught in the act (FLA)"
```

```
2 "Standard investigation (IPL)"
```

```

3 "Notitia criminis (NC)"
4 "Notitia criminis to be verified (NCV)"
5 "Fact Registration (RDF)"
6 "Special Registration (RE)"
7 "Misdemeanor (TC)"
/p_situat
1 "Open"
2 "Closed"
99 "Missing"
/sent_tp
2 'Acquittal'
3 'Joined to other process'
4 'Dismissed - before or after sentencing'
5 'Conviction'
6 'Federal jurisdiction declined to State'
7 'Indicted'
8 'Forwarded to another unit'
9 'Prescription'
10 'Parole'
11 'Indictment Refusal'
12 'Sursis'
13 'Criminal case suspended'
14 'Case dismissed/dropped'
15 'Plea Bargain'
16 'Transformed in misdemeanor'
99 'Missing'.

```

*Recode string variables that should be numeric.

*Missing values were converted to one because there was only value 1 originally, which represented cases where no crime was found.

*Hence, 1 was converted to 0 to represent no (crime), and spaces (SYSMIS), to 99(missing value).

```

RECODE
d_crime
('1'=0)(' '=99)(' '=1)
INTO
d_crime_recoded.
EXECUTE.

```

*Missing values were converted to zero because there was only value 1 originally, and spaces (SYSMIS), to 99(missing value).

*I've inferred that only cases where the perpetrator was identified had one as value, and missing represented cases where the author was not found.

```

RECODE
d_author
('1'=1)(' '=99)(' '=0)
INTO
d_author_recoded.
EXECUTE.

```

```

RECODE
d_prosec
d_arrest
("N o"=0) ("Sim"=1) (" "=99)
INTO
d_prosec_recoded
d_arrest_recoded.
EXECUTE.

```

```

RECODE
n_crimin
(CONVERT)
INTO

```

```
n_crimin_recoded.
EXECUTE.
```

```
RECODE
n_arrest
n_arre_f
n_arre_w
n_search
(''=99)(CONVERT)
INTO
n_arrest_recoded
n_arre_f_recoded
n_arre_w_recoded
n_search_recoded.
EXECUTE.
```

```
RECODE
n_indict
(''=99)(CONVERT)
INTO
n_indict_recoded.
EXECUTE.
```

*Adjust missing values.

```
RECODE
n_crimin_recoded (SYSMIS=99)(ELSE=COPY)
/n_arrest_recoded (SYSMIS=99)(ELSE=COPY)
/n_arre_f_recoded (SYSMIS=99)(ELSE=COPY)
/n_arre_w_recoded (SYSMIS=99)(ELSE=COPY)
/n_search_recoded (SYSMIS=99)(ELSE=COPY)
/n_indict_recoded (SYSMIS=999)(ELSE=COPY).
EXECUTE.
```

MISSING VALUES

```
n_arre_f_recoded (99)
n_arre_w_recoded (99)
n_search_recoded (99)
n_indict_recoded (999)
n_arrest_recoded(99)
n_crimin_recoded(99)
d_crime_recoded(99)
d_arrest_recoded(99)
d_prosec_recoded(99)
d_author_recoded(99).
```

DELETE VARIABLES

```
n_arre_f
n_arre_w
n_search
n_indict
n_arrest
n_crimin
d_crime
d_arrest
d_prosec
d_author.
```

RENAME VARIABLES

```
(d_arrest_recoded=d_arrest)
(d_author_recoded=d_author)
(d_crime_recoded=d_crime)
(d_prosec_recoded=d_prosec)
(n_arre_f_recoded=n_arre_f)
```

```
(n_arre_w_recoded=n_arre_w)
(n_arrest_recoded=n_arrest)
(n_crimin_recoded=n_crimin)
(n_indict_recoded=n_indict)
(n_search_recoded=n_search).
```

*Add metadata to newly created variables.

VARIABLE LABELS

```
d_arrest 'Dummy for arrests'
d_author 'Dummy for perpetrator identification'
d_crime 'Dummy for proved crime existence'
d_prosec 'Dummy for public prosecutor demand'
n_arre_f 'Number of caught in the act arrests'
n_arre_w 'Number of arrest warrants'
n_arrest 'Number of arrests'
n_crimin 'Number of criminals involved'
n_indict 'Number of indicted'
n_search 'Number of search warrants'.
```

VALUE LABELS

```
d_arrest
0"No"
1"Yes"
99"Missing"
/d_author
0"No"
1"Yes"
99"Missing"
/d_crime
0"No"
1"Yes"
99"Missing"
/d_prosec
0"No"
1"Yes"
99"Missing"
/n_arre_f
99"Missing"
/n_arre_w
99"Missing"
/n_arrest
99"Missing"
/n_crimin
99"Missing"
/n_indict
999"Missing"
/n_search
99"Missing".
```

*Format newly created variables values.

FORMATS

```
d_arrest(F2)
d_author(F2)
d_crime(F2)
d_prosec(F2)
n_arre_f(F2)
n_arre_w(F2)
n_arrest(F2)
n_crimin(F2)
n_indict(F3)
n_search(F2).
```


*Recode string variable that should be date.

*I've created a copy to check the results, then deleted it.

STRING

close_dt_recoded (A10)

crime_dt_recoded (A10)

open_dt_recoded (A10)

prosec_dt_recoded (A10)

report_d_recoded (A10)

sent_dt_recoded (A10).

DO REPEAT X = close_dt crime_dt open_dt prosec_dt report_d sent_dt / Y = close_dt_recoded crime_dt_recoded
open_dt_recoded prosec_dt_recoded report_d_recoded sent_dt_recoded.

RECODE X (ELSE=COPY) INTO Y.

END REPEAT.

EXECUTE.

ALTER TYPE

close_dt (ADATE10)

crime_dt (ADATE10)

open_dt (ADATE10)

prosec_dt (ADATE10)

report_d (ADATE10)

sent_dt (ADATE10).

DELETE VARIABLES close_dt_recoded crime_dt_recoded open_dt_recoded prosec_dt_recoded report_d_recoded
sent_dt_recoded.

*Recode string variable that should be currency.

DO REPEAT X = value_ca value_es.

COMPUTE X=(REPLACE(REPLACE(X,'R\$', ''), '-','')).

END REPEAT.

EXECUTE.

DO REPEAT X = value_ca value_es / Y = value_ca_recoded value_es_recoded.

RECODE X (CONVERT) (ELSE=SYSMIS) INTO Y.

END REPEAT.

EXECUTE.

FORMATS value_ca_recoded(DOLLAR11.2) value_es_recoded(DOLLAR11.2).

DELETE VARIABLES value_ca value_es.

RENAME VARIABLES (value_ca_recoded=value_ca) (value_es_recoded=value_es).

VARIABLE LABELS value_ca 'Calculated value' value_es 'Estimated value'.

*Recode string variable that should be numeric.

RECODE p_durati (CONVERT) (ELSE=SYSMIS) INTO p_durati_recoded.

EXECUTE.

FORMATS p_durati_recoded(F4).

DELETE VARIABLES p_durati.

RENAME VARIABLES (p_durati_recoded=p_durati).

VARIABLE LABELS p_durati 'Investigation length in days'.

*Create foreign key ar_la_year to merge environmental law information.

COMPUTE crim_art=(REPLACE(crim_art,'180 -','180')).

COMPUTE crim_law=(

(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Replace(Re
place(Replace(Replace(Replace

(crim_law

,'Lei',''), 'Código Penal', '2848/1940'), '* /', '*CDC', '80781990'), '*LAD', '113432006'), 'CORRIGIR', ''), 'Decreto-Lei', ''), 'Lei
Complementar', ''), 'Complementar', ''), 'Decreto-', ''

, '{LCP}', ''), '/', ''), '* ', '{CLT}', ''), 'Decreto', ''), 'CTB', '95031997')

)

).

EXECUTE.

STRING ar_la_year(A27).

```
COMPUTE ar_la_year=CONCAT(crim_art,crim_law).
```

```
EXECUTE.
```

```
ALTER TYPE ar_la_year (A=AMIN).
```

```
*Add metadata to the newly created variable.
```

```
VARIABLE LABELS ar_la_year 'Crime ID (article+law+year)'.
```

```
*Save current data file.
```

```
SORT CASES by ar_la_year.
```

```
SAVE OUTFILE='E:\OneDrive\data\PF\PF_DMAPH_sorted_ar_la_year.sav'  
/COMPRESSED.
```

```
*Import environmental law information dataset.
```

```
*GET DATA
```

```
/TYPE=XLSX
```

```
/FILE='E:\OneDrive\data\PF\done\ar_la_year_environmental_law.xlsx'
```

```
/SHEET=name 'Final_law_num'
```

```
/CELLRANGE=FULL
```

```
/READNAMES=ON
```

```
/DATATYPEMIN PERCENTAGE=95.0
```

```
/HIDDEN IGNORE=YES.
```

```
*EXECUTE.
```

```
*DATASET NAME environmental_law WINDOW=FRONT.
```

```
*Add metadata.
```

```
*VARIABLE LABELS
```

```
ar_la_year 'Crime ID (article+law+year)'
```

```
art 'Article number'
```

```
law 'Law number'
```

```
l_year 'Law year'
```

```
dmaph_area 'Police area'
```

```
law_chap 'Law Chapter'
```

```
env_cat 'Environmental category'
```

```
art_abs 'Crime abstract'
```

```
law_nm 'Law name'.
```

```
*VALUE LABELS
```

```
dmaph_area
```

```
0 'Other'
```

```
1 'Environment'
```

```
2 'Historical/Cultural heritage'
```

```
/law_chap
```

```
1 'Abuse of authority'
```

```
2 'Against environmental administration'
```

```
3 'Against fauna'
```

```
4 'Against flora'
```

```
5 'Against honor'
```

```
6 'Against intellectual property'
```

```
7 'Against inviolability of secrets'
```

```
8 'Against justice administration'
```

```
9 'Against life'
```

```
10 'Against marriage'
```

```
11 'Against personal freedom'
```

```
12 'Against property'
```

```
13 'Against public health'
```

```
14 'Against public peace'
```

```
15 'Against public services safety'
```

```
16 'Against public trust'
```

```
17 'Against the inviolability of the home'
```

```
18 'Against the organization of labor'
```

```
19 'Against the person'
```

```
20 'Agrarian reform'
```

```
21 'By natural person against public administration'
```

22 'By public server against public administration'
 23 'Child protection'
 24 'Collective danger'
 25 'Consumer'
 26 'Crimes against indigenous'
 27 'Criminal organization'
 28 'Customs police'
 29 'Drugs'
 30 'Economic order'
 31 'Electoral'
 32 'Environment'
 33 'Environmental administration'
 34 'Financial system'
 35 'Firearms'
 36 'Fiscal id'
 37 'Fiscal order'
 38 'Historical heritage'
 39 'Laundering'
 40 'Municipal government responsibility'
 41 'National security'
 42 'No crime'
 43 'Non-existent'
 44 'Non-existent '
 45 'Pollution'
 46 'Postal service'
 47 'Privilege of invention'
 48 'Public bid'
 49 'Sexual exploration'
 50 'Special judicial court'
 51 'Telecommunications'
 52 'Telephone tapping'
 53 'Torture'
 /env_cat
 1 'Cultural heritage'
 2 'Environmental administration'
 3 'Fauna'
 4 'Fishing'
 5 'Flora'
 6 'Generic'
 7 'Health'
 8 'Historical heritage'
 9 'Land'
 10 'Mining'
 11 'Pollution'
 12 'Related'
 /art_abs
 1 'Abuse of authority'
 2 'Active corruption'
 3 'Alteration of cultural heritage construction'
 4 'Animal killing through pollution'
 5 'Animal mistreatment'
 6 'Appropriation'
 7 'Arson'
 8 'Atlantic forest destruction'
 9 'Attack against public utilities safety'
 10 'Attack against transport safety'
 11 'Bigamy'
 12 'Boundary alteration/water usurpation/scourge'
 13 'Breach of confidentiality'
 14 'Brothel'
 15 'Build on cultural heritage area'
 16 'Burglary'
 17 'Child corruption'

- 18 'Child pornography'
- 19 'Child pornography distribution'
- 20 'Child prostitution'
- 21 'Coal production'
- 22 'Coercion in the course of a process'
- 23 'Collapse'
- 24 'Computer invasion'
- 25 'Concussion'
- 26 'Consumer'
- 27 'Contempt'
- 28 'Copyright infringement'
- 29 'Corruption or pollution of drinking water'
- 30 'Counterfeiting currency'
- 31 'Counterfeiting currency materials'
- 32 'Counterfeiting currency -similar'
- 33 'Counterfeiting private document'
- 34 'Counterfeiting public document'
- 35 'Counterfeiting public documents'
- 36 'Counterfeiting seal or public sign'
- 37 'Crime apology'
- 38 'Crime incitement'
- 39 'Crimes against indigenous'
- 40 'Criminal association'
- 41 'Criminal condescendence'
- 42 'Criminal organization'
- 43 'Damage'
- 44 'Damage conservation unit'
- 45 'Damage cultural heritage'
- 46 'Damage of plants - dunes and mangroves'
- 47 'Damage ornamental plant'
- 48 'Danger to life or health '
- 49 'Destruction of protected forest'
- 50 'Disease or plague'
- 51 'Disobedience'
- 52 'Disobedience to court decision'
- 53 'Document suppression'
- 54 'Drug trafficking'
- 55 'Drugs - personal consumption'
- 56 'Economic order'
- 57 'Elections'
- 58 'Embezzlement'
- 59 'Escape from prison'
- 60 'Explosion'
- 61 'Extortion'
- 62 'Loss/damage of book or document'
- 63 'Fake privilege attribution'
- 64 'Fake receipt'
- 65 'False testimony or export report'
- 66 'Financial system'
- 67 'Firearm firing'
- 68 'Firearms'
- 69 'Fiscal id'
- 70 'Fiscal order'
- 71 'Fishing - prohibited place or time'
- 72 'Food corruption'
- 73 'Forest arson'
- 74 'Forest misdemeanor'
- 75 'Frustration of labor rights'
- 76 'Gambling'
- 77 'Graffiti on cultural heritage area'
- 78 'Harmful substances - generic'
- 79 'Hinder environmental policing'
- 80 'Historical heritage'

81 'Historical heritage damage'
 82 'Homicide'
 83 'Human trafficking'
 84 'Identity falsehood'
 85 'Ideological falsehood'
 86 'Illegal activity'
 87 'Illegal allotment'
 88 'Illegal carrying of legal firearm'
 89 'Illegal carrying of permitted firearm'
 90 'Illegal chainsaw'
 91 'Illegal embarrassment'
 92 'Illegal firearm trade'
 93 'Illegal license emission'
 94 'Illegal lobby'
 95 'Illegal mining'
 96 'Illegal pesticide packing'
 97 'Illegal possession of permitted firearm'
 98 'Illegal possession of restricted-use firearm'
 99 'Illegal property document'
 100 'Illegal telecommunication'
 101 'Illegal timber trade'
 102 'Illegal wildlife trading'
 103 'Illicit trafficking of cultural property'
 104 'Incendiary balloon'
 105 'Influence trafficking'
 106 'Inserting false data in information system'
 107 'Insufficient health measures'
 108 'International firearm trafficking'
 109 'Introduction of foreign species'
 110 'Invasion of union lands'
 111 'Kidnapping'
 112 'Larceny by trick'
 113 'Logging in protected forest'
 114 'Logging in public forest'
 115 'Explosives or toxic gas'
 116 'Medicament corruption'
 117 'Medicament without prescription'
 118 'Mining inside forest'
 119 'Money laundry'
 120 'Motor vehicle identification adulteration'
 121 'Municipal government responsibility crime'
 122 'National security'
 123 'No crime'
 124 'Non-existent'
 125 'Non-existent '
 126 'Passive corruption'
 127 'Pesticide'
 128 'Physical injury'
 129 'Poaching'
 130 'Poaching/forest products material inside conservation unit'
 131 'Poisoning of water, food or medicament'
 132 'Pollution'
 133 'Postal service'
 134 'Predatory fishing'
 135 'Pretend to be a public servant'
 136 'Prevarication'
 137 'Prevent forest regeneration'
 138 'Private militia'
 139 'Procedural fraud'
 140 'Profession without legal conditions'
 141 'Public bid'
 142 'Public bid fraud'
 143 'Public document or book theft of destruction'

144 'Public notice or signal destruction'
 145 'Public role usurpation'
 146 'Public server fraud in licensing'
 147 'Resistance'
 148 'Robbery'
 149 'Sexual exploration facilitation'
 150 'Signature misrecognition'
 151 'Slander/libel - crime'
 152 'Slander/libel - dignity'
 153 'Slavery'
 154 'Smuggling of legal products'
 155 'Smuggling of prohibited products'
 156 'Special judicial court'
 157 'Stolen goods trade'
 158 'Telecommunications'
 159 'Telephone tapping'
 160 'Theft'
 161 'Threat'
 162 'Torture'
 163 'Toxic substance'
 164 'Unauthorized data modification in information system'
 165 'Unauthorized pesticide'
 166 'Unfulfillment of environmental obligations'
 167 'Unlicensed activities that generate pollution'
 168 'Unlicensed mining'
 169 'Use of false document'
 170 'Use of false document on environmental licensing'
 171 'Usurpation '
 172 'Whaling'
 /law_nm
 1 'Abuse of authority'
 2 'Agrarian law'
 3 'Archeological and prehistoric monuments law'
 4 'Brazilian telecommunications code'
 5 'Child corruption'
 6 'Child protection'
 7 'Consumer'
 8 'Crimes against the economic order law'
 9 'Electoral code'
 10 'Environmental crime law'
 11 'Fauna protection law'
 12 'Financial institution operation secret'
 13 'Financial system'
 14 'Firearms'
 15 'Firearms - old'
 16 'Fiscal id'
 17 'Fiscal order'
 18 'Indigenous statute'
 19 'Intellectual property of computer programs'
 20 'Law against organized crime'
 21 'Mineral exploration law'
 22 'Misdemeanor law'
 23 'Money laundry law'
 24 'Municipal government responsibility'
 25 'National security'
 26 'National system of public policies on drugs - SISNAD'
 27 'Old forest code'
 28 'Penal code'
 29 'Pesticides law'
 30 'Postal service'
 31 'Prejudice'
 32 'Public bid'
 33 'Public server responsibility'

34 'Special judicial court'
 35 'Telecommunications'
 36 'Telephone tapping'
 37 'Torture'
 38 'Traffic code'
 39 'Urban soil management'
 40 'Whaling prohibition'.

*Save current data file.
 *SORT CASES by ar_la_year.
 *SAVE OUTFILE='E:\OneDrive\data\PF\environmental_law_sorted_ar_la_year.sav'
 /COMPRESSED.
 *DATASET CLOSE environmental_law.

*Merge police and environmental law dataset.
 *DATASET ACTIVATE PF_DMAPH.
 MATCH FILES /FILE=*
 /TABLE='E:\OneDrive\data\PF\done\environmental_law_sorted_ar_la_year.sav'
 /BY ar_la_year.
 EXECUTE.
 MATCH FILES /FILE=*
 /KEEP
 p_id
 crime_mu
 cd_mun_crime
 crime_uf
 crime_dt
 crime_ye
 open_dt
 open_yea
 report_d
 report_y
 close_dt
 p_durati
 d_crime
 d_author
 p_type
 p_situat
 d_prosec
 prosec_dt
 sent_tp
 sent_dt
 sent_yea
 n_indict
 n_search
 n_arre_w
 d_arrest
 n_arrest
 n_arre_f
 n_crimin
 value_es
 value_ca
 open_uni
 spec_unit
 pol_unit
 pol_stat
 env_cat
 dmaph_area
 crim_art
 art
 crim_law
 law
 l_year


```
law_chap
art_abs
law_nm
ar_la_year.
EXECUTE.
```

*Save current data file.

```
SAVE OUTFILE='E:\OneDrive\data\PF\last\PF_DMAPH_duplicate_cases.sav'
/COMPRESSED.
```

*Create dummy variables to flag the number of investigations with the correspondent environmental category.

```
IF env_cat=1 cul_her=1.
IF env_cat=2 env_adm=1.
IF env_cat=3 fauna=1.
IF env_cat=4 fishing=1.
IF env_cat=5 flora=1.
IF env_cat=6 generic=1.
IF env_cat=7 health=1.
IF env_cat=8 his_her=1.
IF env_cat=9 land=1.
IF env_cat=10 mining=1.
IF env_cat=11 pollution=1.
IF env_cat=12 related=1.
EXECUTE.
```

```
*SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_dummy_env_cat.sav'.
DATASET NAME dummy.
```

*Cultural Heritage.

TEMPORARY.

```
SELECT IF cul_her=1.
```

```
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_cul_her.sav'
/keep p_id cul_her
/COMPRESSED.
```

```
GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_cul_her.sav'.
```

DATASET NAME cul_her.

DATASET ACTIVATE cul_her.

* Identify Duplicate Cases.

```
SORT CASES BY p_id(A).
```

MATCH FILES

```
/FILE=*
```

```
/BY p_id
```

```
/FIRST=PrimaryFirst
```

```
/LAST=PrimaryLast.
```

```
DO IF (PrimaryFirst).
```

```
COMPUTE MatchSequence=1-PrimaryLast.
```

```
ELSE.
```

```
COMPUTE MatchSequence=MatchSequence+1.
```

```
END IF.
```

```
LEAVE MatchSequence.
```

```
FORMATS MatchSequence (f7).
```

```
COMPUTE InDupGrp=MatchSequence>0.
```

```
SORT CASES InDupGrp(D).
```

MATCH FILES

```
/FILE=*
```

```
/DROP=PrimaryFirst InDupGrp MatchSequence.
```

```
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
```

```
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
```

```
VARIABLE LEVEL PrimaryLast (ORDINAL).
```

```
FREQUENCIES VARIABLES=PrimaryLast.
```

```
EXECUTE.
```

```

SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

```

```

*rename variable.
RENAME VARIABLES cul_her=cul_her_r.

```

```

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE cul_her.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='cul_her'
  /BY p_id.
EXECUTE.

```

```

* temp.
* select if cul_her_r=1 and related=1.
* FREQUENCIES art_abs /FORMAT dfreq.

```

```

*Against Environmental Administration.
TEMPORARY.
SELECT IF env_adm=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_env_adm.sav'
  /keep p_id env_adm
  /COMPRESSED.

```

```

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_env_adm.sav'.
DATASET NAME env_adm.
DATASET ACTIVATE env_adm.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
  COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
  COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

```

```

*rename variable.
RENAME VARIABLES env_adm=env_adm_r.

```

*Add flag.

```

DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE env_adm.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='env_adm'
  /BY p_id.
EXECUTE.

```

temp.

```

select if env_adm_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

```

*Against Fauna.

```

TEMPORARY.
SELECT IF fauna=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_fauna.sav'
  /keep p_id fauna
  /COMPRESSED.

```

```

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_fauna.sav'.

```

```

DATASET NAME fauna.

```

```

DATASET ACTIVATE fauna.

```

* Identify Duplicate Cases.

```

SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
  COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
  COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

```

*rename variable.

```

RENAME VARIABLES fauna=fauna_r.

```

*Add flag.

```

DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE fauna.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*

```

```

/TABLE='fauna'
/BY p_id.
EXECUTE.

temp.
select if fauna_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

*Fishing.
TEMPORARY.
SELECT IF fishing=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_fishing.sav'
/keep p_id fishing
/COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_fishing.sav'.
DATASET NAME fishing.
DATASET ACTIVATE fishing.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
/FILE=*
/BY p_id
/FIRST=PrimaryFirst
/LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
/FILE=*
/DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES fishing=fishing_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE fishing.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
/TABLE='fishing'
/BY p_id.
EXECUTE.

temp.
select if fishing_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

```

```

*Flora.
TEMPORARY.
SELECT IF flora=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_flora.sav'
/keep p_id flora
/COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_flora.sav'.
DATASET NAME flora.
DATASET ACTIVATE flora.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
/FILE=*
/BY p_id
/FIRST=PrimaryFirst
/LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
/FILE=*
/DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES flora=flora_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE flora.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
/TABLE='flora'
/BY p_id.
EXECUTE.

temp.
select if flora_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

*Generic.
TEMPORARY.
SELECT IF generic=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_generic.sav'
/keep p_id generic
/COMPRESSED.

```

```

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_generic.sav'.
DATASET NAME generic.
DATASET ACTIVATE generic.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
  COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
  COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES generic=generic_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE generic.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='generic'
  /BY p_id.
EXECUTE.

temp.
select if generic_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

*Health.
TEMPORARY.
SELECT IF health=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_health.sav'
  /keep p_id health
  /COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_health.sav'.
DATASET NAME health.
DATASET ACTIVATE health.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES

```

```

/FILE=*
/BY p_id
/FIRST=PrimaryFirst
/LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
/FILE=*
/DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES health=health_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE health.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
/TABLE='health'
/BY p_id.
EXECUTE.

temp.
select if health_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

*His_her.
TEMPORARY.
SELECT IF his_her=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_his_her.sav'
/keep p_id his_her
/COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_his_her.sav'.
DATASET NAME his_her.
DATASET ACTIVATE his_her.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
/FILE=*
/BY p_id
/FIRST=PrimaryFirst
/LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.

```

```

COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES his_her=his_her_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE his_her.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='his_her'
  /BY p_id.
EXECUTE.

temp.
select if his_her_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

*Land.
TEMPORARY.
SELECT IF land=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_land.sav'
  /keep p_id land
  /COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_land.sav'.
DATASET NAME land.
DATASET ACTIVATE land.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES

```



```

/FILE=*
/DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.

*rename variable.
RENAME VARIABLES land=land_r.

*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE land.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='land'
  /BY p_id.
EXECUTE.

temp.
select if land_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.
*Mining.
TEMPORARY.
SELECT IF mining=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_mining.sav'
  /keep p_id mining
  /COMPRESSED.

GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_mining.sav'.
DATASET NAME mining.
DATASET ACTIVATE mining.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.

```

```
EXECUTE.
DELETE VARIABLES PrimaryLast.
```

```
*rename variable.
RENAME VARIABLES mining=mining_r.
```

```
*Add flag.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE mining.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='mining'
  /BY p_id.
EXECUTE.
```

```
temp.
select if mining_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.
```

```
*Pollution.
TEMPORARY.
SELECT IF pollution=1.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_pollution.sav'
  /keep p_id pollution
  /COMPRESSED.
```

```
GET FILE='C:\Users\Administrador\OneDrive\data\PF\last\PF_DMAPH_pollution.sav'.
DATASET NAME pollution.
DATASET ACTIVATE pollution.
* Identify Duplicate Cases.
SORT CASES BY p_id(A).
MATCH FILES
  /FILE=*
  /BY p_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
  COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
  COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
SELECT IF PrimaryLast=1.
EXECUTE.
DELETE VARIABLES PrimaryLast.
```

```
*rename variable.
RENAME VARIABLES pollution=pollution_r.
```

```
*Add flag.
```

```

DATASET ACTIVATE dummy.
SORT CASES BY p_id.
DATASET ACTIVATE pollution.
SORT CASES BY p_id.
DATASET ACTIVATE dummy.
MATCH FILES /FILE=*
  /TABLE='pollution'
  /BY p_id.
EXECUTE.

```

```

temp.
select if pollution_r=1 and related=1.
FREQUENCIES art_abs /FORMAT dfreq.

```

```

*drop environmental category flags.
DELETE VARIABLES cul_her to pollution.

```

```

*add metadata.
VARIABLE LABELS
cul_her_r "Case related to Cultural Heritage crime"
env_adm_r "Case related to Environmental Administration crime"
fauna_r "Case related to Fauna crime"
fishing_r "Case related to Fishing crime"
flora_r "Case related to Flora crime"
generic_r "Case related to Generic crime"
health_r "Case related to Health crime"
his_her_r "Case related to Historical Heritage crime"
land_r "Case related to Land crime"
mining_r "Case related to Mining crime"
pollution_r "Case related to Pollution crime"
related "Environmental case with connection to other crimes".

```

```

*Save dataset with related crimes variables.
SAVE
OUTFILE='C:\Users\Administrador\OneDrive\data\PF\last\environmental_crime_investigation_Brazil_with_related_crimes.sav'.

```

```

*Create case_id to hide the true investigation_id from the public.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
AGGREGATE
  /OUTFILE='C:\Users\Administrador\OneDrive\data\PF\investigation_id.sav'
  /PRESORTED
  /BREAK=p_id
  /N_BREAK=N.

```

```

GET FILE='C:\Users\Administrador\OneDrive\data\PF\investigation_id.sav'.
DATASET NAME investigation_id.
DATASET ACTIVATE investigation_id.
DELETE VARIABLES N_BREAK.

```

```

STRING case_id(A7).
Compute temp = $casenum.
Loop #1 = 1 to 7.
Compute case_id = Concat(char.Substr('123456789ABCDEFGHIJKLMNQRSTUUVWXYZ', MOD(temp-1, 35)+1, 1),
  LTRIM(case_id)).
Compute temp = Trunc((temp-1)/35).
End Loop If temp = 0.
Compute case_id = char.LPAD(RTRIM(case_id), 7, '0').
EXECUTE.
Delete Variables temp.

```

```

* Identify Duplicate Cases.
DATASET ACTIVATE investigation_id.
SORT CASES BY case_id(A).
MATCH FILES
  /FILE=*
  /BY case_id
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE MatchSequence=MatchSequence+1.
END IF.
LEAVE MatchSequence.
FORMATS MatchSequence (f7).
COMPUTE InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
EXECUTE.
DELETE VARIABLES PrimaryLast.

SORT CASES by p_id.
SAVE OUTFILE='C:\Users\Administrador\OneDrive\data\PF\done\investigation_id.sav'.

*Match files to add case_id.
DATASET ACTIVATE dummy.
SORT CASES BY p_id.
MATCH FILES /FILE=*
  /TABLE='investigation_id'
  /BY p_id.
EXECUTE.

*delete original investigation_id.
DELETE VARIABLES p_id.

*Adjust report and close dates.
IF (SYSMIS(report_d) AND close_dt>1) report_d=close_dt.
IF (SYSMIS(close_dt) AND report_d>1) close_dt=report_d.
EXECUTE.

*Adjust p_situat.
DO IF sysmis(report_d).
COMPUTE p_situat=1.
ELSE.
COMPUTE p_situat=2.
END IF.
EXECUTE.

IF (sent_dt>=1) p_situat=2.
EXECUTE.

*Delete "-" from missing values.
IF crime_ye="-" crime_ye="".
EXECUTE.
MISSING VALUES crime_ye ("" ).

IF report_y="-" report_y="".

```

EXECUTE.
MISSING VALUES report_y ("").

*Save dataset with case_id.
SAVE
OUTFILE='C:\Users\Administrador\OneDrive\data\PF\done\environmental_crime_investigation_Brazil_with_case_id.sav'
/KEEP case_id ALL.
DATASET CLOSE investigation_id.
DATASET NAME env_cases.
Save original PF data for descriptive and robustness analysis.
GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\environmental_crime_investigation_Brazil_with_case_id.sav'.
DATASET NAME PF WINDOW=FRONT.
*Select only closed cases.
SELECT IF (close_dt<=DATE.DMY(31,12,2020) AND close_dt>=DATE.DMY(1,1,2010)).
EXECUTE.

*Create a flag for municipalities completely inside caatinga.
*Get the file with the names of municipalities.
GET DATA
/TYPE=XLS
/FILE='E:\OneDrive\data\IBGE\municipalities_caatinga.xls'
/SHEET=name 'municipalities_caatinga'
/CELLRANGE=FULL
/READNAMES=ON
/DATATYPEMIN PERCENTAGE=95.0.
EXECUTE.

RENAME VARIABLES
CD_MUN=cd_mun_crime.

SORT CASES BY cd_mun_crime.

DATASET NAME FlagData.
*Create the flag.
COMPUTE Caatinga=1.
EXECUTE.
ALTER TYPE Caatinga(F1).
*Delete other fields.
DELETE VARIABLES NM_MUN SIGLA_UF.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\IBGE\caatinga_municipalities_flag'.

DATASET ACTIVATE PF.
SORT CASES BY cd_mun_crime.
MATCH FILES FILE=*
/TABLE='FlagData'
/BY cd_mun_crime.
EXECUTE.

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\done\pf_dataset.sav'
/COMPRESSED.

SAVE TRANSLATE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\done\pf_dataset.xlsx'
/TYPE=XLS
/VERSION=12
/MAP
/FIELDNAMES VALUE=NAMES

/CELLS=VALUES.

Get saved file.

GET FILE="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\environmental_crime_investigation_Brazil_with_case_id.sav".

*Display number of crimes investigated.

* show n.

*108,028.

*Eliminate duplicates.

SORT CASES BY case_id.

MATCH FILES FILE = * / FIRST = unique_flag /BY case_id.

IF (unique_flag = 1) unique_case = 1.

EXECUTE.

SELECT IF (unique_case = 1).

EXECUTE.

*Display number of unique cases.

* show n.

*50634

*Select only closed cases.

SELECT IF p_situat=2.

EXECUTE.

*Display number of unique cases.

show n.

*45,902.

* Check for missing values before transposing to avoid error (casestovars only works with no missing).

* FREQUENCIES VARIABLES=env_cat /FORMAT DFREQ.

* Statistics

env_cat Environmental category

N Valid 43594

Missing 2308

* Delete env_cat missing cases.

SELECT IF NOT SYSMIS(env_cat).

EXECUTE.

*Display number of unique cases.

show n.

*43594.

DELETE VARIABLES

env_cat

dmaph_area

crim_art

art

crim_law

law

l_year

law_chap

art_abs

law_nm

ar_la_year

unique_flag

unique_case.

*Save dataset with unique environmental case_id.
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
 UFRN\Tese\1_research\Data\PF\environmental_crime_investigation_Brazil_with_unique_case_id.sav'
 /COMPRESSED.

*Filter and aggregate data for each year.
 SORT CASES by cd_mun_crime.

TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2010) AND close_dt>=DATE.DMY(1,1,2010)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2010.sav'.

* For the year 2011.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2011) AND close_dt>=DATE.DMY(1,1,2011)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2011.sav'.

* For the year 2012.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2012) AND close_dt>=DATE.DMY(1,1,2012)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2012.sav'.

* For the year 2013.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2013) AND close_dt>=DATE.DMY(1,1,2013)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2013.sav'.

* For the year 2014.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2014) AND close_dt>=DATE.DMY(1,1,2014)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2014.sav'.

* For the year 2015.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2015) AND close_dt>=DATE.DMY(1,1,2015)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2015.sav'.

* For the year 2016.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2016) AND close_dt>=DATE.DMY(1,1,2016)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2016.sav'.

* For the year 2017.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2017) AND close_dt>=DATE.DMY(1,1,2017)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2017.sav'.

* For the year 2018.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2018) AND close_dt>=DATE.DMY(1,1,2018)).
 SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2018.sav'.

* For the year 2019.
 TEMPORARY.
 SELECT IF (close_dt<=DATE.DMY(31,12,2019) AND close_dt>=DATE.DMY(1,1,2019)).

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2019.sav'.

* For the year 2020.

TEMPORARY.

SELECT IF (close_dt<=DATE.DMY(31,12,2020) AND close_dt>=DATE.DMY(1,1,2020)).

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2020.sav'.

*Aggregate investigations.

*For year 2010.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2010.sav'.

DATASET NAME temp_2010 WINDOW=FRONT.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2010.sav'

/BREAK=cd_mun_crime

/p_durati_2010=MEAN(p_durati)

/d_crime_2010=SUM(d_crime)

/d_author_2010=SUM(d_author)

/d_prosec_2010=SUM(d_prosec)

/n_indict_2010=SUM(n_indict)

/n_search_2010=SUM(n_search)

/n_arre_w_2010=SUM(n_arre_w)

/d_arrest_2010=SUM(d_arrest)

/n_arrest_2010=SUM(n_arrest)

/n_arre_f_2010=SUM(n_arre_f)

/n_crimin_2010=SUM(n_crimin)

/value_es_2010=SUM(value_es)

/value_ca_2010=SUM(value_ca)

/related_2010=SUM(related)

/cul_her_r_2010=SUM(cul_her_r)

/env_adm_r_2010=SUM(env_adm_r)

/fauna_r_2010=SUM(fauna_r)

/fishing_r_2010=SUM(fishing_r)

/flora_r_2010=SUM(flora_r)

/generic_r_2010=SUM(generic_r)

/health_r_2010=SUM(health_r)

/his_her_r_2010=SUM(his_her_r)

/land_r_2010=SUM(land_r)

/mining_r_2010=SUM(mining_r)

/pollution_r_2010=SUM(pollution_r).

*For year 2011.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2011.sav'.

DATASET NAME temp_2011 WINDOW=FRONT.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2011.sav'

/BREAK=cd_mun_crime

/p_durati_2011=MEAN(p_durati)

/d_crime_2011=SUM(d_crime)

/d_author_2011=SUM(d_author)

/d_prosec_2011=SUM(d_prosec)

/n_indict_2011=SUM(n_indict)

/n_search_2011=SUM(n_search)

/n_arre_w_2011=SUM(n_arre_w)

/d_arrest_2011=SUM(d_arrest)

/n_arrest_2011=SUM(n_arrest)


```

/n_arre_f_2011=SUM(n_arre_f)
/n_crimin_2011=SUM(n_crimin)
/value_es_2011=SUM(value_es)
/value_ca_2011=SUM(value_ca)
/related_2011=SUM(related)
/cul_her_r_2011=SUM(cul_her_r)
/env_adm_r_2011=SUM(env_adm_r)
/fauna_r_2011=SUM(fauna_r)
/fishing_r_2011=SUM(fishing_r)
/flora_r_2011=SUM(flora_r)
/generic_r_2011=SUM(generic_r)
/health_r_2011=SUM(health_r)
/his_her_r_2011=SUM(his_her_r)
/land_r_2011=SUM(land_r)
/mining_r_2011=SUM(mining_r)
/pollution_r_2011=SUM(pollution_r).

```

*For year 2012.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2012.sav'.

DATASET NAME temp_2012 WINDOW=FRONT.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2012.sav'

```

/BREAK=cd_mun_crime
/p_durati_2012=MEAN(p_durati)
/d_crime_2012=SUM(d_crime)
/d_author_2012=SUM(d_author)
/d_prosec_2012=SUM(d_prosec)
/n_indict_2012=SUM(n_indict)
/n_search_2012=SUM(n_search)
/n_arre_w_2012=SUM(n_arre_w)
/d_arrest_2012=SUM(d_arrest)
/n_arrest_2012=SUM(n_arrest)
/n_arre_f_2012=SUM(n_arre_f)
/n_crimin_2012=SUM(n_crimin)
/value_es_2012=SUM(value_es)
/value_ca_2012=SUM(value_ca)
/related_2012=SUM(related)
/cul_her_r_2012=SUM(cul_her_r)
/env_adm_r_2012=SUM(env_adm_r)
/fauna_r_2012=SUM(fauna_r)
/fishing_r_2012=SUM(fishing_r)
/flora_r_2012=SUM(flora_r)
/generic_r_2012=SUM(generic_r)
/health_r_2012=SUM(health_r)
/his_her_r_2012=SUM(his_her_r)
/land_r_2012=SUM(land_r)
/mining_r_2012=SUM(mining_r)
/pollution_r_2012=SUM(pollution_r).

```

*For year 2013.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2013.sav'.

DATASET NAME temp_2013 WINDOW=FRONT.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2013.sav'
/BREAK=cd_mun_crime

```

/p_durati_2013=MEAN(p_durati)
/d_crime_2013=SUM(d_crime)
/d_author_2013=SUM(d_author)
/d_prosec_2013=SUM(d_prosec)
/n_indict_2013=SUM(n_indict)
/n_search_2013=SUM(n_search)
/n_arre_w_2013=SUM(n_arre_w)
/d_arrest_2013=SUM(d_arrest)
/n_arrest_2013=SUM(n_arrest)
/n_arre_f_2013=SUM(n_arre_f)
/n_crimin_2013=SUM(n_crimin)
/value_es_2013=SUM(value_es)
/value_ca_2013=SUM(value_ca)
/related_2013=SUM(related)
/cul_her_r_2013=SUM(cul_her_r)
/env_adm_r_2013=SUM(env_adm_r)
/fauna_r_2013=SUM(fauna_r)
/fishing_r_2013=SUM(fishing_r)
/flora_r_2013=SUM(flora_r)
/generic_r_2013=SUM(generic_r)
/health_r_2013=SUM(health_r)
/his_her_r_2013=SUM(his_her_r)
/land_r_2013=SUM(land_r)
/mining_r_2013=SUM(mining_r)
/pollution_r_2013=SUM(pollution_r).

```

*For year 2014.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2014.sav'.

DATASET NAME temp_2014 WINDOW=FRONT.

AGGREGATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2014.sav'

/BREAK=cd_mun_crime

/p_durati_2014=MEAN(p_durati)

/d_crime_2014=SUM(d_crime)

/d_author_2014=SUM(d_author)

/d_prosec_2014=SUM(d_prosec)

/n_indict_2014=SUM(n_indict)

/n_search_2014=SUM(n_search)

/n_arre_w_2014=SUM(n_arre_w)

/d_arrest_2014=SUM(d_arrest)

/n_arrest_2014=SUM(n_arrest)

/n_arre_f_2014=SUM(n_arre_f)

/n_crimin_2014=SUM(n_crimin)

/value_es_2014=SUM(value_es)

/value_ca_2014=SUM(value_ca)

/related_2014=SUM(related)

/cul_her_r_2014=SUM(cul_her_r)

/env_adm_r_2014=SUM(env_adm_r)

/fauna_r_2014=SUM(fauna_r)

/fishing_r_2014=SUM(fishing_r)

/flora_r_2014=SUM(flora_r)

/generic_r_2014=SUM(generic_r)

/health_r_2014=SUM(health_r)

/his_her_r_2014=SUM(his_her_r)

/land_r_2014=SUM(land_r)

/mining_r_2014=SUM(mining_r)

```
/pollution_r_2014=SUM(pollution_r).
```

*For year 2015.

```
GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2015.sav'.
```

```
DATASET NAME temp_2015 WINDOW=FRONT.
```

```
AGGREGATE
```

```
  /OUTFILE='E:\OneDrive\Academica\1-Doutorado
```

```
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2015.sav'
```

```
  /BREAK=cd_mun_crime
```

```
  /p_durati_2015=MEAN(p_durati)
```

```
  /d_crime_2015=SUM(d_crime)
```

```
  /d_author_2015=SUM(d_author)
```

```
  /d_prosec_2015=SUM(d_prosec)
```

```
  /n_indict_2015=SUM(n_indict)
```

```
  /n_search_2015=SUM(n_search)
```

```
  /n_arre_w_2015=SUM(n_arre_w)
```

```
  /d_arrest_2015=SUM(d_arrest)
```

```
  /n_arrest_2015=SUM(n_arrest)
```

```
  /n_arre_f_2015=SUM(n_arre_f)
```

```
  /n_crimin_2015=SUM(n_crimin)
```

```
  /value_es_2015=SUM(value_es)
```

```
  /value_ca_2015=SUM(value_ca)
```

```
  /related_2015=SUM(related)
```

```
  /cul_her_r_2015=SUM(cul_her_r)
```

```
  /env_adm_r_2015=SUM(env_adm_r)
```

```
  /fauna_r_2015=SUM(fauna_r)
```

```
  /fishing_r_2015=SUM(fishing_r)
```

```
  /flora_r_2015=SUM(flora_r)
```

```
  /generic_r_2015=SUM(generic_r)
```

```
  /health_r_2015=SUM(health_r)
```

```
  /his_her_r_2015=SUM(his_her_r)
```

```
  /land_r_2015=SUM(land_r)
```

```
  /mining_r_2015=SUM(mining_r)
```

```
  /pollution_r_2015=SUM(pollution_r).
```

*For year 2016.

```
GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2016.sav'.
```

```
DATASET NAME temp_2016 WINDOW=FRONT.
```

```
AGGREGATE
```

```
  /OUTFILE='E:\OneDrive\Academica\1-Doutorado
```

```
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2016.sav'
```

```
  /BREAK=cd_mun_crime
```

```
  /p_durati_2016=MEAN(p_durati)
```

```
  /d_crime_2016=SUM(d_crime)
```

```
  /d_author_2016=SUM(d_author)
```

```
  /d_prosec_2016=SUM(d_prosec)
```

```
  /n_indict_2016=SUM(n_indict)
```

```
  /n_search_2016=SUM(n_search)
```

```
  /n_arre_w_2016=SUM(n_arre_w)
```

```
  /d_arrest_2016=SUM(d_arrest)
```

```
  /n_arrest_2016=SUM(n_arrest)
```

```
  /n_arre_f_2016=SUM(n_arre_f)
```

```
  /n_crimin_2016=SUM(n_crimin)
```

```
  /value_es_2016=SUM(value_es)
```

```
  /value_ca_2016=SUM(value_ca)
```

```
  /related_2016=SUM(related)
```

```
  /cul_her_r_2016=SUM(cul_her_r)
```

```

/env_adm_r_2016=SUM(env_adm_r)
/fauna_r_2016=SUM(fauna_r)
/fishing_r_2016=SUM(fishing_r)
/flora_r_2016=SUM(flora_r)
/generic_r_2016=SUM(generic_r)
/health_r_2016=SUM(health_r)
/his_her_r_2016=SUM(his_her_r)
/land_r_2016=SUM(land_r)
/mining_r_2016=SUM(mining_r)
/pollution_r_2016=SUM(pollution_r).

```

*For year 2017.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2017.sav'.

DATASET NAME temp_2017 WINDOW=FRONT.

AGGREGATE

```

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2017.sav'
/BREAK=cd_mun_crime
/p_durati_2017=MEAN(p_durati)
/d_crime_2017=SUM(d_crime)
/d_author_2017=SUM(d_author)
/d_prosec_2017=SUM(d_prosec)
/n_indict_2017=SUM(n_indict)
/n_search_2017=SUM(n_search)
/n_arre_w_2017=SUM(n_arre_w)
/d_arrest_2017=SUM(d_arrest)
/n_arrest_2017=SUM(n_arrest)
/n_arre_f_2017=SUM(n_arre_f)
/n_crimin_2017=SUM(n_crimin)
/value_es_2017=SUM(value_es)
/value_ca_2017=SUM(value_ca)
/related_2017=SUM(related)
/cul_her_r_2017=SUM(cul_her_r)
/env_adm_r_2017=SUM(env_adm_r)
/fauna_r_2017=SUM(fauna_r)
/fishing_r_2017=SUM(fishing_r)
/flora_r_2017=SUM(flora_r)
/generic_r_2017=SUM(generic_r)
/health_r_2017=SUM(health_r)
/his_her_r_2017=SUM(his_her_r)
/land_r_2017=SUM(land_r)
/mining_r_2017=SUM(mining_r)
/pollution_r_2017=SUM(pollution_r).

```

*For year 2018.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2018.sav'.

DATASET NAME temp_2018 WINDOW=FRONT.

AGGREGATE

```

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2018.sav'
/BREAK=cd_mun_crime
/p_durati_2018=MEAN(p_durati)
/d_crime_2018=SUM(d_crime)
/d_author_2018=SUM(d_author)
/d_prosec_2018=SUM(d_prosec)
/n_indict_2018=SUM(n_indict)
/n_search_2018=SUM(n_search)

```

```

/n_arre_w_2018=SUM(n_arre_w)
/d_arrest_2018=SUM(d_arrest)
/n_arrest_2018=SUM(n_arrest)
/n_arre_f_2018=SUM(n_arre_f)
/n_crimin_2018=SUM(n_crimin)
/value_es_2018=SUM(value_es)
/value_ca_2018=SUM(value_ca)
/related_2018=SUM(related)
/cul_her_r_2018=SUM(cul_her_r)
/env_adm_r_2018=SUM(env_adm_r)
/fauna_r_2018=SUM(fauna_r)
/fishing_r_2018=SUM(fishing_r)
/flora_r_2018=SUM(flora_r)
/generic_r_2018=SUM(generic_r)
/health_r_2018=SUM(health_r)
/his_her_r_2018=SUM(his_her_r)
/land_r_2018=SUM(land_r)
/mining_r_2018=SUM(mining_r)
/pollution_r_2018=SUM(pollution_r).

```

*For year 2019.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2019.sav'.

DATASET NAME temp_2019 WINDOW=FRONT.

AGGREGATE

```

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2019.sav'
/BREAK=cd_mun_crime
/p_durati_2019=MEAN(p_durati)
/d_crime_2019=SUM(d_crime)
/d_author_2019=SUM(d_author)
/d_prosec_2019=SUM(d_prosec)
/n_indict_2019=SUM(n_indict)
/n_search_2019=SUM(n_search)
/n_arre_w_2019=SUM(n_arre_w)
/d_arrest_2019=SUM(d_arrest)
/n_arrest_2019=SUM(n_arrest)
/n_arre_f_2019=SUM(n_arre_f)
/n_crimin_2019=SUM(n_crimin)
/value_es_2019=SUM(value_es)
/value_ca_2019=SUM(value_ca)
/related_2019=SUM(related)
/cul_her_r_2019=SUM(cul_her_r)
/env_adm_r_2019=SUM(env_adm_r)
/fauna_r_2019=SUM(fauna_r)
/fishing_r_2019=SUM(fishing_r)
/flora_r_2019=SUM(flora_r)
/generic_r_2019=SUM(generic_r)
/health_r_2019=SUM(health_r)
/his_her_r_2019=SUM(his_her_r)
/land_r_2019=SUM(land_r)
/mining_r_2019=SUM(mining_r)
/pollution_r_2019=SUM(pollution_r).

```

*For year 2020.

GET FILE='E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\temp_2020.sav'.

DATASET NAME temp_2020 WINDOW=FRONT.

AGGREGATE

```

/OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2020.sav'
/BREAK=cd_mun_crime
/p_durati_2020=MEAN(p_durati)
/d_crime_2020=SUM(d_crime)
/d_author_2020=SUM(d_author)
/d_prosec_2020=SUM(d_prosec)
/n_indict_2020=SUM(n_indict)
/n_search_2020=SUM(n_search)
/n_arre_w_2020=SUM(n_arre_w)
/d_arrest_2020=SUM(d_arrest)
/n_arrest_2020=SUM(n_arrest)
/n_arre_f_2020=SUM(n_arre_f)
/n_crimin_2020=SUM(n_crimin)
/value_es_2020=SUM(value_es)
/value_ca_2020=SUM(value_ca)
/related_2020=SUM(related)
/cul_her_r_2020=SUM(cul_her_r)
/env_adm_r_2020=SUM(env_adm_r)
/fauna_r_2020=SUM(fauna_r)
/fishing_r_2020=SUM(fishing_r)
/flora_r_2020=SUM(flora_r)
/generic_r_2020=SUM(generic_r)
/health_r_2020=SUM(health_r)
/his_her_r_2020=SUM(his_her_r)
/land_r_2020=SUM(land_r)
/mining_r_2020=SUM(mining_r)
/pollution_r_2020=SUM(pollution_r).

```

*Merge all files.

```

GET FILE='E:\OneDrive\data\IBGE\municipalities_id.sav'.
DATASET NAME PF_all_env_crime_final_wide WINDOW=FRONT.

```

*Rename municipality ID to match PF data.

```

RENAME VARIABLES
CD_MUN=cd_mun_crime.
SORT CASES by cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2010.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2011.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2012.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2013.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2014.sav'

```

```

/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2015.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2016.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2017.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2018.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2019.sav'
/BY cd_mun_crime.
MATCH FILES /FILE=*
/FILE='E:\OneDrive\Academica\1-Doutorado '+
'UFRN\Tese\1_research\Data\PF\PF_temp_aggregate_2020.sav'
/BY cd_mun_crime.
EXECUTE.
DELETE VARIABLES s_munici_uf_concat.

```

```

*Convert null into 0.
DO REPEAT X = p_durati_2010 to pollution_r_2020.
IF SYSMIS(X) X=0.
END REPEAT.
EXECUTE.
*adjust decimals and width.
ALTER TYPE cul_her_r_2010 to related_2020(F3.2)
value_ca_2010 to value_es_2020(F12.2).

```

```

*Save final SPSS PF file.
SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_all_env_crime_final_wide.sav'
/COMPRESSED.

```

```

SAVE TRANSLATE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\PF\PF_all_env_crime_final_wide.csv'
/TYPE=CSV
/ENCODING='UTF8'
/MAP
/REPLACE
/FIELDNAMES
/CELLS=VALUES.

```

Import dbf data to GIS file.

```

arcpy.conversion.TableToGeodatabase(
    Input_Table=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\PF\PF_all_env_crime_final_wide.csv",
    Output_Geodatabase=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"
)

```

Create and populate CD-MUN field (string) to merge.

```
import arcpy

# Specify the input feature class and the field properties
in_table = "PF_all_env_crime_final_wide"
field_name = "CD_MUN"
field_type = "TEXT"
field_length = 7
field_is_nullable = "NULLABLE"
field_is_required = "NON_REQUIRED"

# Use the AddField function to add the field
arcpy.management.AddField(
    in_table,
    field_name,
    field_type,
    field_precision=None,
    field_scale=None,
    field_length=field_length,
    field_alias="",
    field_is_nullable=field_is_nullable,
    field_is_required=field_is_required,
    field_domain=""
)

arcpy.management.CalculateField(
    in_table="PF_all_env_crime_final_wide",
    field="CD_MUN",
    expression="!cd_mun_crime!",
    expression_type="PYTHON3",
    code_block="",
    field_type="TEXT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Create a copy of the municipalities feature class

```
arcpy.conversion.ExportFeatures(
    in_features=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs",
    out_features=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\PF_all_env_closed_cases_municipalities_within_caatinga_wgs",
    where_clause="",
    use_field_alias_as_name="NOT_USE_ALIASES",
    field_mapping=r"CD_MUN \"CD_MUN\" true true false 7 Text 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,CD_MUN,0,7;NM_MUN \"NM_MUN\" true true false 60 Text 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,NM_MUN,0,60;SIGLA_UF \"SIGLA_UF\" true true false 2 Text 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,SIGLA_UF,0,2;AREA_KM2 \"AREA_KM2\" true true false 8 Double 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,AREA_KM2,-1,-1;Shape_Length \"Shape_Length\" false true true 8 Double 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,Shape_Length,-1,-1;Shape_Area \"Shape_Area\" false true true 8 Double 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\municipalities_within_caatinga_wgs,Shape_Area,-1,-1",
    sort_field=None
)
```

Join PF table data to municipalities feature class.

```
arcpy.management.JoinField(
    in_data="PF_all_env_closed_cases_municipalities_within_caatinga_wgs",
    in_field="CD_MUN",
    join_table="PF_all_env_crime_final_wide",
    join_field="CD_MUN",

    fields="d_arrest_2010;d_arrest_2011;d_arrest_2012;d_arrest_2013;d_arrest_2014;d_arrest_2015;d_arrest_2016;d_arrest_2017;d_arrest_2018;d_arrest_2019;d_arrest_2020;d_author_2010;d_author_2011;d_author_2012;d_author_2013;d_author_2014;d_author_2015;d_author_2016;d_author_2017;d_author_2018;d_author_2019;d_author_2020;d_crime_2010;d_crime_2011;d_crime_2012;d_crime_2013;d_crime_2014;d_crime_2015;d_crime_2016;d_crime_2017;d_crime_2018;d_crime_2019;d_crime_2020;d_prosec_2010;d_prosec_2011;d_prosec_2012;d_prosec_2013;d_prosec_2014;d_prosec_2015;d_prosec_2016;d_prosec_2017;d_prosec_2018;d_prosec_2019;d_prosec_2020;n_arre_f_2010;n_arre_f_2011;n_arre_f_2012;n_arre_f_2013;n_arre_f_2014;n_arre_f_2015;n_arre_f_2016;n_arre_f_2017;n_arre_f_2018;n_arre_f_2019;n_arre_f_2020;n_arre_w_2010;n_arre_w_2011;n_arre_w_2012;n_arre_w_2013;n_arre_w_2014;n_arre_w_2015;n_arre_w_2016;n_arre_w_2017;n_arre_w_2018;n_arre_w_2019;n_arre_w_2020;n_arrest_2010;n_arrest_2011;n_arrest_2012;n_arrest_2013;n_arrest_2014;n_arrest_2015;n_arrest_2016;n_arrest_2017;n_arrest_2018;n_arrest_2019;n_arrest_2020;n_crimin_2010;n_crimin_2011;n_crimin_2012;n_crimin_2013;n_crimin_2014;n_crimin_2015;n_crimin_2016;n_crimin_2017;n_crimin_2018;n_crimin_2019;n_crimin_2020;n_indict_2010;n_indict_2011;n_indict_2012;n_indict_2013;n_indict_2014;n_indict_2015;n_indict_2016;n_indict_2017;n_indict_2018;n_indict_2019;n_indict_2020;n_search_2010;n_search_2011;n_search_2012;n_search_2013;n_search_2014;n_search_2015;n_search_2016;n_search_2017;n_search_2018;n_search_2019;n_search_2020;p_durati_2010;p_durati_2011;p_durati_2012;p_durati_2013;p_durati_2014;p_durati_2015;p_durati_2016;p_durati_2017;p_durati_2018;p_durati_2019;p_durati_2020;value_ca_2010;value_ca_2011;value_ca_2012;value_ca_2013;value_ca_2014;value_ca_2015;value_ca_2016;value_ca_2017;value_ca_2018;value_ca_2019;value_ca_2020;value_es_2010;value_es_2011;value_es_2012;value_es_2013;value_es_2014;value_es_2015;value_es_2016;value_es_2017;value_es_2018;value_es_2019;value_es_2020;cul_her_r_2010;cul_her_r_2011;cul_her_r_2012;cul_her_r_2013;cul_her_r_2014;cul_her_r_2015;cul_her_r_2016;cul_her_r_2017;cul_her_r_2018;cul_her_r_2019;cul_her_r_2020;env_adm_r_2010;env_adm_r_2011;env_adm_r_2012;env_adm_r_2013;env_adm_r_2014;env_adm_r_2015;env_adm_r_2016;env_adm_r_2017;env_adm_r_2018;env_adm_r_2019;env_adm_r_2020;fauna_r_2010;fauna_r_2011;fauna_r_2012;fauna_r_2013;fauna_r_2014;fauna_r_2015;fauna_r_2016;fauna_r_2017;fauna_r_2018;fauna_r_2019;fauna_r_2020;fishing_r_2010;fishing_r_2011;fishing_r_2012;fishing_r_2013;fishing_r_2014;fishing_r_2015;fishing_r_2016;fishing_r_2017;fishing_r_2018;fishing_r_2019;fishing_r_2020;flora_r_2010;flora_r_2011;flora_r_2012;flora_r_2013;flora_r_2014;flora_r_2015;flora_r_2016;flora_r_2017;flora_r_2018;flora_r_2019;flora_r_2020;generic_r_2010;generic_r_2011;generic_r_2012;generic_r_2013;generic_r_2014;generic_r_2015;generic_r_2016;generic_r_2017;generic_r_2018;generic_r_2019;generic_r_2020;health_r_2010;health_r_2011;health_r_2012;health_r_2013;health_r_2014;health_r_2015;health_r_2016;health_r_2017;health_r_2018;health_r_2019;health_r_2020;his_her_r_2010;his_her_r_2011;his_her_r_2012;his_her_r_2013;his_her_r_2014;his_her_r_2015;his_her_r_2016;his_her_r_2017;his_her_r_2018;his_her_r_2019;his_her_r_2020;land_r_2010;land_r_2011;land_r_2012;land_r_2013;land_r_2014;land_r_2015;land_r_2016;land_r_2017;land_r_2018;land_r_2019;land_r_2020;mining_r_2010;mining_r_2011;mining_r_2012;mining_r_2013;mining_r_2014;mining_r_2015;mining_r_2016;mining_r_2017;mining_r_2018;mining_r_2019;mining_r_2020;pollution_r_2010;pollution_r_2011;pollution_r_2012;pollution_r_2013;pollution_r_2014;pollution_r_2015;pollution_r_2016;pollution_r_2017;pollution_r_2018;pollution_r_2019;pollution_r_2020;related_2010;related_2011;related_2012;related_2013;related_2014;related_2015;related_2016;related_2017;related_2018;related_2019;related_2020",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```


Summarize Federal Police mining investigations

Intersect PF municipality level data with the study grid.

```
arcpy.analysis.TabulateIntersection(
    in_zone_features="grid_net",
    zone_fields="OID_1",
    in_class_features="PF_all_env_closed_cases_municipalities_within_caatinga_wgs",
    out_table=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\PF_grid_net_TabulateIntersection",

    class_fields="d_arrest_2010;d_arrest_2011;d_arrest_2012;d_arrest_2013;d_arrest_2014;d_arrest_2015;d_arrest_2016;d_arrest_2017;d_arrest_2018;d_arrest_2019;d_arrest_2020;d_author_2010;d_author_2011;d_author_2012;d_author_2013;d_author_2014;d_author_2015;d_author_2016;d_author_2017;d_author_2018;d_author_2019;d_author_2020;d_crime_2010;d_crime_2011;d_crime_2012;d_crime_2013;d_crime_2014;d_crime_2015;d_crime_2016;d_crime_2017;d_crime_2018;d_crime_2019;d_crime_2020;d_prosec_2010;d_prosec_2011;d_prosec_2012;d_prosec_2013;d_prosec_2014;d_prosec_2015;d_prosec_2016;d_prosec_2017;d_prosec_2018;d_prosec_2019;d_prosec_2020;n_arre_f_2010;n_arre_f_2011;n_arre_f_2012;n_arre_f_2013;n_arre_f_2014;n_arre_f_2015;n_arre_f_2016;n_arre_f_2017;n_arre_f_2018;n_arre_f_2019;n_arre_f_2020;n_arre_w_2010;n_arre_w_2011;n_arre_w_2012;n_arre_w_2013;n_arre_w_2014;n_arre_w_2015;n_arre_w_2016;n_arre_w_2017;n_arre_w_2018;n_arre_w_2019;n_arre_w_2020;n_arrest_2010;n_arrest_2011;n_arrest_2012;n_arrest_2013;n_arrest_2014;n_arrest_2015;n_arrest_2016;n_arrest_2017;n_arrest_2018;n_arrest_2019;n_arrest_2020;n_crimin_2010;n_crimin_2011;n_crimin_2012;n_crimin_2013;n_crimin_2014;n_crimin_2015;n_crimin_2016;n_crimin_2017;n_crimin_2018;n_crimin_2019;n_crimin_2020;n_indict_2010;n_indict_2011;n_indict_2012;n_indict_2013;n_indict_2014;n_indict_2015;n_indict_2016;n_indict_2017;n_indict_2018;n_indict_2019;n_indict_2020;n_search_2010;n_search_2011;n_search_2012;n_search_2013;n_search_2014;n_search_2015;n_search_2016;n_search_2017;n_search_2018;n_search_2019;n_search_2020;p_durati_2010;p_durati_2011;p_durati_2012;p_durati_2013;p_durati_2014;p_durati_2015;p_durati_2016;p_durati_2017;p_durati_2018;p_durati_2019;p_durati_2020;value_ca_2010;value_ca_2011;value_ca_2012;value_ca_2013;value_ca_2014;value_ca_2015;value_ca_2016;value_ca_2017;value_ca_2018;value_ca_2019;value_ca_2020;value_es_2010;value_es_2011;value_es_2012;value_es_2013;value_es_2014;value_es_2015;value_es_2016;value_es_2017;value_es_2018;value_es_2019;value_es_2020;cul_her_r_2010;cul_her_r_2011;cul_her_r_2012;cul_her_r_2013;cul_her_r_2014;cul_her_r_2015;cul_her_r_2016;cul_her_r_2017;cul_her_r_2018;cul_her_r_2019;cul_her_r_2020;env_adm_r_2010;env_adm_r_2011;env_adm_r_2012;env_adm_r_2013;env_adm_r_2014;env_adm_r_2015;env_adm_r_2016;env_adm_r_2017;env_adm_r_2018;env_adm_r_2019;env_adm_r_2020;fauna_r_2010;fauna_r_2011;fauna_r_2012;fauna_r_2013;fauna_r_2014;fauna_r_2015;fauna_r_2016;fauna_r_2017;fauna_r_2018;fauna_r_2019;fauna_r_2020;fishing_r_2010;fishing_r_2011;fishing_r_2012;fishing_r_2013;fishing_r_2014;fishing_r_2015;fishing_r_2016;fishing_r_2017;fishing_r_2018;fishing_r_2019;fishing_r_2020;flora_r_2010;flora_r_2011;flora_r_2012;flora_r_2013;flora_r_2014;flora_r_2015;flora_r_2016;flora_r_2017;flora_r_2018;flora_r_2019;flora_r_2020;generic_r_2010;generic_r_2011;generic_r_2012;generic_r_2013;generic_r_2014;generic_r_2015;generic_r_2016;generic_r_2017;generic_r_2018;generic_r_2019;generic_r_2020;health_r_2010;health_r_2011;health_r_2012;health_r_2013;health_r_2014;health_r_2015;health_r_2016;health_r_2017;health_r_2018;health_r_2019;health_r_2020;his_her_r_2010;his_her_r_2011;his_her_r_2012;his_her_r_2013;his_her_r_2014;his_her_r_2015;his_her_r_2016;his_her_r_2017;his_her_r_2018;his_her_r_2019;his_her_r_2020;land_r_2010;land_r_2011;land_r_2012;land_r_2013;land_r_2014;land_r_2015;land_r_2016;land_r_2017;land_r_2018;land_r_2019;land_r_2020;mining_r_2010;mining_r_2011;mining_r_2012;mining_r_2013;mining_r_2014;mining_r_2015;mining_r_2016;mining_r_2017;mining_r_2018;mining_r_2019;mining_r_2020;pollution_r_2010;pollution_r_2011;pollution_r_2012;pollution_r_2013;pollution_r_2014;pollution_r_2015;pollution_r_2016;pollution_r_2017;pollution_r_2018;pollution_r_2019;pollution_r_2020;related_2010;related_2011;related_2012;related_2013;related_2014;related_2015;related_2016;related_2017;related_2018;related_2019;related_2020",
    sum_fields=None,
    xy_tolerance=None,
    out_units="HECTARES"
)
```

Calculate the weighted mean for each year across rows that share the same OID_1, utilizing the PERCENTAGE column as weight

```
# Import required libraries
import arcpy
import pandas as pd
import numpy as np

# Define the geodatabase path
geodatabase_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"

# Define the table name
table_name = "PF_grid_net_TabulateIntersection"

# Convert the table to a Pandas DataFrame
field_names = [f.name for f in arcpy.ListFields(f"{geodatabase_path}\\{table_name}")]
np_array = arcpy.da.TableToNumPyArray(f"{geodatabase_path}\\{table_name}", field_names)
df = pd.DataFrame(np_array)

# Generate the list of columns to aggregate based on new class fields
new_fields = [
    'd_arrest', 'd_author', 'd_crime', 'd_prosec', 'n_arre_f', 'n_arre_w', 'n_arrest',
    'n_crimin', 'n_indict', 'n_search', 'p_durati', 'value_ca', 'value_es',
    'cul_her_r', 'env_adm_r', 'fauna_r', 'fishing_r', 'flora_r', 'generic_r',
    'health_r', 'his_her_r', 'land_r', 'mining_r', 'pollution_r', 'related'
]

report_cols = [f'{prefix}_{year}' for year in range(2010, 2021) for prefix in new_fields]

# Initialize an empty DataFrame to store aggregated values
agg_df = pd.DataFrame()

# Group by 'OID_1' and calculate weighted mean for each group
for name, group in df.groupby('OID_1'):
    weighted_means = {}
    for col in report_cols:
        weighted_mean = (group[col] * group['PERCENTAGE']).sum() / group['PERCENTAGE'].sum()
        weighted_means[col] = weighted_mean
    weighted_means['OID_1'] = name
    agg_df = agg_df.append(weighted_means, ignore_index=True)

# Reorder columns
agg_df = agg_df[['OID_1'] + report_cols]

# Convert the DataFrame to a structured NumPy array
structured_np_array = agg_df.to_records(index=False)

# Save this DataFrame back into your geodatabase as a new table
output_table = f"{geodatabase_path}\\PF_agg_grid_net_TabulateIntersection"
```

```
arcpy.da.NumPyArrayToTable(structured_np_array, output_table)
```

Join Federal police data to the main dataset.

```
arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID_1",
    join_table="PF_agg_grid_net_TabulateIntersection",
    join_field="OID_1",

    fields="mining_r_2010;mining_r_2011;mining_r_2012;mining_r_2013;mining_r_2014;mining_r_2015;mining_r_2016;mining_r_2017;mining_r_2018;mining_r_2019;mining_r_2020",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

IBAMA

Download fines layer from IBAMA geoserver

<http://siscom.ibama.gov.br/geoserver/ows?service=wfs&version=1.3.0&request=GetCapabilities>

Clip IBAMA fines points using municipalities completely inside Caatinga as mask

```
arcpy.analysis.PairwiseClip(
    in_features="vw_brasil_adm_auto_infracao_p",
    clip_features="municipalities_within_caatinga_wgs",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\IBAMA_fines",
    cluster_tolerance=None
)
```

Add Year field

```
processing.run("qgis:fieldcalculator", {'INPUT':
    IBAMA_fines, 'FIELD_NAME': 'year_fined', 'FIELD_TYPE': 2, 'FIELD_LENGTH': 4, 'FIELD_PRECISION': 3, 'NEW_FIELD': True, 'FORMULA': 'to_int( right( \"%f_year\", 4) )'; 'OUTPUT':
    E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\IBAMA_fines })
```

Select fines applied between 2010 and 2020

```
arcpy.analysis.Select(
    in_features="IBAMA_fines",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\IBAMA_fines_2010_2020",
    where_clause="f_year IN ('2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019', '2020')"
```

Summarize IBAMA fines

```
import arcpy

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)

    # Execute the SelectLayerByAttribute tool
    arcpy.management.SelectLayerByAttribute(
        in_layer_or_view="IBAMA_fines_2010_2020",
        selection_type="NEW_SELECTION",
        where_clause=f"f_year = '{year_str}'",
        invert_where_clause=None
    )

    # Create a new layer for the selected features
    selected_layer = arcpy.management.MakeFeatureLayer("IBAMA_fines_2010_2020", "selected_layer")

    # Execute the SummarizeWithin tool with the selected layer
    arcpy.analysis.SummarizeWithin(
        in_polygons=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net",
        in_sum_features=selected_layer,
        out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\ibama_" + year_str,
        keep_all_polygons="KEEP_ALL",
        sum_fields=None,
        sum_shape="ADD_SHAPE_SUM",
        shape_unit="KILOMETERS",
        group_field=None,
        add_min_maj="NO_MIN_MAJ",
        add_group_percent="NO_PERCENT",
        out_group_table=None
    )

    # Clear the selection
    arcpy.management.SelectLayerByAttribute(
        in_layer_or_view=selected_layer,
        selection_type="CLEAR_SELECTION"
    )
```

Rename

```
# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_table = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\ibama_" + year_str
    new_field_name = f"ibama_{year_str}"

    # Alter field
```

```

arcpy.management.AlterField(
    in_table=input_table,
    field="Point_Count",
    new_field_name=new_field_name,
    new_field_alias=f"IBAMA fines {year_str}",
    field_type="LONG",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)

```

Join

```

# Import the ArcPy library
import arcpy

# Define the base file path for convenience and reusability
base_path = r'E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"

# Iterate from 2010 to 2021
for year in range(2010, 2021):
    year_str = str(year)

    # Define the join table based on the current year
    join_table = f"{base_path}\\ibama_{year_str}"

    # Define the new field name based on the current year
    new_field_name = f"ibama_{year_str}"

    print(f"Joining {new_field_name} from {join_table} to grid_net...")

    # Join field
    arcpy.management.JoinField(
        in_data="grid_net",
        in_field="OID_1",
        join_table=join_table,
        join_field="OID_1",
        fields=new_field_name,
        fm_option="NOT_USE_FM",
        field_mapping=None
    )
    print(f"Successfully joined {new_field_name}.")

```

VALUED-MRI (Mining Related Illegal Income)

```

# Define the years for which MRI will be calculated and the minimum year for indexing
YEARS = range(2010, 2021)
MIN_YEAR = 2010

# Function to populate valued_dict from VALUED_final table
def populate_valued_dict(valued_final_table: str) -> Dict[str, Dict[int, int]]:
    valued_dict = {}
    with arcpy.da.SearchCursor(valued_final_table, ["Mineral"] + [f"Valued_{year}" for year in YEARS]) as cursor:
        for row in cursor:
            mineral = row[0].lower()
            valued_dict[mineral] = {}
            for year in YEARS:
                valued_dict[mineral][year] = row[year - MIN_YEAR + 1]
    return valued_dict

# Function to check if a field exists in a table
def field_exists(table: str, field: str) -> bool:
    return field in [f.name for f in arcpy.ListFields(table)]

# Function to add MRI fields to grid_rtm table
def add_mri_fields():
    for year in YEARS:
        mri_field = f"MRI_{year}"
        if not field_exists("grid_rtm", mri_field):
            arcpy.AddField_management("grid_rtm", mri_field, "DOUBLE")

# Main function to calculate MRI
def calculate_mri(valued_dict: Dict[str, Dict[int, int]]):
    percent_area_field_names = [f'{mineral.capitalize()}_PercentArea_{year}' for mineral in valued_dict.keys() for year in YEARS]
    all_field_names = percent_area_field_names + [f"MRI_{year}" for year in YEARS]

    with arcpy.da.UpdateCursor("grid_rtm", all_field_names) as cursor:
        for row in cursor:
            for year in YEARS:
                sum_relative_risks = 0
                sum_percent_areas = 0

                for mineral, year_valued_dict in valued_dict.items():
                    valued = year_valued_dict[year]
                    percent_area_field_name = f'{mineral.capitalize()}_PercentArea_{year}'
                    percent_area = row[all_field_names.index(percent_area_field_name)]

                    if percent_area is not None:
                        percent_area /= 100.0

                if valued is None or percent_area is None:
                    continue

```

```

        relative_risk = valued * percent_area
        sum_relative_risks += relative_risk
        sum_percent_areas += percent_area

    avg_rr = sum_relative_risks / len(valued_dict)
    mri = avg_rr * sum_percent_areas

    # Cap the MRI value at 10
    if mri > 10:
        mri = 10

    mri_field_name = f"MRI_{year}"
    row[all_field_names.index(mri_field_name)] = mri

    cursor.updateRow(row)

# Define the path to VALUED_final table
valued_final_table = f'{base_directory}\\{geodatabase_name}\\VALUED_final'

# Populate valued_dict
valued_dict = populate_valued_dict(valued_final_table)

# Add MRI fields to grid_rtm table
add_mri_fields()

# Calculate MRI
calculate_mri(valued_dict)

```

Join MRI into the main grid

```

arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID_1",
    join_table="grid_rtm",
    join_field="OID_1",
    fields="MRI_2010;MRI_2011;MRI_2012;MRI_2013;MRI_2014;MRI_2015;MRI_2016;MRI_2017;MRI_2018;MRI_2019;MRI_2020",
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

IBGE

Step 1. SPSS

* Encoding: UTF-8.

*Get 2010 population (census) dataset.

GET DATA

/TYPE=XLSX

/FILE='E:\OneDrive\data\IBGE\populacao\tabela1552.xlsx'

/SHEET=name 'Tabela'

/CELLRANGE=FULL

/READNAMES=ON

/DATATYPEMIN PERCENTAGE=95.0

/HIDDEN IGNORE=YES.

EXECUTE.

DATASET NAME pop_2010 WINDOW=FRONT.

*Get 2011-2020 population (census) dataset.

GET DATA

/TYPE=XLSX

/FILE='E:\OneDrive\data\IBGE\populacao\tabela6579.xlsx'

/SHEET=name 'Tabela'

/CELLRANGE=FULL

/READNAMES=ON

/DATATYPEMIN PERCENTAGE=95.0

/HIDDEN IGNORE=YES.

EXECUTE.

DATASET NAME pop_1120 WINDOW=FRONT.

*Add 2010 data to 2011-2020 dataset.

SORT CASES BY Cód.

```

DATASET ACTIVATE pop_2010.
SORT CASES BY Cód.
ALTER TYPE Cód (A40).
DATASET ACTIVATE pop_1120.
MATCH FILES /FILE=*
  /FILE='pop_2010'
  /RENAME (BrasileMunicípio = d0)
  /BY Cód
  /DROP= d0.
EXECUTE.
DATASET NAME pop WINDOW=FRONT.

```

```

*reorder.
MATCH FILES /FILE=* /KEEP Cód BrasileMunicípio @2010 to @2020.
EXECUTE.

```

```

*Rename.
RENAME VARIABLES
@2010=pop_2010
@2011=pop_2011
@2012=pop_2012
@2013=pop_2013
@2014=pop_2014
@2015=pop_2015
@2016=pop_2016
@2017=pop_2017
@2018=pop_2018
@2019=pop_2019
@2020=pop_2020.

```

```

FORMATS pop_2010 to pop_2020(F12).

```

```

ALTER TYPE Cód(A7).
SORT CASES BY Cód.
SAVE OUTFILE= 'E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\IBGE\pop_2010_2020.sav'.

```

```

*Get 2010-2020 GDP dataset.

```

```

GET DATA
  /TYPE=XLSX
  /FILE='E:\OneDrive\data\IBGE\PIB_municipio\tabela5938 .xlsx'
  /SHEET=name 'Tabela'
  /CELLRANGE=FULL
  /READNAMES=ON
  /DATATYPEMIN PERCENTAGE=95.0
  /HIDDEN IGNORE=YES.
EXECUTE.
DATASET NAME pib WINDOW=FRONT.

```

```

*Rename.
RENAME VARIABLES

```

```
@2010=pib_2010
@2011=pib_2011
@2012=pib_2012
@2013=pib_2013
@2014=pib_2014
@2015=pib_2015
@2016=pib_2016
@2017=pib_2017
@2018=pib_2018
@2019=pib_2019
@2020=pib_2020.
```

```
ALTER TYPE Cód(A7).
SORT CASES BY Cód.
SAVE OUTFILE= 'E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\IBGE\pib_2010_2020.sav' /DROP BrasileMunicípio.
```

```
*Merge both datasets.
DATASET CLOSE pib.
DATASET ACTIVATE pop.
MATCH FILES /FILE=*
/FILE= 'E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\IBGE\pib_2010_2020.sav'
/BY Cód.
EXECUTE.
```

```
RENAME VARIABLES Cód=CD_MUN.
DELETE VARIABLES BrasileMunicípio.
SAVE OUTFILE= 'E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\IBGE\pop_pib_2010_2020.sav'.
```

```
*Compute pib per capita.
COMPUTE gdp_2010=pib_2010/pop_2010.
COMPUTE gdp_2011=pib_2011/pop_2011.
COMPUTE gdp_2012=pib_2012/pop_2012.
COMPUTE gdp_2013=pib_2013/pop_2013.
COMPUTE gdp_2014=pib_2014/pop_2014.
COMPUTE gdp_2015=pib_2015/pop_2015.
COMPUTE gdp_2016=pib_2016/pop_2016.
COMPUTE gdp_2017=pib_2017/pop_2017.
COMPUTE gdp_2018=pib_2018/pop_2018.
COMPUTE gdp_2019=pib_2019/pop_2019.
COMPUTE gdp_2020=pib_2020/pop_2020.
EXECUTE.
```

```
*Compute "relative distance to the average income" (rdai), calculated by [("GDP per capita of
the respective municipality" - "Brazilian GDP per capita") / ("GDP per capita of the respective
municipality")].
```

```
COMPUTE rdai_2010=(gdp_2010-20.37)/gdp_2010.
COMPUTE rdai_2011=(gdp_2011-22.75)/gdp_2011.
COMPUTE rdai_2012=(gdp_2012-24.83)/gdp_2012.
```



```

COMPUTE rdai_2013=(gdp_2013-26.52)/gdp_2013.
COMPUTE rdai_2014=(gdp_2014-28.5)/gdp_2014.
COMPUTE rdai_2015=(gdp_2015-29.33)/gdp_2015.
COMPUTE rdai_2016=(gdp_2016-30.42)/gdp_2016.
COMPUTE rdai_2017=(gdp_2017-31.71)/gdp_2017.
COMPUTE rdai_2018=(gdp_2018-33.59)/gdp_2018.
COMPUTE rdai_2019=(gdp_2019-35.16)/gdp_2019.
COMPUTE rdai_2020=(gdp_2020-35.94)/gdp_2020.
EXECUTE.

```

*Adjust metadata.

FORMATS pib_2010 to pib_2020 (F14.2).

VARIABLE LABELS

```

pop_2010 'Municipality population - 2010'
pop_2011 'Municipality population - 2011'
pop_2012 'Municipality population - 2012'
pop_2013 'Municipality population - 2013'
pop_2014 'Municipality population - 2014'
pop_2015 'Municipality population - 2015'
pop_2016 'Municipality population - 2016'
pop_2017 'Municipality population - 2017'
pop_2018 'Municipality population - 2018'
pop_2019 'Municipality population - 2019'
pop_2020 'Municipality population - 2020'
pib_2010 'Municipality GDP - 2010'
pib_2011 'Municipality GDP - 2011'
pib_2012 'Municipality GDP - 2012'
pib_2013 'Municipality GDP - 2013'
pib_2014 'Municipality GDP - 2014'
pib_2015 'Municipality GDP - 2015'
pib_2016 'Municipality GDP - 2016'
pib_2017 'Municipality GDP - 2017'
pib_2018 'Municipality GDP - 2018'
pib_2019 'Municipality GDP - 2019'
pib_2020 'Municipality GDP - 2020'
gdp_2010 'Municipality GDP per capita - 2010'
gdp_2011 'Municipality GDP per capita - 2011'
gdp_2012 'Municipality GDP per capita - 2012'
gdp_2013 'Municipality GDP per capita - 2013'
gdp_2014 'Municipality GDP per capita - 2014'
gdp_2015 'Municipality GDP per capita - 2015'
gdp_2016 'Municipality GDP per capita - 2016'
gdp_2017 'Municipality GDP per capita - 2017'
gdp_2018 'Municipality GDP per capita - 2018'
gdp_2019 'Municipality GDP per capita - 2019'
gdp_2020 'Municipality GDP per capita - 2020'
rdai_2010 'Relative distance to the average GDP per capita - 2010'
rdai_2011 'Relative distance to the average GDP per capita - 2011'
rdai_2012 'Relative distance to the average GDP per capita - 2012'
rdai_2013 'Relative distance to the average GDP per capita - 2013'
rdai_2014 'Relative distance to the average GDP per capita - 2014'

```

```
rdai_2015 'Relative distance to the average GDP per capita - 2015'
rdai_2016 'Relative distance to the average GDP per capita - 2016'
rdai_2017 'Relative distance to the average GDP per capita - 2017'
rdai_2018 'Relative distance to the average GDP per capita - 2018'
rdai_2019 'Relative distance to the average GDP per capita - 2019'
rdai_2020 'Relative distance to the average GDP per capita - 2020'.
SAVE OUTFILE= 'E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1 research\Data\IBGE\pib per capita 2010 2020.sav'.
```

*Create a dataset to be used on GIS.

SAVE TRANSLATE

/OUTFILE='E:\OneDrive\Academica\1-Doutorado

UFRN\Tese\1 research\Data\IBGE\pib per capita 2010 2020.dbf'

/TYPE=DB4

/REPLACE.

GIS

Import spss data

[illegible]

Create a new feature layer to join spss data

```
arcpy.conversion.FeatureClassToFeatureClass(
    in_features="municipalities_within_caatinga_wgs",
    out_path=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    out_name="municipalities_within_caatinga_wgs_pib_per_capita_2010_2020",
    where_clause="",
    field_mapping="CD_MUN \"CD_MUN\" true true false 7 Text 0 0,First,#,municipalities_within_caatinga_wgs,CD_MUN,0,7;NM_MUN \"NM_MUN\" true true false 60 Text 0
0,First,#,municipalities_within_caatinga_wgs,NM_MUN,0,60;SIGLA_UF \"SIGLA_UF\" true true false 2 Text 0
0,First,#,municipalities_within_caatinga_wgs,SIGLA_UF,0,2;AREA_KM2 \"AREA_KM2\" true true false 8 Double 0 0,First,#,municipalities_within_caatinga_wgs,AREA_KM2,-1,-
1;Shape_Length \"Shape_Length\" false true true 8 Double 0 0,First,#,municipalities_within_caatinga_wgs,Shape_Length,-1,-1;Shape_Area \"Shape_Area\" false true true 8
Double 0 0,First,#,municipalities_within_caatinga_wgs,Shape_Area,-1,-1',
    config_keyword=""
)
```

Join spss data with municipality feature class

```
arcpy.management.JoinField(
    in_data="municipalities_within_caatinga_wgs_pib_per_capita_2010_2020",
    in_field="CD_MUN",
    join_table="pib_per_capita_2010_2020",
    join_field="CD_MUN",
    fields=None,
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

Summarize IBGE Data

Intersect IBGE data with the study grid.

```
arcpy.analysis.TabulateIntersection(
    in_zone_features="grid_net",
    zone_fields="OID_1",
    in_class_features="municipalities_within_caatinga_wgs_pib_per_capita_2010_2020",
    out_table=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\IBGE_grid_net_TabulateIntersection",
    class_fields="rdai_2010;rdai_2011;rdai_2012;rdai_2013;rdai_2014;rdai_2015;rdai_2016;rdai_2017;rdai_2018;rdai_2019;rdai_2020",
    sum_fields=None,
    xy_tolerance=None,
    out_units="HECTARES"
)
```

Calculate the weighted mean for each year across rows that share the same OID_1, utilizing the PERCENTAGE column as weight

```
# Import required libraries
import arcpy
import pandas as pd
import numpy as np

# Enable overwriting output
arcpy.env.overwriteOutput = True
arcpy.env.workspace = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb"

# Define variables
geodatabase_path = arcpy.env.workspace
table_name = "IBGE_grid_net_TabulateIntersection"
output_table = f"{geodatabase_path}\\IBGE_agg_grid_net_TabulateIntersection"

# Delete output table if it exists
if arcpy.Exists(output_table):
    arcpy.Delete_management(output_table)

# Convert table to Pandas DataFrame
field_names = [f.name for f in arcpy.ListFields(f"{geodatabase_path}\\{table_name}")]
np_array = arcpy.da.TableToNumPyArray(f"{geodatabase_path}\\{table_name}", field_names)
df = pd.DataFrame(np_array)

# Initialize an empty DataFrame for aggregated values
agg_df = pd.DataFrame()

# Define the RDAI columns to focus on, matching the case in the DataFrame
rdai_cols = [f'RDAI_{year}' for year in range(2010, 2021)]

# Group by 'OID_1' and calculate weighted mean for each group
for name, group in df.groupby('OID_1'):
    weighted_means = {}
    for col in rdai_cols:
        if 'PERCENTAGE' in group.columns and col in group.columns:
            weighted_mean = (group[col] * group['PERCENTAGE']).sum() / group['PERCENTAGE'].sum()
            weighted_means[col] = weighted_mean
    weighted_means['OID_1'] = name
    agg_df = agg_df.append(weighted_means, ignore_index=True)

# Save aggregated DataFrame back into geodatabase
structured_np_array = agg_df.to_records(index=False)
```

```
arcpy.da.NumPyArrayToTable(structured_np_array, output_table)
```

Join IBGE data to the main dataset.

```
arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID_1",
    join_table="IBGE_agg_grid_net_TabulateIntersection",
    join_field="OID_1",
    fields="rdai_2010;rdai_2011;rdai_2012;rdai_2013;rdai_2014;rdai_2015;rdai_2016;rdai_2017;rdai_2018;rdai_2019;rdai_2020",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

OSM

#Gas Stations

Step 1. Download gas stations from Open Street Map Project using QuickOSM plugin
(GitHub - 3liz/QuickOSM: QGIS plugin to fetch OSM data with the Overpass API)

```
<osm-script output="xml" timeout="25">
  <union>
    <query type="node">
      <has-kv k="amenity" v="fuel"/>
      <bbox-query {{bbox}}/>
    </query>
    <query type="way">
      <has-kv k="amenity" v="fuel"/>
      <bbox-query {{bbox}}/>
    </query>
    <query type="relation">
      <has-kv k="amenity" v="fuel"/>
      <bbox-query {{bbox}}/>
    </query>
  </union>
</osm-script>
```

Clip gas stations using Caatinga municipalities as mask

```
arcpy.analysis.PairwiseClip(
    in_features="OSM_gas_station_caatinga_buffer_clipped",
    clip_features="municipalities_within_caatinga_wgs",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\OSM_gas_station",
    cluster_tolerance=None
)
```

#Roads

Download complete South America file from OSM

(<https://download.geofabrik.de/south-america-latest.osm.pbf>)

Save municipalities within Caatinga layer to ".poly" using "osmpoly_export"

(https://github.com/nextgis/osmpoly_export)

Use OSM convert ([Osmconvert - OpenStreetMap Wiki](#)) to clip features from the area of interest (municipalities within Caatinga 50km buffer)

Command:

Convert south-america-latest.osm.pbf -B=caatinga.poly -out-pbf -o= south-america-latest.osm_01.pbf

Select only the following types of roads:

motorway	A restricted access major divided highway, normally with 2 or more running lanes plus emergency hard shoulder. Equivalent to the Freeway, Autobahn, etc..
trunk	The most important roads in a country's system that aren't motorways. (Need not necessarily be a divided highway.)
primary	The next most important roads in a country's system. (Often link larger towns.)
secondary	The next most important roads in a country's system. (Often link towns.)
tertiary	The next most important roads in a country's system. (Often link smaller towns and villages)
unclassified	The least important through roads in a country's system – i.e. minor roads of a lower classification than tertiary, but which serve a purpose other than access to properties. (Often link villages and hamlets.)
residential	Roads which serve as an access to housing, without function of connecting settlements. Often lined with housing.
track	Roads for mostly agricultural or forestry uses.

Source: <https://wiki.openstreetmap.org/wiki/Key:highway>

```
processing.run("qgis:selectbyexpression", {'INPUT':'D:/GIS/south-america-latest.osm_01.pbf|layername=lines', 'EXPRESSION':'\"highway\" in(\r\n\'motorway\',\r\n\'trunk\',\r\n\'primary\',\r\n\'secondary\',\r\n\'tertiary\',\r\n\'unclassified\',\r\n\'residential\',\r\n\'track\')\r\n', 'METHOD':0})
```

Export selected features

```
processing.run("native:savefeatures", {'INPUT':QgsProcessingFeatureSourceDefinition("D:/GIS/south-america-latest.osm_01.pbf|layername=lines", selectedFeaturesOnly=True, featureLimit=-1, geometryCheck=QgsFeatureRequest.GeometryAbortOnInvalid), 'OUTPUT':'E:/OneDrive/GIS/OSM/OSM_roads_caatinga_buffer_selected/OSM_roads_caatinga_buffer_selected.shp', 'LAYER_NAME':'OSM_roads_caatinga_buffer_selected', 'DATASOURCE_OPTIONS':'', 'LAYER_OPTIONS':''})
```

Clip using Caatinga municipalities as mask

```
arcpy.analysis.PairwiseClip(
    in_features="OSM_roads_caatinga_buffer_selected",
    clip_features="municipalities_within_caatinga_wgs",
    out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/thesis/thesis.gdb/OSM_roads",
    cluster_tolerance=None
)
```

Summarize OSM data

Roads

Summarize

```
arcpy.analysis.SummarizeWithin(
    in_polygons=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net",
    in_sum_features="OSM_roads",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\roads_km",
    keep_all_polygons="KEEP_ALL",
    sum_fields=None,
    sum_shape="ADD_SHAPE_SUM",
    shape_unit="KILOMETERS",
    group_field=None,
    add_min_maj="NO_MIN_MAJ",
    add_group_percent="NO_PERCENT",
    out_group_table=None
)
```

Rename

```
arcpy.management.AlterField(
    in_table="roads_km",
    field="sum_Length_KILOMETERS",
    new_field_name="roads_km",
    new_field_alias="Sum of roads length in km",
    field_type="DOUBLE",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)
```

Join

```
arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID",
    join_table="roads_km",
    join_field="OID_1",
    fields="roads_km",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

Gas stations

Summarize

```
arcpy.analysis.SummarizeWithin(
    in_polygons=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net",
    in_sum_features="OSM_gas_station",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\gas",
    keep_all_polygons="KEEP_ALL",
    sum_fields=None,
    sum_shape="ADD_SHAPE_SUM",
    shape_unit="KILOMETERS",
    group_field=None,
    add_min_maj="NO_MIN_MAJ",
    add_group_percent="NO_PERCENT",
    out_group_table=None
)
```

Rename

```
arcpy.management.AlterField(
    in_table="gas",
    field="Point_Count",
    new_field_name="gas",
    new_field_alias="Number of gas stations",
    field_type="LONG",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)
```

Join

```
arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID_1",
    join_table="gas",
    join_field="OID_1",
    fields="gas",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

CPRM MINING OCCURRENCE

Step 1. Download CPRM Mining Occurrence from
(<https://geoportal.cprm.gov.br/downloads/ocorrencias.gdb.zip>).

Clip CPRM points using municipalities completely within Caatinga as mask

```

arcpy.analysis.PairwiseClip(
    in_features="RM_LAYER",
    clip_features="municipalities_within_caatinga_wgs",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\CPRM_mining_occurrence_municipalities_caatinga_clip",
    cluster_tolerance=None
)

```

Summarize CPRM mining POI

Summarize

```

arcpy.analysis.SummarizeWithin(
    in_polygons=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net",
    in_sum_features="CPRM_mining_occurrence_municipalities_caatinga_clip",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\CPRM_grid",
    keep_all_polygons="KEEP_ALL",
    sum_fields=None,
    sum_shape="ADD_SHAPE_SUM",
    shape_unit="KILOMETERS",
    group_field=None,
    add_min_maj="NO_MIN_MAJ",
    add_group_percent="NO_PERCENT",
    out_group_table=None
)

```

Rename

```

arcpy.management.AlterField(
    in_table="CPRM_grid",
    field="Point_Count",
    new_field_name="cprm_poi",
    new_field_alias="Geological Service of Brazil - CPRM Points of Interest",
    field_type="LONG",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)

```

Join

```

arcpy.management.JoinField(
    in_data="grid_net",
    in_field="OID_1",
    join_table="CPRM_grid",
    join_field="OID_1",
    fields="cprm_poi",
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Mapbiomas

Step 1. Download MapBiomas raster files

#I have used Google Earth Engine to download MapBiomas transition raster files of municipalities completely within caatinga for the years 2009-2010 to 2019-2020 (collection 7).

Source script:

https://code.earthengine.google.com/?accept_repo=users%2Fmapbiomas%2Fuser-toolkit&scriptPath=users%2Fmapbiomas%2Fuser-toolkit%3Amapbiomas-user-toolkit-lulc.js

ArcGIS

Merge transition raster layers

#Google Earth Engine crops big files into small chunks when exporting to Drive. It is necessary to merge all four parts together.

```
arcpy.management.MosaicToNewRaster(
    input_rasters="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2009_2010-0000000000-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2009_2010-0000000000-0000031744.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2009_2010-0000031744-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2009_2010-0000031744-0000031744.tif",
    output_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    raster_dataset_name_with_extension="caatinga_2010",

    coordinate_system_for_the_raster='GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]',
    pixel_type="16_BIT_SIGNED",
    cellsize=None,
    number_of_bands=1,
    mosaic_method="LAST",
    mosaic_colormap_mode="FIRST"
)

arcpy.management.MosaicToNewRaster(
    input_rasters="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2010_2011-0000000000-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2010_2011-0000000000-0000031744.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2010_2011-0000031744-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2010_2011-0000031744-0000031744.tif",
    output_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    raster_dataset_name_with_extension="caatinga_2011",

    coordinate_system_for_the_raster='GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]',
    pixel_type="16_BIT_SIGNED",
    cellsize=None,
    number_of_bands=1,
    mosaic_method="LAST",
    mosaic_colormap_mode="FIRST"
)

arcpy.management.MosaicToNewRaster(
    input_rasters="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2011_2012-0000000000-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2011_2012-0000000000-0000031744.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2011_2012-0000031744-0000000000.tif";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data\MapBiomas\mapbiomas-brazil-collection-71-caatinga-2011_2012-0000031744-0000031744.tif",
    output_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    raster_dataset_name_with_extension="caatinga_2012",

    coordinate_system_for_the_raster='GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]',
    pixel_type="16_BIT_SIGNED",
    cellsize=None,
    number_of_bands=1,
    mosaic_method="LAST",
    mosaic_colormap_mode="FIRST"
)

arcpy.management.MosaicToNewRaster(
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)

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Exploratory Analysis based on pixel counting

Excel

Create attribute tables for Mapbiomas rasters

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Export attribute tables

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sort_field=None

)

```

Aggregate values using Excel:

Format value column as 4 digit number, inserting zeros to the left of values smaller than a thousand: custom number category, type "0000";

Split columns in 2, leaving 2 decimals in each new column: one for the last year (year_before), one for the current year(year_after);

Insert labels for MapBiomass transition rasters (download MapBiomass labels for collection 7 from https://mapbiomas-br-site.s3.amazonaws.com/downloads/_EN__C%C3%B3digos_da_legenda_Cole%C3%A7%C3%A3o_7.pdf

Create variable "area_ha" (=pixel count*900*0.0001)

Check values and sums of all transitions to Mining between 2009 and 2020:

Select all transition to mining: "year_after=30"

Export to "mapbiomas_caatinga_transition_mining_ha"

After evaluating the values, it was possible to conclude that the method used by MapBiomass to detect mining explorations on the caatinga biome has improved on the collection 7, but it is still in development. The Caatinga biome has an official area of 84,445,300 ha and the area which is the object of interest 69,620,940 (82%). Approximately 74% of Caatinga territory was required for mining between 2010 and 2020.

Table 27

Areas of interest of the present study

Item	Area (ha)	Proportion to study area)
Study area (Municipalities completely inside Caatinga)	69,620,940	-

Area required for mining (2010-2020)	42,646,73	61%
	2	
Licensed mining tenements in operation (2010-2020)	20,857,89	30%
	4	
Total active mining tenements* (2010-2020)	72,537,48	104%
	2	

Note. The data for study area are from Brasil | Cidades e Estados |, by IBGE, 2019, (<https://www.ibge.gov.br/cidades-e-estados>). The data for mining tenements are from SIGMINE, Sistema de Informações Geográficas Da Mineração, by ANM, 2023, (<http://sigmine.dnpm.gov.br>).

Hence, it does not seem probable that only 0,1% of this area (or even 0,46% of the area that has been licensed for mining) has been explored during eleven years. If only transitions to mining were to be considered, the total explored area inside the studied region would sum just 2088 ha, which would only correspond to 0,01% of the area with a valid mining license.

Table 28

Land use transitions to mining inside Caatinga

Label	Pixel Value	Area (ha) 2009 - 2020		
		Col. 6	Col.7.1	Difference
Mining to Mining	3030	45,926	87,415	90%
Savanna Formation to Mining	0430	1,042	1,036	-1%
Mosaic of Uses to Mining	2130	427	354	-17%
Pasture to Mining	1530	440	334	-24%
Other Temporary Crops to Mining	4130	92	141	53%
Grassland to Mining	1230	139	65	-54%
Urban Area to Mining	2430	112	61	-46%
Other non-Vegetated Areas to Mining	2530	557	52	-91%

River, Lake and Ocean to Mining	3330	152	32	-79%
Forest Formation to Mining	0330	33	11	-67%
Rocky Outcrop to Mining	2930	10	3	-71%
Other Perennial Crops to Mining	4830	4	1	-84%
Total		48,934	89,503	

Note. MapBiomias Collection 7 Transition Maps, by Mapbiomas, 2021, October 25, (https://mapbiomas.org/en/colecoes-mapbiomas-1?cama_set_language=en).

Because of an apparent lack of data about mining in the Caatinga, a proxy was created from the same source, Mapbiomas Collection 7, which has 36 classifications of land use.

Table 29

Mapbiomas collection 7 land use classes

COLLECTION 7 CLASSES	NEW ID
1. Forest	1
1.1. Forest Formation	3
1.2. Savanna Formation	4
1.3. Mangrove	5
1.4. Wooded Sandbank Vegetation	49
2. Non-Forest Natural Formation	10
2.1. Wetland	11
2.2. Grassland	12
2.3. Salt Flat	32
2.4. Rocky Outcrop	29
2.5. Herbaceous Sandbank Vegetation	50
2.5. Other non-Forest Formations	13
3. Farming	14
3.1. Pasture	15
3.2. Agriculture	18
3.2.1. Temporary Crop	19
3.2.1.1. Soybean	39
3.2.1.2. Sugar cane	20
3.2.1.3. Rice	40
3.2.1.4. Cotton (beta)	62
3.2.1.5. Other Temporary Crops	41
3.2.2. Perennial Crop	36
3.2.1.1. Coffee	46
3.2.1.2. Citrus	47
3.2.1.3. Other Perennial Crops	48
3.3. Forest Plantation	9
3.4. Mosaic of Uses	21
4. Non-vegetated area	22
4.1. Beach, Dune and Sand Spot	23
4.2. Urban Area	24

4.3. Mining	30
4.4. Other non-Vegetated Areas	25
5. Water	26
5.1. River, Lake and Ocean	33
5.2. Aquaculture	31
6. Non-Observed	27

Note. From Legend Codes, by Mapbiomas, 2022, ([https://mapbiomas-br-](https://mapbiomas-br-site.s3.amazonaws.com/downloads/_EN__C%C3%B3digos_da_legenda_Cole%C3%A7%C3%A3o_7.pdf)

[site.s3.amazonaws.com/downloads/_EN__C%C3%B3digos_da_legenda_Cole%C3%A7%C3%A3o_7.pdf](https://mapbiomas-br-site.s3.amazonaws.com/downloads/_EN__C%C3%B3digos_da_legenda_Cole%C3%A7%C3%A3o_7.pdf)).

MapBiomas transition rasters pixels have values composed by the soil usage in the year before and after: (ID year 1 x 100) + ID year2. According to MapBiomas (2023a):

303 = forest that remained forest

315 = forest that has been converted to pasture

1515 = pasture that remained pasture

1524 = pasture that has been converted to urban infrastructure.

By analyzing eleven years of soil transition in the region, 374 combinations of these 36 values were found. Because of the evident remote sensing image similitude with mineral explorations, in addition to all transitions to mining, all changes from forest and non-forest natural formation to Rocky Outcrop (29) and Other Non-Vegetated Areas (25) that happened inside a mining tenement from 2010 to 2020 were chosen to compose the proxy, as presented below.

Table 30

Mining proxy composition.

COLLECTION 7 CLASSES	NEW ID		COLLECTION 7 CLASSES	NEW ID	Transition ID
All transitions		TO	Mining	30	
Mining	30	TO	Mining		3030
Savanna Formation	04				0430
Mosaic of Uses	21				2130
Pasture	15				1530
Other Temporary Crops	41				4130
Grassland	12				1230
Urban Area	24				2430
Other non-Vegetated Areas	25				2530
River, Lake and Ocean	33				3330

Forest Formation	03			0330
Rocky Outcrop	29			2930
Other Perennial Crops	48			4830
AND				
Forest Formation	3			0329 0325
Savanna Formation	4			0429 0425
Mangrove	5			0525
Wooded Sandbank Vegetation	49			4925
Wetland	11	TO	Rocky Outcrop & Other non-Vegetated Areas	29 & 25 1229 1225
Grassland	12			3225
Salt Flat	32			2925
Rocky Outcrop*	29			5025
Herbaceous Sandbank Vegetation	50			

Considering that MapBiomass rasters have a 30 m resolution, by counting the number of pixels and multiplying per 900, it was possible to estimate the area in square meters. Transitions from rocky outcrop to rocky outcrop, non-vegetated areas to non-vegetated areas and between each other were excluded because of the probability of not representing a significant change in the reality.

Also, only transitions to mining, rocky outcrop and non-vegetated areas that happened in Caatinga were chosen. Hence, the transitions selected to compose the mining proxy had the following estimated area between 2010 and 2020:

Table 31

Estimated transition area in Caatinga between 2010 and 2020 of values chosen to compose the mining proxy variable

Label	Value	Area (ha)
Mining to Mining	3030	87414.84
Savanna Formation to Mining	430	1035.54
Mosaic of Uses to Mining	2130	354.24
Pasture to Mining	1530	334.26
Other Temporary Crops to Mining	4130	140.67
Grassland to Mining	1230	64.62
Urban Area to Mining	2430	60.93
Other Non-Vegetated Areas to Mining	2530	51.57
River, Lake and Ocean to Mining	3330	32.31

Forest Formation to Mining	330	10.8
Rocky Outcrop to Mining	2930	2.88
Other Perennial Crops to Mining	4830	0.63
Savanna Formation to Rocky Outcrop	429	15226.74
Grassland to Rocky Outcrop	1229	4884.48
Mosaic of Uses to Rocky Outcrop	2129	1664.91
River, Lake and Ocean to Rocky Outcrop	3329	400.32
Pasture to Rocky Outcrop	1529	359.91
Forest Formation to Rocky Outcrop	329	231.93
Pasture to Other Non-Vegetated Areas	1525	243258.5
Mosaic of Uses to Other Non-Vegetated Areas	2125	95985.81
River, Lake and Ocean to Other Non-Vegetated Areas	3325	17656.38
Grassland to Other Non-Vegetated Areas	1225	16282.53
Savanna Formation to Other Non-Vegetated Areas	425	15850.8
Other Temporary Crops to Other Non-Vegetated Areas	4125	9993.78
Forest Formation to Other Non-Vegetated Areas	325	4985.64
Wooded Sandbank Vegetation to Other Non-Vegetated Areas	4925	1014.66
Other Perennial Crops to Other Non-Vegetated Areas	4825	226.71
Herbaceous Sandbank Vegetation to Other Non-Vegetated Areas	5025	73.08
Mangrove to Other Non-Vegetated Areas	525	29.61
Salt Flat to Other Non-Vegetated Areas	3225	22.77
Total		517651.85

Added to the 89,503 ha of mining, the estimated proxy area has grown to 517,651.85 ha, or 51,765 ha per year, which corresponds to 0.6% of Caatinga and 0.07% of the studied region. With the pixel values chosen, a table was constructed to reclassify all other pixel as null (0, 'nodata'), creating a reclass table containing only the selected transition values.

End of exploratory analysis

Reclassify rasters

Convert the reclassification table into a geodatabase table using “Excel to Table”

```
arcpy.conversion.ExcelToTable(

    Input_Excel_File=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Excel\reclass_table_all_transitions.xlsx",

    Output_Table=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_table",

    Sheet="Sheet1",

    field_names_row=1,

    cell_range=""

)
```

Reclassify Mapbiomas transition raster

[illegible]

Convert Mapbiomas transition raster into polygons

```

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2010",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2010", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2011",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2011", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2012",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2012", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2013",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2013", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2014",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2014", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2015",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2015", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2016",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2016", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2017",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2017", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2018",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2018", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2019",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2019", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

arcpy.conversion.RasterToPolygon(r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\reclass_caatinga_wgs_2020",
r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\polygon_reclass_caatinga_wgs_2020", "NO_SIMPLIFY", "Value",
"SINGLE_OUTER_PART", None)

```

Create layers for each kind of (proxy) mining exploration

I had to create an alternative file, encompassing all mining tenements, in order to filter only the explorations that happened inside legal tenements to avoid considering legitimate mining, illegal.

SPSS

*Get anm final dataset.

```

GET FILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_all.sav'.
SHOW N.
*N 913775.

```

*Drop >2020 cases.

```

SELECT IF year_process<2021.
EXECUTE.
show n.
*N 877010.

```

*Select cases that had an event or a valid title between 2010 and 2020.

```

SELECT IF event_title=1.

```

EXECUTE.

*Show number of Active cases.

show n.

*N 404648.

RENAME VARIABLES

IDSubstancia.1=subs

suse.1=suse.

*Categorize substances.

IF ANY(subs, 101300, 101301) subs=1.

IF ANY(subs, 706100,706107,706109,706108,706104,706103,706106) subs=2.

IF ANY(subs, 200200,701100,701202,200204,200201,200202,701205,200207,701201) subs=3.

IF ANY(subs, 104900,104901) subs=4.

IF ANY(subs, 711700,200800,711703,711708,711701,711705) subs=5.

IF ANY(subs, 702400,702401,702600,702402,200701,702404) subs=6.

IF ANY(subs, 100900,100901) subs=7.

IF ANY(subs, 102100,102101) subs=8.

IF ANY(subs, 701400,200300,701700,200302,200303,702201,701401,701703,701402,200301) subs=9.

IF ANY(subs, 300101) subs=10.

EXECUTE.

*Label substances names

VALUE LABELS

subs

1 'Iron'

2 'Granite'

3 'Sand'

4 'Gold'

5 'Quartzite'

6 'Limestone'

7 'Copper'

8 'Manganese'

9 'Clay'

10 'Phosphate'.

*drop unused variables.

DELETE VARIABLES subs_count IDTipoUsoSubstancia.1 IDSubstancia.2 to suse.23.

*Rename Variables bigger then 8 char.

RENAME VARIABLES

last_event=last_eve

event_count=event_ct

event_title=event_ti

dttitlect_all=dttitleca

titlect_all=titlecta

NMPessoa=name

fine_sum=afs_sum

fine_sum_2003=afs_2003

fine_sum_2004=afs_2004

fine_sum_2005=afs_2005

fine_sum_2006= afs_2006

fine_sum_2007= afs_2007
fine_sum_2008= afs_2008
fine_sum_2009= afs_2009
fine_sum_2010= afs_2010
fine_sum_2011= afs_2011
fine_sum_2012= afs_2012
fine_sum_2013= afs_2013
fine_sum_2014= afs_2014
fine_sum_2015= afs_2015
fine_sum_2016= afs_2016
fine_sum_2017= afs_2017
fine_sum_2018= afs_2018
fine_sum_2019= afs_2019
fine_sum_2020= afs_2020
fine_sum_2021= afs_2021
fine_sum_2022= afs_2022
auto_sum_2003= aa_2003
auto_sum_2004= aa_2004
auto_sum_2005= aa_2005
auto_sum_2006= aa_2006
auto_sum_2007= aa_2007
auto_sum_2008= aa_2008
auto_sum_2009= aa_2009
auto_sum_2010= aa_2010
auto_sum_2011= aa_2011
auto_sum_2012= aa_2012
auto_sum_2013= aa_2013
auto_sum_2014= aa_2014
auto_sum_2015= aa_2015
auto_sum_2016= aa_2016
auto_sum_2017= aa_2017
auto_sum_2018= aa_2018
auto_sum_2019= aa_2019
auto_sum_2020= aa_2020
auto_sum_2021= aa_2021
auto_sum_2022= aa_2022
ledays=ledsum
legal_2003= led_2003
legal_2004= led_2004
legal_2005= led_2005
legal_2006= led_2006
legal_2007= led_2007
legal_2008= led_2008
legal_2009= led_2009
legal_2010= led_2010
legal_2011= led_2011
legal_2012= led_2012
legal_2013= led_2013
legal_2014= led_2014
legal_2015= led_2015
legal_2016= led_2016
legal_2017= led_2017


```

legal_2018= led_2018
legal_2019= led_2019
legal_2020= led_2020
legal_2021= led_2021
legal_2022= led_2022
anm_f_key= anm_key
year_process= year_pro
cfem.2003= cfem2003
cfem.2004= cfem2004
cfem.2005= cfem2005
cfem.2006= cfem2006
cfem.2007= cfem2007
cfem.2008= cfem2008
cfem.2009= cfem2009
cfem.2010= cfem2010
cfem.2011= cfem2011
cfem.2012= cfem2012
cfem.2013= cfem2013
cfem.2014= cfem2014
cfem.2015= cfem2015
cfem.2016= cfem2016
cfem.2017= cfem2017
cfem.2018= cfem2018
cfem.2019= cfem2019
cfem.2020= cfem2020
cfem.2021= cfem2021
cfem.2022= cfem2022.

```

```

DO REPEAT
X=cfem2003 to tah.
FORMATS X(F14.2).
END REPEAT.
EXECUTE.

```

*Save Final ANM all dataset.

```

SAVE OUTFILE='E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Data\ANM\done\Final_ANM_all.sav'.

```

*The difference is that all mining tenements were chosen here.

Step 2. Add SPSS data to the ANM layer

Create specific gdb

```
arcpy.management.CreateFileGDB(
    out_folder_path=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS",
    out_name="mining_explorations",
    out_version="CURRENT"
)
```

Import SPSS Final ANM dataset to Mapbiomas geodatabase using r

```
# Load necessary libraries
library(arcgisbinding)
library(foreign) # for reading .sav files

# Initialize the ArcGIS R Bridge
arc.check_product()

# Set the paths for the input and output files
input_file_path <- "E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\Data\\ANM\\done\\Final_ANM_all.sav"
output_gdb_path <- "E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\mining_explorations.gdb"

# Read the .sav file into an R data frame
input_data <- read.spss(input_file_path, to.data.frame=TRUE)

# Convert the R data frame to an ArcGIS table and save it to the geodatabase
arc.write(
    path = paste0(output_gdb_path, "\\Final_ANM_all"),
    data = input_data
)
```

Create a layer with all mining tenements available

"ANM_all_available_mining_tenements_caatinga_municipalities_wgs"

```
arcpy.management.Merge(
    inputs=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Ativos_ANM_Nacional_caatinga_wgs";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Inativos_ANM_Nacional_caatinga_wgs",
    output=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\ANM_all_available_mining_tenements_caatinga_municipalities_wgs",
    field_mappings=r"process" true true false 12 Text 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Ativos_ANM_Nacional_caatinga_wgs,process,0,12,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Inativos_ANM_Nacional_caatinga_wgs,process,0,12,Shape_Length "Shape_Length" false true true 8 Double 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Ativos_ANM_Nacional_caatinga_wgs,Shape_Length,-1,-1,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Inativos_ANM_Nacional_caatinga_wgs,Shape_Length,-1,-1,Shape_Area "Shape_Area" false true true 8 Double 0 0,First,#,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Ativos_ANM_Nacional_caatinga_wgs,Shape_Area,-1,-1,E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\Inativos_ANM_Nacional_caatinga_wgs,Shape_Area,-1,-1,
    add_source="NO_SOURCE_INFO"
)
```

Perform a Join, adding the SPSS variables into the geospatial layer

```
arcpy.management.JoinField(
    in_data="ANM_all_available_mining_tenements_caatinga_municipalities_wgs",
    in_field="process",
    join_table="Final_ANM_all",
    join_field="process",
    fields=None,
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

Delete cases with missing data (n= 42,300), which are outside the scope of the research.

```
arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="ANM_all_available_mining_tenements_caatinga_municipalities_wgs",
    selection_type="NEW_SELECTION",
    where_clause="process_1 IS NULL",
    invert_where_clause=None
)
arcpy.management.DeleteRows(
    in_rows="ANM_all_available_mining_tenements_caatinga_municipalities_wgs"
)
```

Repair geometries

```
arcpy.management.RepairGeometry(
    in_features="ANM_all_available_mining_tenements_caatinga_municipalities_wgs",
    delete_null="DELETE_NULL",
    validation_method="ESRI"
)
```

Create layers of legal and illegal mining polygons per year

Create layers with polygons that had a legal title and are older than the year in reference

```
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", selection_type="NEW_SELECTION",
    where_clause="LED_2010<>0 AND YEAR_PRO<=2010")
arcpy.CopyFeatures_management(in_features="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2010", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", selection_type="NEW_SELECTION",
    where_clause="LED_2011<>0 AND YEAR_PRO<=2011")
arcpy.CopyFeatures_management(in_features="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2011", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", selection_type="NEW_SELECTION",
    where_clause="LED_2012<>0 AND YEAR_PRO<=2012")
arcpy.CopyFeatures_management(in_features="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2012", config_keyword="", spatial_grid_1="0", spatial_grid_2="0", spatial_grid_3="0")
arcpy.SelectLayerByAttribute_management(in_layer_or_view="ANM_all_available_mining_tenements_caatinga_municipalities_wgs", selection_type="NEW_SELECTION",
    where_clause="LED_2013<>0 AND YEAR_PRO<=2013")
```



```

arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2015",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2015",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2015", cluster_tolerance="")
arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2016",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2016",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2016", cluster_tolerance="")
arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2017",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2017",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2017", cluster_tolerance="")
arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2018",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2018",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2018", cluster_tolerance="")
arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2019",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2019",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2019", cluster_tolerance="")
arcpy.Erase_analysis(in_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_wgs_2020",
erase_features="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/legal_wgs_2020",
out_feature_class="E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/GIS/mining_explorations.gdb/no_title_diff_wgs_2020", cluster_tolerance="")

```

Reproject legal layers

```

import arcpy

# Define the base file paths
input_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\legal_wgs_"
output_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\legal_wgs_{}_rep"

# Define the coordinate systems
out_coor_system =
'GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]'
in_coor_system =
'GEOGCS["GCS_SIRGAS_2000",DATUM["D_SIRGAS_2000",SPHEROID["GRS_1980",6378137.0,298.257222101]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]'
VERTCS["WGS_1984_Geoid",VDATUM["WGS_1984_Geoid"],PARAMETER["Vertical_Shift",0.0],PARAMETER["Direction",1.0],UNIT["Meter",1.0]]

# Iterate through the years 2010 to 2020
for year in range(2010, 2021): # 2021 is exclusive, so it will iterate up to 2020
    # Format the input and output dataset paths
    in_dataset = f"{input_base_path}{year}"
    out_dataset = output_base_path.format(year)

    # Execute the Project function
    arcpy.management.Project(
        in_dataset=in_dataset,
        out_dataset=out_dataset,
        out_coor_system=out_coor_system,
        transform_method="SIRGAS_2000_To_WGS_1984_1",
        in_coor_system=in_coor_system,
        preserve_shape="NO_PRESERVE_SHAPE",
        max_deviation=None,
        vertical="NO_VERTICAL"
    )

```

Create legal exploration layer

#The selection of legal explorations was made clipping every (proxy) transition inside legal tenements.

```

import arcpy

# Base names for input, clip, and output feature classes
input_base_name = "polygon_reclass_caatinga_wgs_"
clip_base_name = "legal_wgs_{}_rep"
output_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\legal_exploration_wgs_{}"

# Iterate through the years 2010 to 2020
for year in range(2010, 2021): # 2021 is exclusive, so it will iterate up to 2020
    # Formulate the names for input, clip, and output feature classes for the current year
    in_features = f"{input_base_name}{year}"
    clip_features = clip_base_name.format(year)
    out_feature_class = output_base_path.format(year)

    # Execute the PairwiseClip function
    arcpy.analysis.PairwiseClip(
        in_features=in_features,
        clip_features=clip_features,
        out_feature_class=out_feature_class,
        cluster_tolerance=None
    )

```

Create Illegal exploration layer

Reproject

```

import arcpy

# Define the base file paths and coordinate systems
input_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\no_title_diff_wgs_"
output_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\no_title_diff_wgs_{}_rep"
out_coor_system =
'GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]]'

```

```
in_coor_system =
'GEOGCS["GCS_SIRGAS_2000",DATUM["D_SIRGAS_2000",SPHEROID["GRS_1980",6378137.0,298.257222101]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.017453292519943
3]],VERTCS["WGS_1984_Geoid",VDATUM["WGS_1984_Geoid"],PARAMETER["Vertical_Shift",0.0],PARAMETER["Direction",1.0],UNIT["Meter",1.0]]'
```

```
# Iterate through the years 2010 to 2020
for year in range(2010, 2021): # 2021 is exclusive, so it will iterate up to 2020
    # Format the input and output dataset paths
    in_dataset = f'{input_base_path}{year}'
    out_dataset = output_base_path.format(year)
```

```
# Execute the Project function
arcpy.management.Project(
    in_dataset=in_dataset,
    out_dataset=out_dataset,
    out_coor_system=out_coor_system,
    transform_method="SIRGAS_2000_To_WGS_1984_1",
    in_coor_system=in_coor_system,
    preserve_shape="NO_PRESERVE_SHAPE",
    max_deviation=None,
    vertical="NO_VERTICAL"
)
```

#The selection of Illegal explorations was made clipping every (proxy) transition inside no_title_diff mining tenements, polygons that had no title in that year and the part that overlapped a legal mining tenement was erased (=difference)

```
import arcpy
```

```
# Base names for input, clip, and output feature classes
input_base_name = "polygon_reclass_caatinga_wgs_"
clip_base_name = "no_title_diff_wgs_{}_rep"
output_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\illegal_exploration_wgs_{}"
```

```
# Iterate through the years 2010 to 2020
for year in range(2010, 2021): # 2021 is exclusive, so it will iterate up to 2020
    # Formulate the names for input, clip, and output feature classes for the current year
    in_features = f'{input_base_name}{year}'
    clip_features = clip_base_name.format(year)
    out_feature_class = output_base_path.format(year)
```

```
# Execute the PairwiseClip function
arcpy.analysis.PairwiseClip(
    in_features=in_features,
    clip_features=clip_features,
    out_feature_class=out_feature_class,
    cluster_tolerance=None
)
```

Create outside explorations

Outside transitions were selected clipping polygons that do not intersect with any mining polygon (legal or not).

```
import arcpy
```

```
# Base names for input and selection feature classes
input_base_name = "polygon_reclass_caatinga_wgs_"
legal_base_name = "legal_wgs_{}_rep"
no_title_base_name = "no_title_diff_wgs_{}_rep"
output_base_path = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\mining_explorations.gdb\outside_exploration_wgs_{}"
```

```
# Iterate through the years 2010 to 2020
for year in range(2010, 2021): # 2021 is exclusive, so it will iterate up to 2020
    # Formulate the names for input and selection feature classes for the current year
    in_layer = f'{input_base_name}{year}'
    select_features_legal = legal_base_name.format(year)
    select_features_no_title = no_title_base_name.format(year)
    out_feature_class = output_base_path.format(year)
```

```
# Execute the SelectLayerByLocation functions and CopyFeatures function
arcpy.management.SelectLayerByLocation(
    in_layer=in_layer,
    overlap_type="INTERSECT",
    select_features=select_features_legal,
    search_distance=None,
    selection_type="NEW_SELECTION",
    invert_spatial_relationship="INVERT"
)
arcpy.management.SelectLayerByLocation(
    in_layer=in_layer,
    overlap_type="INTERSECT",
    select_features=select_features_no_title,
    search_distance=None,
    selection_type="SUBSET_SELECTION",
    invert_spatial_relationship="INVERT"
)
arcpy.management.CopyFeatures(
    in_features=in_layer,
    out_feature_class=out_feature_class,
    config_keyword=""
)
```

```
    spatial_grid_1=None,  
    spatial_grid_2=None,  
    spatial_grid_3=None  
)
```

Step 3. Summarize MapBiomas data (mining exploration and urban area data)

Copy grid to mining explorations geodatabase:

Outside exploration

```
import arcpy
import os

# Define base_directory and geodatabase_name
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS"
geodatabase_name = "mining_explorations.gdb"

sum_features = "outside_exploration_wgs"

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_polygons = os.path.join(base_directory, geodatabase_name, "grid_net")
    input_sum_features = os.path.join(base_directory, geodatabase_name, f"{sum_features}_{year_str}")
    output_feature_class = os.path.join(base_directory, geodatabase_name, f"{sum_features}_grid_{year_str}")

    # Summarize within
    try:
        arcpy.analysis.SummarizeWithin(
            in_polygons=input_polygons,
            in_sum_features=input_sum_features,
            out_feature_class=output_feature_class,
            keep_all_polygons="KEEP_ALL",
            sum_fields=None,
            sum_shape="ADD_SHAPE_SUM",
            shape_unit="HECTARES",
            group_field=None,
            add_min_maj="NO_MIN_MAJ",
            add_group_percent="NO_PERCENT",
            out_group_table=None
        )
    except arcpy.ExecuteError as e:
        print(f"Error: {e}")
    except Exception as e:
        print(f"An error occurred: {e}")
```

Adjust metadata

```
# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_table = os.path.join(base_directory, geodatabase_name, f"{sum_features}_grid_{year_str}")
    new_field_name = f"out_{year_str}"

    # Alter field
    try:
        arcpy.management.AlterField(
            in_table=input_table,
            field="sum_Area_HECTARES",
            new_field_name=new_field_name,
            new_field_alias=f"Mining exploration outside polygons {year_str}",
            field_type="DOUBLE",
            field_length=8,
            field_is_nullable="NULLABLE",
            clear_field_alias="DO_NOT_CLEAR"
        )
    except arcpy.ExecuteError as e:
        print(f"Error: {e}")
    except Exception as e:
        print(f"An error occurred: {e}")
```

Join all layers to grid using OID as foreign key.

```
# Iterate from 2010 to 2020 for joining fields
for year in range(2010, 2021):
    year_str = str(year)
    input_data = "grid_net"
    in_field = "OID_1"
    join_table_name = "outside_exploration_wgs_grid"
    join_table = os.path.join(base_directory, geodatabase_name, f"{join_table_name}_{year_str}")
    join_field = "OID_1"
    fields = f"out_{year_str}"

    # Join field
    try:
        arcpy.management.JoinField(
            in_data=input_data,
            in_field=in_field,
            join_table=join_table,
            join_field=join_field,
            fields=fields,
            fm_option="NOT_USE_FM",
            field_mapping=None
        )
    except arcpy.ExecuteError as e:
```

```

    print(f"Error: {e}")
except Exception as e:
    print(f"An error occurred: {e}")

```

Legal exploration

```

import os
import arcpy

# Base directory and geodatabase name
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS"
geodatabase_name = "mining_explorations.gdb"

# Iterate through years 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)

    # Define the file paths
    summarized_layer = os.path.join(base_directory, geodatabase_name, f"legal_exploration_wgs_{year_str}")
    out_feature_class = os.path.join(base_directory, geodatabase_name, f"legal_exploration_wgs_grid_{year_str}")
    in_table = out_feature_class
    new_field_name = f"leg_{year_str}"
    join_table = out_feature_class

    # Summarize within
    arcpy.gapro.SummarizeWithin(
        summarized_layer=summarized_layer,
        out_feature_class=out_feature_class,
        polygon_or_bin="POLYGON",
        bin_type="",
        bin_size=None,
        summary_polygons="grid_net",
        sum_shape="ADD_SUMMARY",
        shape_units="HECTARES",
        standard_summary_fields=None,
        weighted_summary_fields=None,
        group_by_field=None,
        add_minority_majority="NO_MIN_MAJ",
        add_percentages=None,
        group_by_summary=None
    )

    # Adjust metadata
    arcpy.management.AlterField(
        in_table=in_table,
        field="sum_area_hectares",
        new_field_name=new_field_name,
        new_field_alias=f"Legal mining exploration {year_str}",
        field_type="DOUBLE",
        field_length=8,
        field_is_nullable="NON_NULLABLE",
        clear_field_alias="DO_NOT_CLEAR"
    )

    # Join all layers to grid using OID as foreign key
    arcpy.management.JoinField(
        in_data="grid_net",
        in_field="OID_1",
        join_table=join_table,
        join_field="OID_1",
        fields=new_field_name,
        fm_option="NOT_USE_FM",
        field_mapping=None
    )

```

No title exploration

```

import arcpy
import os

# Initialize the base directory and geodatabase name
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\\"
geodatabase_name = "thesis.gdb"

# Define the feature to be summarized
sum_features = "no_title_diff_exploration_wgs"

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_polygons = os.path.join(base_directory, geodatabase_name, "grid_net")
    input_sum_features = os.path.join(base_directory, geodatabase_name, f"{sum_features}_{year_str}")
    output_feature_class = os.path.join(base_directory, geodatabase_name, f"no_title_grid_{year_str}")

    # Summarize within
    arcpy.analysis.SummarizeWithin(
        in_polygons=input_polygons,
        in_sum_features=input_sum_features,
        out_feature_class=output_feature_class,
        keep_all_polygons="KEEP_ALL",

```



```

sum_fields=None,
sum_shape="ADD_SHAPE_SUM",
shape_unit="HECTARES",
group_field=None,
add_min_maj="NO_MIN_MAJ",
add_group_percent="NO_PERCENT",
out_group_table=None
)

# Adjust metadata
input_table = os.path.join(base_directory, geodatabase_name, f"no_title_grid_{year_str}")
new_field_name = f"no_title_{year_str}"

arcpy.management.AlterField(
    in_table=input_table,
    field="sum_Area_HECTARES",
    new_field_name=new_field_name,
    new_field_alias=f"No title mining exploration {year_str}",
    field_type="DOUBLE",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)

# Join all layers to grid using OID as foreign key
join_table_name = "no_title_grid"
input_data = "grid_net"
in_field = "OID_1"
join_table = os.path.join(base_directory, geodatabase_name, f"{join_table_name}_{year_str}")
join_field = "OID_1"
fields = f"no_title_{year_str}"

arcpy.management.JoinField(
    in_data=input_data,
    in_field=in_field,
    join_table=join_table,
    join_field=join_field,
    fields=fields,
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Urban area

Select and convert to polygon

```

import arcpy

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)

    # Modify the input and output names with the current year
    in_layer = "caatinga_" + year_str
    out_feature_class = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\urban_" + year_str

    # Execute the SelectLayerByAttribute tool
    arcpy.management.SelectLayerByAttribute(
        in_layer_or_view=in_layer,
        selection_type="NEW_SELECTION",
        where_clause="Value IN (2424, 1524, 2124, 2524, 4124, 424, 324, 1224, 2324, 4824, 3324, 4924, 3924, 2924, 2024, 3224, 3024, 24)",
        invert_where_clause=None
    )

    # Execute the RasterToPolygon tool
    arcpy.conversion.RasterToPolygon(
        in_raster=in_layer,
        out_polygon_features=out_feature_class,
        simplify="NO_SIMPLIFY",
        raster_field="Value",
        create_multipart_features="SINGLE_OUTER_PART",
        max_vertices_per_feature=None
    )

```

Summarize

```

import arcpy

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)

    # Modify the input and output names with the current year
    in_polygons = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net"
    in_sum_features = "urban_" + year_str
    out_feature_class = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\urban_grid_" + year_str

    # Execute the SummarizeWithin tool
    arcpy.analysis.SummarizeWithin(
        in_polygons=in_polygons,
        in_sum_features=in_sum_features,
        out_feature_class=out_feature_class,
        keep_all_polygons="KEEP_ALL",
        sum_fields=None,
        sum_shape="ADD_SHAPE_SUM",

```

```

shape_unit="HECTARES",
group_field=None,
add_min_maj="NO_MIN_MAJ",
add_group_percent="NO_PERCENT",
out_group_table=None
)

```

Adjust metadata

```

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_table = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\urban_grid_" + year_str
    new_field_name = f"urban_{year_str}"

    # Alter field
    arcpy.management.AlterField(
        in_table=input_table,
        field="sum_Area_HECTARES",
        new_field_name=new_field_name,
        new_field_alias=f"Urban area {year_str}",
        field_type="DOUBLE",
        field_length=8,
        field_is_nullable="NULLABLE",
        clear_field_alias="DO_NOT_CLEAR"
    )

```

Join all layers to grid using OID as foreign key.

```

# Iterate from 2010 to 2020
for year in range(2010, 2021):
    year_str = str(year)
    input_data = "grid_net"
    in_field = "OID_1"
    join_table = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\urban_grid_" + year_str
    join_field = "OID_1"
    fields = f"urban_{year_str}"

    # Join field
    arcpy.management.JoinField(
        in_data=input_data,
        in_field=in_field,
        join_table=join_table,
        join_field=join_field,
        fields=fields,
        fm_option="NOT_USE_FM",
        field_mapping=None
    )

```

Final dataset assembling step

Step 1. Convert dataset from wide to long format.

```

import os
import arcpy
import pandas as pd

# Set the base directory and geodatabase
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\"
geodatabase_name = "thesis.gdb"
data_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Data"

# Full path to the table
table_path = os.path.join(base_directory, geodatabase_name, "grid_final")

# List of fields to fetch from the table
fields = arcpy.ListFields(table_path)
field_names = [field.name for field in fields if field.type not in ["Geometry", "Blob", "OID"]]

# Convert the ArcGIS table to a NumPy array and then to a Pandas DataFrame
np_array = arcpy.da.TableToNumPyArray(table_path, field_names)
df = pd.DataFrame(np_array)

# Drop columns if they exist in DataFrame
columns_to_drop = ['OBJECTID', 'Shape_Length', 'Shape_Area']
df.drop([col for col in columns_to_drop if col in df.columns], axis=1, inplace=True)

# Define identifier variables that will remain constant in the long-form DataFrame
id_vars = ['OID_1', 'roads_km', 'gas', 'cprm_poi', 'Area_ha']

# Melt the DataFrame to long format
df_long = pd.melt(df, id_vars=id_vars, var_name='Variable', value_name='Value')

# Extract the year and variable type from the 'Variable' column
df_long['Year'] = df_long['Variable'].str.extract(r'\d{4}')
df_long['Variable'] = df_long['Variable'].str.extract(r'[a-zA-Z_]+')

# Pivot the table to rearrange it into the desired long format
df_long_pivot = df_long.pivot(index=['OID_1', 'Year'] + id_vars[1:], columns='Variable', values='Value').reset_index()

# Save the DataFrame to a new table inside the geodatabase

```

```
output_table_path = os.path.join(data_directory, "grid_final_long.csv")
df_long.pivot.to_csv(output_table_path, index=False)
```

Import the created long format final dataset table

```
arcpy.conversion.TableToTable(
    in_rows="grid_final_long.csv",
    out_path=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    out_name="grid_final_long",
    where_clause="",
    field_mapping="OID_1 \"OID_1\" true true false 4 Long 0 0,First,#,grid_final_long.csv,OID_1,-1,-1;Year \"Year\" true true false 4 Long 0 0,First,#,grid_final_long.csv,Year,-1,-1;roads_km \"roads_km\" true true false 8 Double 0 0,First,#,grid_final_long.csv,roads_km,-1,-1;gas \"gas\" true true false 4 Long 0 0,First,#,grid_final_long.csv,gas,-1,-1;cprm_poi \"cprm_poi\" true true false 4 Long 0 0,First,#,grid_final_long.csv,cprm_poi,-1,-1;Area_ha \"Area_ha\" true true false 8 Double 0 0,First,#,grid_final_long.csv,Area_ha,-1,-1;MRI \"MRI\" true true false 8 Double 0 0,First,#,grid_final_long.csv,MRI,-1,-1;RDAI \"RDAI\" true true false 8 Double 0 0,First,#,grid_final_long.csv,RDAI,-1,-1;area \"area\" true true false 8 Double 0 0,First,#,grid_final_long.csv,area,-1,-1;ibama \"ibama\" true true false 4 Long 0 0,First,#,grid_final_long.csv,ibama,-1,-1;leg \"leg\" true true false 8000 Text 0 0,First,#,grid_final_long.csv,leg,0,8000;mean_LED \"mean_LED\" true true false 8000 Text 0 0,First,#,grid_final_long.csv,mean_LED,0,8000;mining_r \"mining_r\" true true false 8 Double 0 0,First,#,grid_final_long.csv,mining_r,-1,-1;myp \"myp\" true true false 8 Double 0 0,First,#,grid_final_long.csv,myp,-1,-1;no_title \"no_title\" true true false 8000 Text 0 0,First,#,grid_final_long.csv,no_title,0,8000;out \"out\" true true false 8000 Text 0 0,First,#,grid_final_long.csv,out,0,8000;pct \"pct\" true true false 4 Long 0 0,First,#,grid_final_long.csv,pct,-1,-1;sum_AAU \"sum_AAU\" true true false 8 Double 0 0,First,#,grid_final_long.csv,sum_AAU,-1,-1;sum_AFS \"sum_AFS\" true true false 8 Double 0 0,First,#,grid_final_long.csv,sum_AFS,-1,-1;sum_CFEM \"sum_CFEM\" true true false 8 Double 0 0,First,#,grid_final_long.csv,sum_CFEM,-1,-1;urban \"urban\" true true false 8 Double 0 0,First,#,grid_final_long.csv,urban,-1,-1',
    config_keyword=""
)
```

Create grids for each year based on grid_net

```
import arcpy
import os

# Base directory and geodatabase
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis"
geodatabase_name = "thesis.gdb"

# Full path to the original feature class
original_feature_path = os.path.join(base_directory, geodatabase_name, "grid_net")

# Loop through the years 2010-2020
for year in range(2010, 2021):
    # Generate the name of the new feature class
    new_feature_name = f"grid_net_{year}"

    # Full path to the new feature class
    new_feature_path = os.path.join(base_directory, geodatabase_name, new_feature_name)

    # Check if the feature class already exists. If so, delete it.
    if arcpy.Exists(new_feature_path):
        arcpy.Delete_management(new_feature_path)

    # Copy the original feature class to create a new one
    arcpy.CopyFeatures_management(original_feature_path, new_feature_path)

    print(f"Created feature class for year {year}: {new_feature_name}")
```

Join fields from final dataset to the respective feature layer

```
import arcpy

# Define your workspace and feature class paths
workspace = "E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\"
feature_class_base = "grid_net_"

# Define your table and the range of years
table = "grid_final_long"
years = range(2010, 2021)

# Loop through each year
for year in years:
    # Create the feature class name for the specific year
    feature_class_year = f"{feature_class_base}{year}"

    # Create a SQL query to select records for the specific year
    sql_query = f"Year = {year}"

    # Select the records for the specific year
    arcpy.management.SelectLayerByAttribute(
        in_layer_or_view=table,
        selection_type="NEW_SELECTION",
        where_clause=sql_query
    )

    # Join the filtered table records to the feature class
    arcpy.management.JoinField(
        in_data=f"{workspace}{feature_class_year}",
        in_field="OID_1",
        join_table=table,
        join_field="OID_1"
    )

    print(f"Completed join for year {year}")
```

Merge all layers

```
arcpy.management.Merge(
```

```
inputs="grid_net_2020;grid_net_2019;grid_net_2018;grid_net_2017;grid_net_2016;grid_net_2015;grid_net_2014;grid_net_2013;grid_net_2012;grid_net_2011;grid_net_2010",
output=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_long",
field_mappings='OID_1 "OID" true true false 4 Long 0 0,First,#,grid_net_2020,OID_1,-1,-1,grid_net_2019,OID_1,-1,-1,grid_net_2018,OID_1,-1,-1,grid_net_2017,OID_1,-1,-1,grid_net_2016,OID_1,-1,-1,grid_net_2015,OID_1,-1,-1,grid_net_2014,OID_1,-1,-1,grid_net_2013,OID_1,-1,-1,grid_net_2012,OID_1,-1,-1,grid_net_2011,OID_1,-1,-1,grid_net_2010,OID_1,-1,-1;Shape_Length "Shape_Length" false true true 8 Double 0 0,First,#,grid_net_2020,Shape_Length,-1,-1,grid_net_2019,Shape_Length,-1,-1,grid_net_2018,Shape_Length,-1,-1,grid_net_2017,Shape_Length,-1,-1,grid_net_2016,Shape_Length,-1,-1,grid_net_2015,Shape_Length,-1,-1,grid_net_2014,Shape_Length,-1,-1,grid_net_2013,Shape_Length,-1,-1,grid_net_2012,Shape_Length,-1,-1,grid_net_2011,Shape_Length,-1,-1,grid_net_2010,Shape_Length,-1,-1;Shape_Area "Shape_Area" false true true 8 Double 0 0,First,#,grid_net_2020,Shape_Area,-1,-1,grid_net_2019,Shape_Area,-1,-1,grid_net_2018,Shape_Area,-1,-1,grid_net_2017,Shape_Area,-1,-1,grid_net_2016,Shape_Area,-1,-1,grid_net_2015,Shape_Area,-1,-1,grid_net_2014,Shape_Area,-1,-1,grid_net_2013,Shape_Area,-1,-1,grid_net_2012,Shape_Area,-1,-1,grid_net_2011,Shape_Area,-1,-1,grid_net_2010,Shape_Area,-1,-1;OID_12 "OID_1" true true false 4 Long 0 0,First,#,grid_net_2020,OID_12,-1,-1,grid_net_2019,OID_12,-1,-1,grid_net_2018,OID_12,-1,-1,grid_net_2017,OID_12,-1,-1,grid_net_2016,OID_12,-1,-1,grid_net_2015,OID_12,-1,-1,grid_net_2014,OID_12,-1,-1,grid_net_2013,OID_12,-1,-1,grid_net_2012,OID_12,-1,-1,grid_net_2011,OID_12,-1,-1,grid_net_2010,OID_12,-1,-1;Year "Year" true true false 4 Long 0 0,First,#,grid_net_2020,Year,-1,-1,grid_net_2019,Year,-1,-1,grid_net_2018,Year,-1,-1,grid_net_2017,Year,-1,-1,grid_net_2016,Year,-1,-1,grid_net_2015,Year,-1,-1,grid_net_2014,Year,-1,-1,grid_net_2013,Year,-1,-1,grid_net_2012,Year,-1,-1,grid_net_2011,Year,-1,-1,grid_net_2010,Year,-1,-1;mining_r "mining_r" true true false 8 Double 0 0,First,#,grid_net_2020,mining_r,-1,-1,grid_net_2019,mining_r,-1,-1,grid_net_2018,mining_r,-1,-1,grid_net_2017,mining_r,-1,-1,grid_net_2016,mining_r,-1,-1,grid_net_2015,mining_r,-1,-1,grid_net_2014,mining_r,-1,-1,grid_net_2013,mining_r,-1,-1,grid_net_2012,mining_r,-1,-1,grid_net_2011,mining_r,-1,-1,grid_net_2010,mining_r,-1,-1;ibama "ibama" true true false 4 Long 0 0,First,#,grid_net_2020,ibama,-1,-1,grid_net_2019,ibama,-1,-1,grid_net_2018,ibama,-1,-1,grid_net_2017,ibama,-1,-1,grid_net_2016,ibama,-1,-1,grid_net_2015,ibama,-1,-1,grid_net_2014,ibama,-1,-1,grid_net_2013,ibama,-1,-1,grid_net_2012,ibama,-1,-1,grid_net_2011,ibama,-1,-1,grid_net_2010,ibama,-1,-1;sum_AAU "sum_AAU" true true false 8 Double 0 0,First,#,grid_net_2020,sum_AAU,-1,-1,grid_net_2019,sum_AAU,-1,-1,grid_net_2018,sum_AAU,-1,-1,grid_net_2017,sum_AAU,-1,-1,grid_net_2016,sum_AAU,-1,-1,grid_net_2015,sum_AAU,-1,-1,grid_net_2014,sum_AAU,-1,-1,grid_net_2013,sum_AAU,-1,-1,grid_net_2012,sum_AAU,-1,-1,grid_net_2011,sum_AAU,-1,-1,grid_net_2010,sum_AAU,-1,-1;MRI "MRI" true true false 8 Double 0 0,First,#,grid_net_2020,MRI,-1,-1,grid_net_2019,MRI,-1,-1,grid_net_2018,MRI,-1,-1,grid_net_2017,MRI,-1,-1,grid_net_2016,MRI,-1,-1,grid_net_2015,MRI,-1,-1,grid_net_2014,MRI,-1,-1,grid_net_2013,MRI,-1,-1,grid_net_2012,MRI,-1,-1,grid_net_2011,MRI,-1,-1,grid_net_2010,MRI,-1,-1;roads_km "roads_km" true true false 8 Double 0 0,First,#,grid_net_2020,roads_km,-1,-1,grid_net_2019,roads_km,-1,-1,grid_net_2018,roads_km,-1,-1,grid_net_2017,roads_km,-1,-1,grid_net_2016,roads_km,-1,-1,grid_net_2015,roads_km,-1,-1,grid_net_2014,roads_km,-1,-1,grid_net_2013,roads_km,-1,-1,grid_net_2012,roads_km,-1,-1,grid_net_2011,roads_km,-1,-1,grid_net_2010,roads_km,-1,-1;gas "gas" true true false 4 Long 0 0,First,#,grid_net_2020,gas,-1,-1,grid_net_2019,gas,-1,-1,grid_net_2018,gas,-1,-1,grid_net_2017,gas,-1,-1,grid_net_2016,gas,-1,-1,grid_net_2015,gas,-1,-1,grid_net_2014,gas,-1,-1,grid_net_2013,gas,-1,-1,grid_net_2012,gas,-1,-1,grid_net_2011,gas,-1,-1,grid_net_2010,gas,-1,-1;cprm_poi "cprm_poi" true true false 4 Long 0 0,First,#,grid_net_2020,cprm_poi,-1,-1,grid_net_2019,cprm_poi,-1,-1,grid_net_2018,cprm_poi,-1,-1,grid_net_2017,cprm_poi,-1,-1,grid_net_2016,cprm_poi,-1,-1,grid_net_2015,cprm_poi,-1,-1,grid_net_2014,cprm_poi,-1,-1,grid_net_2013,cprm_poi,-1,-1,grid_net_2012,cprm_poi,-1,-1,grid_net_2011,cprm_poi,-1,-1,grid_net_2010,cprm_poi,-1,-1;urban "urban" true true false 8 Double 0 0,First,#,grid_net_2020,urban,-1,-1,grid_net_2019,urban,-1,-1,grid_net_2018,urban,-1,-1,grid_net_2017,urban,-1,-1,grid_net_2016,urban,-1,-1,grid_net_2015,urban,-1,-1,grid_net_2014,urban,-1,-1,grid_net_2013,urban,-1,-1,grid_net_2012,urban,-1,-1,grid_net_2011,urban,-1,-1,grid_net_2010,urban,-1,-1;RDAI "RDAI" true true false 8 Double 0 0,First,#,grid_net_2020,RDAI,-1,-1,grid_net_2019,RDAI,-1,-1,grid_net_2018,RDAI,-1,-1,grid_net_2017,RDAI,-1,-1,grid_net_2016,RDAI,-1,-1,grid_net_2015,RDAI,-1,-1,grid_net_2014,RDAI,-1,-1,grid_net_2013,RDAI,-1,-1,grid_net_2012,RDAI,-1,-1,grid_net_2011,RDAI,-1,-1,grid_net_2010,RDAI,-1,-1;Area_ha "Area_ha" true true false 8 Double 0 0,First,#,grid_net_2020,Area_ha,-1,-1,grid_net_2019,Area_ha,-1,-1,grid_net_2018,Area_ha,-1,-1,grid_net_2017,Area_ha,-1,-1,grid_net_2016,Area_ha,-1,-1,grid_net_2015,Area_ha,-1,-1,grid_net_2014,Area_ha,-1,-1,grid_net_2013,Area_ha,-1,-1,grid_net_2012,Area_ha,-1,-1,grid_net_2011,Area_ha,-1,-1,grid_net_2010,Area_ha,-1,-1;area "area" true true false 8 Double 0 0,First,#,grid_net_2020,area,-1,-1,grid_net_2019,area,-1,-1,grid_net_2018,area,-1,-1,grid_net_2017,area,-1,-1,grid_net_2016,area,-1,-1,grid_net_2015,area,-1,-1,grid_net_2014,area,-1,-1,grid_net_2013,area,-1,-1,grid_net_2012,area,-1,-1,grid_net_2011,area,-1,-1,grid_net_2010,area,-1,-1;pct "pct" true true false 4 Long 0 0,First,#,grid_net_2020,pct,-1,-1,grid_net_2019,pct,-1,-1,grid_net_2018,pct,-1,-1,grid_net_2017,pct,-1,-1,grid_net_2016,pct,-1,-1,grid_net_2015,pct,-1,-1,grid_net_2014,pct,-1,-1,grid_net_2013,pct,-1,-1,grid_net_2012,pct,-1,-1,grid_net_2011,pct,-1,-1,grid_net_2010,pct,-1,-1;out "out" true true false 8000 Text 0 0,First,#,grid_net_2020,out,0,8000,grid_net_2019,out,0,8000,grid_net_2018,out,0,8000,grid_net_2017,out,0,8000,grid_net_2016,out,0,8000,grid_net_2015,out,0,8000,grid_net_2014,out,0,8000,grid_net_2013,out,0,8000,grid_net_2012,out,0,8000,grid_net_2011,out,0,8000,grid_net_2010,out,0,8000;no_title "no_title" true true false 8000 Text 0 0,First,#,grid_net_2020,no_title,0,8000,grid_net_2019,no_title,0,8000,grid_net_2018,no_title,0,8000,grid_net_2017,no_title,0,8000,grid_net_2016,no_title,0,8000,grid_net_2015,no_title,0,8000,grid_net_2014,no_title,0,8000,grid_net_2013,no_title,0,8000,grid_net_2012,no_title,0,8000,grid_net_2011,no_title,0,8000,grid_net_2010,no_title,0,8000;leg "leg" true true false 8000 Text 0 0,First,#,grid_net_2020,leg,0,8000,grid_net_2019,leg,0,8000,grid_net_2018,leg,0,8000,grid_net_2017,leg,0,8000,grid_net_2016,leg,0,8000,grid_net_2015,leg,0,8000,grid_net_2014,leg,0,8000,grid_net_2013,leg,0,8000,grid_net_2012,leg,0,8000,grid_net_2011,leg,0,8000,grid_net_2010,leg,0,8000;mean_LED "mean_LED" true true false 8000 Text 0 0,First,#,grid_net_2020,mean_LED,0,8000,grid_net_2019,mean_LED,0,8000,grid_net_2018,mean_LED,0,8000,grid_net_2017,mean_LED,0,8000,grid_net_2016,mean_LED,0,8000,grid_net_2015,mean_LED,0,8000,grid_net_2014,mean_LED,0,8000,grid_net_2013,mean_LED,0,8000,grid_net_2012,mean_LED,0,8000,grid_net_2011,mean_LED,0,8000,grid_net_2010,mean_LED,0,8000;myp "myp" true true false 8 Double 0 0,First,#,grid_net_2020,myp,-1,-1,grid_net_2019,myp,-1,-1,grid_net_2018,myp,-1,-1,grid_net_2017,myp,-1,-1,grid_net_2016,myp,-1,-1,grid_net_2015,myp,-1,-1,grid_net_2014,myp,-1,-1,grid_net_2013,myp,-1,-1,grid_net_2012,myp,-1,-1,grid_net_2011,myp,-1,-1,grid_net_2010,myp,-1,-1;sum_CFEM "sum_CFEM" true true false 8 Double 0 0,First,#,grid_net_2020,sum_CFEM,-1,-1,grid_net_2019,sum_CFEM,-1,-1,grid_net_2018,sum_CFEM,-1,-1,grid_net_2017,sum_CFEM,-1,-1,grid_net_2016,sum_CFEM,-1,-1,grid_net_2015,sum_CFEM,-1,-1,grid_net_2014,sum_CFEM,-1,-1,grid_net_2013,sum_CFEM,-1,-1,grid_net_2012,sum_CFEM,-1,-1,grid_net_2011,sum_CFEM,-1,-1,grid_net_2010,sum_CFEM,-1,-1',
add_source="NO_SOURCE_INFO"
)
```

Adjust metadata

```
import arcpy
import os

# Base directory and geodatabase
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis"
geodatabase_name = "thesis.gdb"

# Full path to the table
table_path = os.path.join(base_directory, geodatabase_name, "grid_final_long")

# Alias mapping
alias_mapping = {
    'OID_1': 'Cell ID',
    'Year': 'Year',
    'mining_r': 'Police investigations',
    'ibama': 'Environmental fines',
    'sum_AAU': 'Mining administrative infractions',
    'sum_AFS': 'Mining fines',
    'MRI': 'Illegal income',
    'roads_km': 'Roads length',
    'gas': 'Gas stations',
    'cprm_poi': 'Geological Service of Brazil - CPRM Points of Interest',
    'urban': 'Urban area',
    'RDAI': 'Legal income',
    'area': 'Mining tenement area',
    'pct': 'Mining tenement count',
    'out': 'Mining exploration outside polygons',
    'no_title': 'Illegal mining exploration',
    'leg': 'Legal mining exploration',
}
```

```

'mean_LED': 'Mining legal days average',
'myp': 'Mining process start average',
'sum_CFEM': 'Mining tax',
'OBJECTID': 'ArcGIS object ID',
'Shape': 'ArcGIS object type',
'Shape_Length': 'ArcGIS shape length',
'Shape_Area': 'ArcGIS shape area',
'Area_ha': 'Cell area'
}

# List all fields in the table
fields = arcpy.ListFields(table_path)

# Loop through each field to set the alias
for field in fields:
    field_name = field.name
    if field_name in alias_mapping:
        arcpy.AlterField_management(
            in_table=table_path,
            field=field_name,
            new_field_alias=alias_mapping[field_name]
        )
    print(f"Updated alias for {field_name} to {alias_mapping[field_name]}")

print("Field aliases for grid_final_long updated successfully.")

```

Aggregate all data to analyze

```

import os
import arcpy

# Define the base directory, geodatabase, and table
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis"
geodatabase_name = "thesis.gdb"
table_path = os.path.join(base_directory, geodatabase_name, "grid_final_long")

# Define the output table where the aggregated data will be stored
output_table_path = os.path.join(base_directory, geodatabase_name, "aggregated_data")

# List of fields to aggregate
fields_to_aggregate = [
    "mining_r", "ibama", "sum_AAU", "sum_AFS", "MRI", "roads_km",
    "gas", "cprm_poi", "urban", "RDAI", "area", "pct", "out",
    "no_title", "leg", "mean_LED", "myp", "sum_CFEM"
]

# Create a list of field-statistic tuples for aggregation
field_statistic_pairs = [(field, "MEAN") for field in fields_to_aggregate]

# Execute the Summary Statistics tool with OID_1 as the case field
arcpy.Statistics_analysis(
    in_table=table_path,
    out_table=output_table_path,
    statistics_fields=field_statistic_pairs,
    case_field="OID_1"
)

print(f"Aggregation complete. Output table stored at {output_table_path}")

```

Join fields from final dataset to the respective feature layer

```

#Duplicate main grid
arcpy.management.CopyFeatures(
    in_features="grid_net",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated",
    config_keyword="",
    spatial_grid_1=None,
    spatial_grid_2=None,
    spatial_grid_3=None
)

#join fields
arcpy.management.JoinField(
    in_data="grid_final_aggregated",
    in_field="OID_1",
    join_table="grid_final_aggregated_data",
    join_field="OID_1",
    fields=None,
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Perform adjustments

Delete cells with no mining tenements

```

arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="grid_final_aggregated",
    selection_type="NEW_SELECTION",
    where_clause="MEAN_area = 0",
    invert_where_clause=None
)

arcpy.management.DeleteRows(
    in_rows="grid_final_aggregated"
)

```


Appendix I Analysis Work Flow

Transform data to natural logarithm

Create new feature layer

```
arcpy.management.CopyFeatures(
    in_features="grid_final_aggregated",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In",
    config_keyword="",
    spatial_grid_1=None,
    spatial_grid_2=None,
    spatial_grid_3=None
)
```

Reproject to Lambert

```
arcpy.management.Project(
    in_dataset="grid_final_aggregated_In",
    out_dataset=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",

    out_coor_system='PROJCS["South_America_Lambert_Conformal_Conic",GEOGCS["GCS_South_American_1969",DATUM["D_South_American_1969",SPHEROID["GRS_1967_Truncated",6378160.0,298.25]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]],PROJECTION["Lambert_Conformal_Conic"],PARAMETER["False_Easting",0.0],PARAMETER["False_Northing",0.0],PARAMETER["Central_Meridian",-60.0],PARAMETER["Standard_Parallel_1",-5.0],PARAMETER["Standard_Parallel_2",-42.0],PARAMETER["Latitude_Of_Origin",-32.0],UNIT["Meter",1.0]],transform_method="SAD_1969_To_WGS_1984_15",

    in_coor_system='GEOGCS["GCS_WGS_1984",DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenwich",0.0],UNIT["Degree",0.0174532925199433]],preserve_shape="NO_PRESERVE_SHAPE",max_deviation=None,vertical="NO_VERTICAL"
)
```

Perform the transformation to LN

```
# Define the path to the geodatabase and the output table where the new fields will be added
base_directory = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis"
geodatabase_name = "thesis.gdb"
output_table_path = os.path.join(base_directory, geodatabase_name, "grid_final_aggregated_In_lambert")

# Fields to transform
fields_to_transform = [
    'MEAN_mining_r', 'MEAN_ibama', 'MEAN_sum_AAU', 'MEAN_sum_AFS', 'MEAN_RDAI', 'MEAN_MRI', 'MEAN_roads_km',
    'MEAN_gas', 'MEAN_cprm_poi', 'MEAN_urban', 'MEAN_area', 'MEAN_pct', 'MEAN_out',
    'MEAN_no_title', 'MEAN_leg', 'MEAN_mean_LED', 'MEAN_myp', 'MEAN_sum_CFEI'
]
```

Add a constant (1) with conditional for zeros and negatives

```
for field in fields_to_transform:
    new_field = "m4ln_" + field
    arcpy.AddField_management(output_table_path, new_field, "DOUBLE")
    arcpy.CalculateField_management(
        in_table=output_table_path,
        field=new_field,
        expression="math.log(!{}! + 1) if !{}! > 0 else -math.log(abs(!{}!) + 1) if !{}! < 0 else 0".format(field, field, field, field),
        expression_type="PYTHON3",
        code_block="import math"
    )
```

Create spatial matrices to test the spatial correlation

Create using fixed distance 25km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\shape_long\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25.swm",
    Conceptualization_of_Spatial_Relationships="FIXED_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=25000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
json:
{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,36"}, {"Average Number of Neighbors", "121,47"}, {"Minimum Number of Neighbors", "8"}, {"Maximum Number of Neighbors", "211"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}}
json:
{"element": "content", "data": "Distance measured in Meters"}
```

Succeeded at sexta-feira, 20 de outubro de 2023 08:48:55 (Elapsed Time: 15,82 seconds)

Create using fixed distance 50km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50.swm",
    Conceptualization_of_Spatial_Relationships="FIXED_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "1,27"}, {"Average Number of Neighbors", "432,13"}, {"Minimum
Number of Neighbors", "14"}, {"Maximum Number of Neighbors", "776"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary",
"0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
json:
{"element": "content", "data": "Distance measured in Meters"}
Succeeded at sexta-feira, 20 de outubro de 2023 09:04:31 (Elapsed Time: 18,98 seconds)
```

Create using fixed distance 75km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis75.swm",
    Conceptualization_of_Spatial_Relationships="FIXED_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=75000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the
potential of running out of memory.
WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 21996, 21997, 21998, 21999, 22000, 22001, 22002, 22316,
22317, 22318, 22319, 22320, 22321, 22322, 22323, 22324, 22325, 22326, 22636, 22637, 22638, 22641, 22642, 22643, 22644, 22645, 22646, 22647, 22648, 22649.
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "2,64"}, {"Average Number of Neighbors", "899,00"}, {"Minimum
Number of Neighbors", "38"}, {"Maximum Number of Neighbors", "1627"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary",
"0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
json:
{"element": "content", "data": "Distance measured in Meters"}
WARNING 001014: Spatial weights matrices containing over 20 million non-zero links may require a large amount of memory to use.
Succeeded at sexta-feira, 20 de outubro de 2023 09:21:43 (Elapsed Time: 26,16 seconds)
```

Create using fixed distance 100km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis100.swm",
    Conceptualization_of_Spatial_Relationships="FIXED_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=100000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
```


WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the potential of running out of memory.

WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 18458, 18459, 18774, 18775, 18776, 18777, 18778, 18779, 18780, 18781, 18782, 19093, 19096, 19097, 19098, 19099, 19100, 19101, 19102, 19103, 19104, 19105, 19106, 19414, 19415, 19420, 19421, 19422, 19426, 19427.

```
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "4,41"}, {"Average Number of Neighbors", "1498,29"}, {"Minimum Number of Neighbors", "62"}, {"Maximum Number of Neighbors", "2575"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
json:
{"element": "content", "data": "Distance measured in Meters"}
WARNING 001014: Spatial weights matrices containing over 20 million non-zero links may require a large amount of memory to use.
Succeeded at sexta-feira, 20 de outubro de 2023 09:19:26 (Elapsed Time: 33,70 seconds)
```

Create using inverse distance 25km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25.swm",
    Conceptualization_of_Spatial_Relationships="INVERSE_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=25000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

Generate Spatial Weights Matrix

=====

Parameters

```
Input Feature Class    E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert
Unique ID Field      OID_1
Output Spatial Weights Matrix File  E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25.swm
Conceptualization of Spatial Relationships  INVERSE_DISTANCE
Distance Method      EUCLIDEAN
Exponent            1
Threshold Distance   25000
Number of Neighbors    8
Row Standardization  ROW_STANDARDIZATION
Input Table
Date/Time Field
Date/Time Interval Type
Date/Time Interval Value
Use Z values
=====
```

Messages

Start Time: sexta-feira, 20 de outubro de 2023 09:29:16

json:

```
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
```

json:

```
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,36"}, {"Average Number of Neighbors", "121,47"}, {"Minimum Number of Neighbors", "8"}, {"Maximum Number of Neighbors", "211"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
```

json:

```
{"element": "content", "data": "Distance measured in Meters"}
```

Succeeded at sexta-feira, 20 de outubro de 2023 09:29:35 (Elapsed Time: 18,61 seconds)

Create using inverse distance 50km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50.swm",
    Conceptualization_of_Spatial_Relationships="INVERSE_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

json:

```
{"element": "content", "data": "Constructing spatial weights based on distance criteria...."}
```

json:

```
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "1,27"}, {"Average Number of Neighbors", "432,13"}, {"Minimum Number of Neighbors", "14"}, {"Maximum Number of Neighbors", "776"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
```

json:

```
{"element": "content", "data": "Distance measured in Meters"}
```

Succeeded at sexta-feira, 20 de outubro de 2023 09:28:28 (Elapsed Time: 23,04 seconds)

Create using inverse distance 75km (min 8 neighbors)

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis75.swm",
    Conceptualization_of_Spatial_Relationships="INVERSE_DISTANCE",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=75000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on distance criteria..."}
WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the
potential of running out of memory.
WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 21996, 21997, 21998, 21999, 22000, 22001, 22002, 22316,
22317, 22318, 22319, 22320, 22321, 22322, 22323, 22324, 22325, 22326, 22636, 22637, 22638, 22641, 22642, 22643, 22644, 22645, 22646, 22647, 22648, 22649.
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "2,64"}, {"Average Number of Neighbors", "899,00"}, {"Minimum
Number of Neighbors", "38"}, {"Maximum Number of Neighbors", "1627"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary",
"0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
json:
{"element": "content", "data": "Distance measured in Meters"}
WARNING 001014: Spatial weights matrices containing over 20 million non-zero links may require a large amount of memory to use.
Succeeded at sexta-feira, 20 de outubro de 2023 09:26:29 (Elapsed Time: 36,94 seconds)
```

Create using k-nearest 8 neighbors

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8.swm",
    Conceptualization_of_Spatial_Relationships="K_NEAREST_NEIGHBORS",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=8,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on k-nearest neighbors...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,02"}, {"Average Number of Neighbors", "8,00"}, {"Minimum Number
of Neighbors", "8"}, {"Maximum Number of Neighbors", "8"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align":
"left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
Succeeded at sexta-feira, 20 de outubro de 2023 09:07:06 (Elapsed Time: 11,31 seconds)
```

Create using k-nearest 16 neighbors

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16.swm",
    Conceptualization_of_Spatial_Relationships="K_NEAREST_NEIGHBORS",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=16,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on k-nearest neighbors...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,05"}, {"Average Number of Neighbors", "16,00"}, {"Minimum Number
of Neighbors", "16"}, {"Maximum Number of Neighbors", "16"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align":
"left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
Succeeded at sexta-feira, 20 de outubro de 2023 09:13:52 (Elapsed Time: 11,63 seconds)
```

Create using k-nearest 50 neighbors

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50.swm",
    Conceptualization_of_Spatial_Relationships="K_NEAREST_NEIGHBORS",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=50,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on k-nearest neighbors...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,15"}, {"Average Number of Neighbors", "50,00"}, {"Minimum Number of Neighbors", "50"}, {"Maximum Number of Neighbors", "50"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
Succeeded at sexta-feira, 20 de outubro de 2023 09:16:53 (Elapsed Time: 12,09 seconds)
```

Create using k-nearest 250 neighbors

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250.swm",
    Conceptualization_of_Spatial_Relationships="K_NEAREST_NEIGHBORS",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=250,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on k-nearest neighbors...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "0,74"}, {"Average Number of Neighbors", "250,00"}, {"Minimum Number of Neighbors", "250"}, {"Maximum Number of Neighbors", "250"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
Succeeded at sexta-feira, 20 de outubro de 2023 09:34:16 (Elapsed Time: 17,52 seconds)
```

Create using k-nearest 500 neighbors

```
arcpy.stats.GenerateSpatialWeightsMatrix(
    Input_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_final_aggregated_In_lambert",
    Unique_ID_Field="OID_1",
    Output_Spatial_Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest500.swm",
    Conceptualization_of_Spatial_Relationships="K_NEAREST_NEIGHBORS",
    Distance_Method="EUCLIDEAN",
    Exponent=1,
    Threshold_Distance=50000,
    Number_of_Neighbors=500,
    Row_Standardization="ROW_STANDARDIZATION",
    Input_Table=None,
    Date_Time_Field=None,
    Date_Time_Interval_Type="",
    Date_Time_Interval_Value=None,
    Use_Z_values=None
)
```

Results

```
json:
{"element": "content", "data": "Constructing spatial weights based on k-nearest neighbors...."}
json:
[{"element": "table", "data": [{"Number of Features", "33990"}, {"Percentage of Spatial Connectivity", "1,47"}, {"Average Number of Neighbors", "500,00"}, {"Minimum Number of Neighbors", "500"}, {"Maximum Number of Neighbors", "500"}], "elementProps": {"striped": "true", "noHeader": true, "title": "Spatial Weights Matrix Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px", "wrap": true}}}]
Succeeded at sexta-feira, 20 de outubro de 2023 09:36:55 (Elapsed Time: 19,83 seconds)
```

Create alternative variables.

The expected manifestation of collinearity within the assembled dataset demanded a systematic approach aimed at its prevention. In response, new geospatial variables were introduced, each reflective of the area of mining tenements in various

dimensions. The engineering of these variables was designed to encapsulate the area-weighted attributes related to both unauthorized and legitimate mining operations, as well as other land uses, thereby trying to address the detected collinearity among pre-existing variables.

Relative Area of Unauthorized Mining (r_no_title):

This variable was generated through the division of no_title by area.

```
arcpy.management.CalculateField(
    in_table="grid_final_aggregated_In_lambert",
    field="r_no_title",
    expression="!no_title_mean! / !anm_mean_area!",
    expression_type="PYTHON3",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Relative Area of Legitimate Mining (r_leg):

Analogous to r_no_title, this variable was derived through the division of leg by area.

```
arcpy.management.CalculateField(
    in_table="grid_final_aggregated_In_lambert",
    field="r_leg",
    expression="!leg_mean! / !anm_mean_area!",
    expression_type="PYTHON3",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Relative Area for transitions outside mining tenements (r_out):

This variable was calculated by dividing mean_out by the discrepancy between the total cell area and the area demarcated for mining tenements. First the shape_area was converted to hectare, then diminished by the mining tenements area. The area of the soil transition outside mining was then divided by the result.

Calculate cell area in ha

```
arcpy.management.CalculateGeometryAttributes(
    in_features="grid_final_aggregated_In_lambert",
    geometry_property="cell_area_ha AREA_GEODESIC",
    length_unit="",
    area_unit="HECTARES",
    coordinate_system=None,
    coordinate_format="SAME_AS_INPUT"
)
```

Calculate relative outside

```
arcpy.management.CalculateField(
    in_table="grid_final_aggregated_In_lambert",
    field="r_out",
    expression="!MEAN_out! / (!cell_area_ha!-!MEAN_area!)",
    expression_type="PYTHON3",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Sum ANM Fines: Accumulate or sum the fines imposed by the National Mining Agency (ANM).

```
arcpy.management.CalculateField(
    in_table="grid_final_aggregated_In_lambert",
    field="anm_fines",
    expression="!MEAN_sum_AFS!+!MEAN_sum_AAU!",
    expression_type="PYTHON3",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Import other PF Variables: add other variables related to the Federal Police (PF).

```
import arcpy

# Specify the table name
table_name = "PF_agg_grid_net_TabulateIntersection"

# List of variable sets for which the sum and mean need to be calculated
```

```

var_sets = [
    'd_arrest_', 'd_author_', 'd_crime_', 'd_prosec_',
    'n_arre_f_', 'n_arre_w_', 'n_arrest_', 'n_crimin_',
    'n_indict_', 'n_search_', 'p_durati_', 'value_ca_',
    'value_es_', 'cul_her_r_', 'env_adm_r_', 'fauna_r_',
    'fishing_r_', 'flora_r_', 'generic_r_', 'health_r_',
    'his_her_r_', 'land_r_', 'mining_r_', 'pollution_r_',
    'related_'
]

# Loop through each variable set
for var_set in var_sets:
    # Create the new field names for the sum and mean
    sum_field = f"sum_{var_set[:-1]}"
    mean_field = f"mean_{var_set[:-1]}"

    # Generate the expression to calculate the sum for the variables from 2010 to 2020
    years = [str(year) for year in range(2010, 2021)]
    sum_expression = "Sum(" + ', '.join([f"$feature.{var_set}{year}" for year in years]) + ")"

    # Generate the expression to calculate the mean for the variables from 2010 to 2020
    mean_expression = "Average(" + ', '.join([f"$feature.{var_set}{year}" for year in years]) + ")"

    # Calculate the sum and store it in the new field
    arcpy.management.CalculateField(
        in_table=table_name,
        field=sum_field,
        expression=sum_expression,
        expression_type="ARCADE",
        code_block="",
        field_type="FLOAT",
        enforce_domains="NO_ENFORCE_DOMAINS"
    )

    # Calculate the mean and store it in the new field
    arcpy.management.CalculateField(
        in_table=table_name,
        field=mean_field,
        expression=mean_expression,
        expression_type="ARCADE",
        code_block="",
        field_type="FLOAT",
        enforce_domains="NO_ENFORCE_DOMAINS"
    )

    Join new fields
    arcpy.management.JoinField(
        in_data=f"E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\grid_final_aggregated_In_lambert",
        in_field="OID_1",
        join_table=f"E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\PF_agg_grid_net_TabulateIntersection",
        join_field="OID_1",

        fields="mean_d_arrest;mean_d_author;mean_d_crime;mean_d_prosec;mean_n_arre_f;mean_n_arre_w;mean_n_arrest;mean_n_crimin;mean_n_indict;mean_n_search;me
an_p_durati;mean_value_ca;mean_value_es;mean_cul_her_r;mean_env_adm_r;mean_fauna_r;mean_fishing_r;mean_flora_r;mean_generic_r;mean_health_r;mean_his_he
r_r;mean_land_r;mean_pollution_r;mean_related;sum_d_arrest;sum_d_author;sum_d_crime;sum_d_prosec;sum_n_arre_f;sum_n_arre_w;sum_n_arrest;sum_n_crimin;su
m_n_indict;sum_n_search;sum_p_durati;sum_value_ca;sum_value_es;sum_cul_her_r;sum_env_adm_r;sum_fauna_r;sum_fishing_r;sum_flora_r;sum_generic_r;sum_health
_r;sum_his_her_r;sum_land_r;sum_mining_r;sum_pollution_r;sum_related",
        fm_option="NOT_USE_FM",
        field_mapping=None
    )
    Create a dummy to check if any environmental police investigation had an effect on no_title:

```

Import IBAMA fines variables

Incorporate or bring in additional variables from the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA).

Download IBAMA dataset from

http://siscom.ibama.gov.br/shpsiscom/adm_auto_infracao_p.zip and import.

```

arcpy.conversion.TableToGeodatabase(
    Input_Table=f"E:\\OneDrive\\data\\IBAMA\\auto_infracao.csv",
    Output_Geodatabase=f"E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\scratch.gdb"
)

```

Select points inside the area and between the studied period

```

arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="adm_auto_infracao_p",
    selection_type="NEW_SELECTION",
    where_clause="dat_hora_a >= timestamp '2010-01-01' And dat_hora_a <= timestamp '2020-12-31'",
    invert_where_clause=None
)

arcpy.management.SelectLayerByLocation(
    in_layer="adm_auto_infracao_p",
    overlap_type="INTERSECT",
    select_features="grid_final_aggregated_In_lambert",
    search_distance=None,
    selection_type="SUBSET_SELECTION",
    invert_spatial_relationship="NOT_INVERT"
)

```

Create new feature with selected cases

```
arcpy.management.CopyFeatures(
    in_features="adm_auto_infracao_p",
    out_feature_class="E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\ibama_adm_auto_infracao_p_2010_2020_inside_grid_net",
    config_keyword="",
    spatial_grid_1=None,
    spatial_grid_2=None,
    spatial_grid_3=None
)
```

Delete cancelled fines (n=342)

```
arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="ibama_adm_auto_infracao_p_2010_2020_inside_grid_net",
    selection_type="NEW_SELECTION",
    where_clause="sit_cancel = 'S'",
    invert_where_clause=None
)
arcpy.management.DeleteRows(
    in_rows="ibama_adm_auto_infracao_p_2010_2020_inside_grid_net"
)
```

Summarize IBAMA data

```
arcpy.analysis.SummarizeWithin(
    in_polygons="E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\grid_net_lambert",
    in_sum_features="ibama_adm_auto_infracao_p_2010_2020_inside_grid_net",
    out_feature_class="E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\ibama_adm_auto_infracao_p_2010_2020_inside_grid_net_summarized",
    keep_all_polygons="ONLY_INTERSECTING",
    sum_fields="val_auto_i Mean;val_auto_i Sum",
    sum_shape="ADD_SHAPE_SUM",
    shape_unit="SQUAREKILOMETERS",
    group_field=None,
    add_min_maj="NO_MIN_MAJ",
    add_group_percent="NO_PERCENT",
    out_group_table=None
)
```

Join ibama fines

```
arcpy.management.JoinField(
    in_data="E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\GIS\\thesis\\thesis.gdb\\grid_final_aggregated_In_lambert",
    in_field="OID_1",
    join_table="ibama_adm_auto_infracao_p_2010_2020_inside_grid_net_summarized",
    join_field="OID_1",
    fields="mean_val_auto_i;sum_val_auto_i;Point_Count",
    fm_option="NOT_USE_FM",
    field_mapping=None
)
```

Adjust names

```
arcpy.management.AlterField(
    in_table="grid_final_aggregated_In_lambert",
    field="mean_val_auto_i",
    new_field_name="ibama_mean_value",
    new_field_alias="IBAMA average fine value",
    field_type="DOUBLE",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)
arcpy.management.AlterField(
    in_table="grid_final_aggregated_In_lambert",
    field="sum_val_auto_i",
    new_field_name="ibama_sum_value",
    new_field_alias="IBAMA sum fine value",
    field_type="DOUBLE",
    field_length=8,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)
arcpy.management.AlterField(
    in_table="grid_final_aggregated_In_lambert",
    field="Point_Count",
    new_field_name="ibama_count",
    new_field_alias="IBAMA number of fines",
    field_type="LONG",
    field_length=4,
    field_is_nullable="NULLABLE",
    clear_field_alias="DO_NOT_CLEAR"
)
```

Calculate Distance to City

Compute the geographic distance from the mining site to the nearest city.

Add APL_Localidades_Cidade from

<https://geoservicos.ibge.gov.br/geoserver/ows?service%3Dwfs&version%3D2.0.0&request=GetCapabilities>

Select cities 50km distant from grid

```
arcpy.management.SelectLayerByLocation(
    in_layer="Cidades",
    overlap_type="WITHIN_A_DISTANCE",
    select_features="grid_final_aggregated_In_lambert",
```

```

search_distance="50 Kilometers",
selection_type="NEW_SELECTION",
invert_spatial_relationship="NOT_INVERT"
)

```

Save cities

```

arcpy.management.CopyFeatures(
    in_features="Cidades",
    out_feature_class="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\cities_points_50km_grid_net",
    config_keyword="",
    spatial_grid_1=None,
    spatial_grid_2=None,
    spatial_grid_3=None
)

```

Calculate distance to nearest city

```

arcpy.analysis.Near(
    in_features="grid_final_aggregated_In_lambert",
    near_features="cities_points_50km_grid_net",
    search_radius=None,
    location="NO_LOCATION",
    angle="NO_ANGLE",
    method="PLANAR",
    field_names="NEAR_DIST city_dist",
    distance_unit="Kilometers"
)

```

Calculate Distance to Gas Station

```

arcpy.analysis.Near(
    in_features="grid_final_aggregated_In_lambert",
    near_features="OSM_gas_station_caatinga_buffer_clipped",
    search_radius=None,
    location="NO_LOCATION",
    angle="NO_ANGLE",
    method="PLANAR",
    field_names="NEAR_DIST gas_dist",
    distance_unit="Kilometers"
)

```

Calculate Distance to CPRM

```

arcpy.analysis.Near(
    in_features="grid_final_aggregated_In_lambert",
    near_features="mining_occurrence_municipalities_caatinga_clip",
    search_radius=None,
    location="NO_LOCATION",
    angle="NO_ANGLE",
    method="PLANAR",
    field_names="NEAR_DIST cprm_dist",
    distance_unit="Kilometers"
)

```

Create a new variable to account for raw GDP

Calculate mean_gdp across years

```

arcpy.management.CalculateField(
    in_table="IBGE_grid",
    field="mean_gdp",

    expression="average($feature.pib_2010,$feature.pib_2011,$feature.pib_2012,$feature.pib_2013,$feature.pib_2014,$feature.pib_2015,$feature.pib_2016,$feature.pib_2017,$feature.pib_2018,$feature.pib_2019,$feature.pib_2020)",
    expression_type="ARCADE",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)

```

Join to the main grid

```

arcpy.management.JoinField(
    in_data="grid_final_aggregated_In_lambert",
    in_field="OID_1",
    join_table="IBGE_grid",
    join_field="OID_1",
    fields="mean_gdp",
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Transform the variables to natural logarithms based on the chosen formula (method 4, which is the same as method 2, but accounting for zeroes and negatives):

```

import arcpy
import math

# Define the table path
output_table_path = "grid_final_aggregated_In_lambert"

# List of variables to undergo transformation
fields_to_transform = [

```

```

'anm_fines', 'ibama_mean_value', 'ibama_sum_value', 'ibama_count', 'city_dist', 'gas_dist', 'cprm_dist', 'mean_d_arrest', 'mean_d_author', 'mean_d_crime',
'mean_d_prosec', 'mean_n_arre_f', 'mean_n_arre_w', 'mean_n_arrest', 'mean_n_crimin', 'mean_n_indict', 'mean_n_search', 'mean_p_durati', 'mean_value_ca',
'mean_value_es', 'mean_cul_her_r', 'mean_env_adm_r', 'mean_fauna_r', 'mean_fishing_r', 'mean_flora_r', 'mean_generic_r', 'mean_health_r', 'mean_his_her_r',
'mean_land_r', 'mean_pollution_r', 'mean_related', 'sum_d_arrest', 'sum_d_author', 'sum_d_crime', 'sum_d_prosec', 'sum_n_arre_f', 'sum_n_arre_w', 'sum_n_arrest',
'sum_n_crimin', 'sum_n_indict', 'sum_n_search', 'sum_p_durati', 'sum_value_ca', 'sum_value_es', 'sum_cul_her_r', 'sum_env_adm_r', 'sum_fauna_r', 'sum_fishing_r',
'sum_flora_r', 'sum_generic_r', 'sum_health_r', 'sum_his_her_r', 'sum_land_r', 'sum_mining_r', 'sum_pollution_r', 'sum_related', 'sum_police', 'mean_gdp'
]

# Execute log transformation for each field
for field in fields_to_transform:
    new_field = "m4ln_" + field # Generate the new field name for the log-transformed variable

    # Add the new field to the dataset
    arcpy.AddField_management(output_table_path, new_field, "DOUBLE")

    # Formulate the expression for log transformation
    log_expression = "math.log(!{!} + 1) if {!} > 0 else -math.log(abs(!{!}) + 1) if {!} < 0 else 0".format(field, field, field, field)

    # Calculate the new log-transformed field
    arcpy.CalculateField_management(
        in_table=output_table_path,
        field=new_field,
        expression=log_expression,
        expression_type="PYTHON3",
        code_block="import math"
    )

```

Join the variables to the analysis grid

```

arcpy.management.JoinField(
    in_data="grid_analysis_lambert",
    in_field="OID_1",
    join_table="grid_final_aggregated_In_lambert",
    join_field="OID_1",
)

```

```

fields="nl_anm_mean_fines;nl_anm_mean_AAU;nl_anm_mean_AFS;nl_ibama_count;nl_ibama_mean_value;nl_ibama_sum_value;nl_ibama_mean;nl_mean_gdp;nl_mean_R
DAI;m4ln_mean_cul_her_r;m4ln_mean_d_arrest;m4ln_mean_d_author;m4ln_mean_d_crime;m4ln_mean_d_prosec;m4ln_mean_env_adm_r;m4ln_mean_fauna_r;m4ln_me
an_fishing_r;m4ln_mean_flora_r;m4ln_mean_generic_r;m4ln_mean_health_r;m4ln_mean_his_her_r;m4ln_mean_land_r;nl_pf_mean_mining_r;m4ln_mean_n_arre_f;m4ln_
mean_n_arre_w;m4ln_mean_n_arrest;m4ln_mean_n_crimin;m4ln_mean_n_indict;m4ln_mean_n_search;m4ln_mean_p_durati;m4ln_mean_pollution_r;m4ln_mean_relate
d;m4ln_mean_value_ca;m4ln_mean_value_es;m4ln_sum_cul_her_r;m4ln_sum_d_arrest;m4ln_sum_d_author;m4ln_sum_d_crime;m4ln_sum_d_prosec;m4ln_sum_env_ad
m_r;m4ln_sum_fauna_r;m4ln_sum_fishing_r;m4ln_sum_flora_r;m4ln_sum_generic_r;m4ln_sum_health_r;m4ln_sum_his_her_r;m4ln_sum_land_r;m4ln_sum_mining_r;m4l
n_sum_n_arre_f;m4ln_sum_n_arre_w;m4ln_sum_n_arrest;m4ln_sum_n_crimin;m4ln_sum_n_indict;m4ln_sum_n_search;m4ln_sum_p_durati;nl_pf_sum;m4ln_sum_polluti
on_r;m4ln_sum_related;nl_pf_sum_value_ca;m4ln_sum_value_es;nl_mean_MRI;nl_cprm_dist;nl_cprm_poi_mean;m4ln_MEAN_urban;m4ln_r_leg;m4ln_city_dist;nl_gas_dis
t;nl_gas;nl_roads_km;nl_anm_mean_myp;m4ln_MEAN_mean_LED;m4ln_MEAN_sum_CFEM;m4ln_MEAN_leg;nl_anm_mean_area;nl_out_mean;nl_anm_pct;m4ln_r_out;m4
ln_MEAN_no_title;m4ln_r_no_title;anm_fines;MEAN_sum_AAU;MEAN_sum_AFS;ibama_count;ibama_mean_value;ibama_sum_value;MEAN_ibama;mean_gdp;MEAN_RDAI;
crime;mean_cul_her_r;mean_d_arrest;mean_d_author;mean_d_crime;mean_d_prosec;mean_env_adm_r;mean_fauna_r;mean_fishing_r;mean_flora_r;mean_generic_r;me
an_health_r;mean_his_her_r;mean_land_r;MEAN_mining_r;mean_n_arre_f;mean_n_arre_w;mean_n_arrest;mean_n_crimin;mean_n_indict;mean_n_search;mean_p_durati
;mean_pollution_r;mean_related;mean_value_ca;mean_value_es;sum_cul_her_r;sum_d_arrest;sum_d_author;sum_d_crime;sum_d_prosec;sum_env_adm_r;sum_fauna_r;s
um_fishing_r;sum_flora_r;sum_generic_r;sum_health_r;sum_his_her_r;sum_land_r;sum_mining_r;sum_n_arre_f;sum_n_arre_w;sum_n_arrest;sum_n_crimin;sum_n_indict;
sum_n_search;sum_p_durati;sum_police;sum_pollution_r;sum_related;sum_value_ca;sum_value_es;MEAN_MRI;cprm_dist;MEAN_cprm_poi;city_dist;MEAN_urban;gas_dist
;MEAN_gas;MEAN_roads_km;MEAN_myp;MEAN_mean_LED;MEAN_sum_CFEM;MEAN_leg;r_leg;MEAN_area;MEAN_pct;MEAN_out;r_out;cell_area_ha;MEAN_no_title;r_no
_title;MEAN_myp;MEAN_RDAI;MEAN_MRI;leg_mean;MEAN_roads_km;MEAN_area;MEAN_out;anm_fines;ibama_interdiction_mean_value;MEAN_ibama;MEAN_sum_AAU;
MEAN_sum_AFS;MEAN_mining_r;MEAN_cprm_poi;MEAN_gas;MEAN_urban",
    fm_option="NOT_USE_FM",
    field_mapping=None
)

```

Adjust metadata


```
# Run global and local cluster analysis to investigate best candidates to spatial lag
# Run global Moran's I
Run global Moran's I for fixed distance 25km
```

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0,998954"}, {"Expected Index", "-0,000029"}, {"Variance", "0,000001"}, {"z-score", "1311,582271"}, {"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_0.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 09:51:16 (Elapsed Time: 21,86 seconds)
```

Run global Moran's I for fixed distance 50km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0,995919"}, {"Expected Index", "-0,000029"}, {"Variance", "0,000000"}, {"z-score", "2503,631222"}, {"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_0.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:01:31 (Elapsed Time: 49,82 seconds)
```

Run global Moran's I for fixed distance 75km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis75.swm",
    number_of_neighbors=None
)
```

Results

```
WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the
potential of running out of memory.
WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 21996, 21997, 21998, 21999, 22000, 22001, 22002, 22316,
22317, 22318, 22319, 22320, 22321, 22322, 22323, 22324, 22325, 22326, 22636, 22637, 22638, 22641, 22642, 22643, 22644, 22645, 22646, 22647, 22648, 22649.
json:
[{"element": "table", "data": [{"Moran's Index", "0,991217"}, {"Expected Index", "-0,000029"}, {"Variance", "0,000000"}, {"z-score", "3656,323461"}, {"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_1.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:03:07 (Elapsed Time: 1 minutes 35 seconds)
```

Run global Moran's I for fixed distance 100km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis100.swm",
    number_of_neighbors=None
)
```

)

Results

WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the potential of running out of memory.

WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 18458, 18459, 18774, 18775, 18776, 18777, 18778, 18779, 18780, 18781, 18782, 19093, 19096, 19097, 19098, 19099, 19100, 19101, 19102, 19103, 19104, 19105, 19106, 19414, 19415, 19420, 19421, 19422, 19426, 19427.

json:

```
{["element": "table", "data": [{"Moran's Index", "0,984620"}], [{"Expected Index", "-0,000029"}], [{"Variance", "0,000000"}], [{"z-score", "4750,535048"}], [{"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
```

Writing html report....

json:

```
{["element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_2.html"}]}
```

Succeeded at sexta-feira, 20 de outubro de 2023 10:05:26 (Elapsed Time: 2 minutes 18 seconds)

Run global Moran's I for Inverse distance 25km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25.swm",
    number_of_neighbors=None
)
```

Results

json:

```
{["element": "table", "data": [{"Moran's Index", "0,999315"}], [{"Expected Index", "-0,000029"}], [{"Variance", "0,000001"}], [{"z-score", "1055,695242"}], [{"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
```

Writing html report....

json:

```
{["element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_3.html"}]}
```

Succeeded at sexta-feira, 20 de outubro de 2023 10:05:47 (Elapsed Time: 20,44 seconds)

Run global Moran's I for Inverse distance 50km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50.swm",
    number_of_neighbors=None
)
```

Results

json:

```
{["element": "table", "data": [{"Moran's Index", "0,997481"}], [{"Expected Index", "-0,000029"}], [{"Variance", "0,000000"}], [{"z-score", "1800,518344"}], [{"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
```

Writing html report....

json:

```
{["element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_4.html"}]}
```

Succeeded at sexta-feira, 20 de outubro de 2023 10:06:33 (Elapsed Time: 45,37 seconds)

Run global Moran's I for inverse distance 75km

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis75.swm",
    number_of_neighbors=None
)
```

Results

WARNING 001420: The number of neighbors for at least one feature exceeds 1000, you may want to change your conceptualization of spatial relationships to avoid the potential of running out of memory.

WARNING 001422: Features with number of neighbors exceeding warning value (only includes first 30): OID_1 = 21996, 21997, 21998, 21999, 22000, 22001, 22002, 22316, 22317, 22318, 22319, 22320, 22321, 22322, 22323, 22324, 22325, 22326, 22636, 22637, 22638, 22641, 22642, 22643, 22644, 22645, 22646, 22647, 22648, 22649.

json:

```
{["element": "table", "data": [{"Moran's Index", "0,994646"}], [{"Expected Index", "-0,000029"}], [{"Variance", "0,000000"}], [{"z-score", "2455,679553"}], [{"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
```

Writing html report....

json:

```
{["element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransi_Result_28096_25688_5.html"}]}
```

Succeeded at sexta-feira, 20 de outubro de 2023 10:07:59 (Elapsed Time: 1 minutes 25 seconds)

Run global Moran's I for k-nearest 8

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0.999786"}, {"Expected Index", "-0.000029"}, {"Variance", "0.000007"}, {"z-score", "379.934370"}, {"p-value", "0.000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\thesis\MoransI_Result_28096_25688_6.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:08:10 (Elapsed Time: 10,08 seconds)
```

Run global Moran's I for k-nearest 16

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0.999747"}, {"Expected Index", "-0.000029"}, {"Variance", "0.000003"}, {"z-score", "538.440444"}, {"p-value", "0.000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\thesis\MoransI_Result_28096_25688_7.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:08:23 (Elapsed Time: 12,54 seconds)
```

Run global Moran's I for k-nearest 50

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0.999048"}, {"Expected Index", "-0.000029"}, {"Variance", "0.000001"}, {"z-score", "950.675918"}, {"p-value", "0.000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\thesis\MoransI_Result_28096_25688_8.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:08:38 (Elapsed Time: 14,34 seconds)
```

Run global Moran's I for k-nearest 250

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0.995507"}, {"Expected Index", "-0.000029"}, {"Variance", "0.000000"}, {"z-score", "2126.957972"}, {"p-value", "0.000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}}]
Writing html report....
```

```
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransl_Result_28096_25688_9.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:09:08 (Elapsed Time: 29,96 seconds)
```

Run global Moran's I for k-nearest 500

```
arcpy.stats.SpatialAutocorrelation(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="OID_1",
    Generate_Report="GENERATE_REPORT",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest500.swm",
    number_of_neighbors=None
)
```

Results

```
json:
[{"element": "table", "data": [{"Moran's Index", "0,992053"}, {"Expected Index", "-0,000029"}, {"Variance", "0,000000"}, {"z-score", "3011,115644"}, {"p-value", "0,000000"}],
"elementProps": {"striped": "true", "noHeader": true, "title": "Global Moran's I Summary", "0": {"align": "left", "pad": "0px", "wrap": true}, "1": {"align": "left", "pad": "0px",
"wrap": true}}]}
Writing html report....
json:
{"element": "content", "data": [{"element": "hyperlink", "data": "E:\\OneDrive\\Academica\\1-Doutorado
UFRN\\Tese\\1_research\\GIS\\thesis\\Moransl_Result_28096_25688_10.html"}]}
Succeeded at sexta-feira, 20 de outubro de 2023 10:10:04 (Elapsed Time: 55,91 seconds)
```

Run Local Moran's I

Run Local Moran's I for fixed distance 25km

```
arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25.swm",
    Apply_False_Discovery_Rate_FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)
```

Results

```
arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25",
    in_fields="LMIIndex;LMIZScore;LMIPValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC_grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25_FieldStatisticsToTable_Numeric;TEXT
    grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
    StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
    Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
    CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In_M
EAN_no_title_matrix_fixdis25_FieldStatisticsToTable_Text",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25_FieldStatisticsToTable_Numeric_TableTo
    Excel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Run Local Moran's I for fixed distance 50km

```
arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50.swm",
    Apply_False_Discovery_Rate_FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)
```

Results

```
arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50",
    in_fields="LMIIndex;LMIZScore;LMIPValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC_grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50_FieldStatisticsToTable_Numeric;TEXT
    grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
    StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
    Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
    CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In_M
EAN_no_title_matrix_fixdis50_FieldStatisticsToTable_Text",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50_FieldStatisticsToTable_Numeric_TableTo
    Excel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Run Local Moran's I for Inverse distance 25km

```
arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
```

```

Distance_Method="EUCLIDEAN_DISTANCE",
Standardization="ROW",
Distance_Band_or_Threshold_Distance=None,
Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25.swm",
Apply_False_Discovery_Rate__FDR_Correction="NO_FDR",
Number_of_Permutations=499,
number_of_neighbors=None
)

```

Results

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25",
    in_fields="LMIIndex;LMIZScore;LMIPValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis.gdb",
    out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4I
n_MEAN_no_title_matrix_inversedis25_FieldStatisticsToTable_Text",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25_FieldStatisticsToTable_Numeric_Tab
leToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Run Local Moran's I for Inverse distance 50km

```

arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50.swm",
    Apply_False_Discovery_Rate__FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)

```

Results

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50",
    in_fields="LMIIndex;LMIZScore;LMIPValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis.gdb",
    out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4I
n_MEAN_no_title_matrix_inversedis50_FieldStatisticsToTable_Text",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50_FieldStatisticsToTable_Numeric_Tab
leToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Run Local Moran's I for k-nearest 8

```

arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8.swm",
    Apply_False_Discovery_Rate__FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)

```

Results

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8",
    in_fields="LMIIndex;LMIZScore;LMIpVValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location="r":E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In
_MEAN_no_title_matrix_knearest8_FieldStatisticsToTable_Text",
    Output_Excel_File="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8_FieldStatisticsToTable_Numeric_Table
ToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Run Local Moran's I for k-nearest 16

```

arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16.swm",
    Apply_False_Discovery_Rate__FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)

```

Results

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16",
    in_fields="LMIIndex;LMIZScore;LMIpVValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location="r":E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(

Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In
_MEAN_no_title_matrix_knearest16_FieldStatisticsToTable_Text",
    Output_Excel_File="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16_FieldStatisticsToTable_Numeric_Tabl
eToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Run Local Moran's I for k-nearest 50

```

arcpy.stats.ClustersOutliers(
    Input_Feature_Class="grid_final_aggregated_In_lambert",
    Input_Field="nl_no_title_mean",
    Output_Feature_Class="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50",
    Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
    Distance_Method="EUCLIDEAN_DISTANCE",
    Standardization="ROW",
    Distance_Band_or_Threshold_Distance=None,
    Weights_Matrix_File="r":E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50.swm",
    Apply_False_Discovery_Rate__FDR_Correction="NO_FDR",
    Number_of_Permutations=499,
    number_of_neighbors=None
)

```

Results

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50",
    in_fields="LMIIndex;LMIZScore;LMIpVValue;COType;NNeighbors;ZTransform;SpatialLag",
    out_location="r":E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50_FieldStatisticsToTable_Text",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM

```

```
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(
```

```
Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50_FieldStatisticsToTable_Text",
Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
)
```

Run Local Moran's I for k-nearest 250

```
arcpy.stats.ClustersOutliers(
Input_Feature_Class="grid_final_aggregated_In_lambert",
Input_Field="nl_no_title_mean",
Output_Feature_Class="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250",
Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
Distance_Method="EUCLIDEAN_DISTANCE",
Standardization="ROW",
Distance_Band_or_Threshold_Distance=None,
Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250.swm",
Apply_False_Discovery_Rate__FDR__Correction="NO_FDR",
Number_of_Permutations=499,
number_of_neighbors=None
)
```

Results

```
arcpy.management.FieldStatisticsToTable(
in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250",
in_fields="LMIIndex;LMIzScore;LMIpVValue;COType;NNeighbors;ZTransform;SpatialLag",
out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250_FieldStatisticsToTable_Text",
group_by_field=None,
out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(
```

```
Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250_FieldStatisticsToTable_Text",
Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
)
```

Run Local Moran's I for k-nearest 500

```
arcpy.stats.ClustersOutliers(
Input_Feature_Class="grid_final_aggregated_In_lambert",
Input_Field="nl_no_title_mean",
Output_Feature_Class="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500",
Conceptualization_of_Spatial_Relationships="GET_SPATIAL_WEIGHTS_FROM_FILE",
Distance_Method="EUCLIDEAN_DISTANCE",
Standardization="ROW",
Distance_Band_or_Threshold_Distance=None,
Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest500.swm",
Apply_False_Discovery_Rate__FDR__Correction="NO_FDR",
Number_of_Permutations=499,
number_of_neighbors=None
)
```

Results

```
arcpy.management.FieldStatisticsToTable(
in_table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500",
in_fields="LMIIndex;LMIzScore;LMIpVValue;COType;NNeighbors;ZTransform;SpatialLag",
out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500_FieldStatisticsToTable_Numeric;TEXT
grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500_FieldStatisticsToTable_Text",
group_by_field=None,
out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(
```

```
Input_Table="grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500_FieldStatisticsToTable_Numeric;grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500_FieldStatisticsToTable_Text",
Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\exploratory\grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
```


)

Incorporate spatial lags to analysis dataset and rename accordingly

Create new grid to analyze data

```
arcpy.management.CopyFeatures(
    in_features=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\grid_net_lambert",
    out_feature_class=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_analysis_lambert",
    config_keyword="",
    spatial_grid_1=None,
    spatial_grid_2=None,
    spatial_grid_3=None
)
```

Join and rename raw sl variables

```
def main():
    # Define the target dataset
    target_dataset = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_analysis_lambert"

    # List of source datasets to join
    source_datasets = [
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_fixdis25",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_knearest500",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_knearest250",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_knearest50",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_knearest16",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_knearest8",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_inversedis50",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_inversedis25",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_raw_fixdis50"
    ]

    for source_dataset in source_datasets:
        source_dataset_fullpath = f"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\{source_dataset}"
        source_dataset_shortcode = source_dataset.split("\")[1] # Extracts the last part of the source_dataset name

        # Perform the join
        arcpy.management.JoinField(target_dataset, "OID_1", source_dataset_fullpath, "OID_1", ["SpatialLag"])

        # Rename the joined field
        arcpy.AlterField_management(target_dataset, "SpatialLag", f"sl_raw_{source_dataset_shortcode}")

if __name__ == "__main__":
    main()
```

Join and rename sl variables

```
def main():
    # Define the target dataset
    target_dataset = r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\grid_analysis_lambert"

    # List of source datasets to join
    source_datasets = [
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis25",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest500",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest250",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest50",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest16",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_knearest8",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis50",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_inversedis25",
        "grid_final_aggregated_In_lisa_lambert_m4In_MEAN_no_title_matrix_fixdis50"
    ]

    for source_dataset in source_datasets:
        source_dataset_fullpath = f"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\{source_dataset}"
        source_dataset_shortcode = source_dataset.split("\")[1] # Extracts the last part of the source_dataset name

        # Perform the join
        arcpy.management.JoinField(target_dataset, "OID_1", source_dataset_fullpath, "OID_1", ["SpatialLag"])

        # Rename the joined field
        arcpy.AlterField_management(target_dataset, "SpatialLag", f"sl_{source_dataset_shortcode}")

if __name__ == "__main__":
    main()
```

Exploratory Regressions

Step 1. Exploratory Regression Model 1

```

arcpy.stats.ExploratoryRegression(
    Input_Features="grid_analysis_lambert",
    Dependent_Variable="nl_no_title_mean",

Candidate_Explanatory_Variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprrm_poi_mean;nl_gas;nl_ibama_mean;sl_knearest8",
    Weights_Matrix_File="E:\\OneDrive\\Academica\\1-Doutorado
UFRR\\Tese\\1_research\\GIS\\matrix\\grid_final_aggregated_in_lambert_spatial_weights_matrix_knearest8.swm",
    Output_Report_File="E:\\OneDrive\\Academica\\1-Doutorado UFRR\\Tese\\1_research\\Analisis\\Results\\exploratory\\regressions\\report_er_1.txt",
    Output_Results_Table="E:\\OneDrive\\Academica\\1-Doutorado UFRR\\Tese\\1_research\\Analisis\\Analisis\\Analisis.gdb\\results_er_1",
    Maximum_Number_of_Explanatory_Variables=14,
    Minimum_Number_of_Explanatory_Variables=1,
    Minimum_Acceptable_Adj_R_Squared=0.1,
    Maximum_Coefficient_p_value_Cutoff=0.1,
    Maximum_VIF_Value_Cutoff=10,
    Minimum_Acceptable_Jarque_Bera_p_value=0.1,
    Minimum_Acceptable_Spatial_Autocorrelation_p_value=0.1
)

```

***** Exploratory Regression Global Summary (NL_NO_TITLE_MEAN) *****

Search Criterion	Cutoff	Trials #	Passed %	Passed
Min Adjusted R-Squared	> 0.10	16383	12288	75.00
Max Coefficient p-value	< 0.10	16383	1427	8.71
Max VIF Value	< 10.00	16383	16383	100.00
Min Jarque-Bera p-value	> 0.10	16383	0	0.00
Min Spatial Autocorrelation p-value	> 0.10	43	0	0.00

Summary of Variable Significance			
Variable	% Significant	% Negative	% Positive
NL_MEAN_MRI	100.00	0.00	100.00
NL_ROADS_KM	100.00	0.00	100.00
NL_ANM_MEAN_AREA	100.00	0.00	100.00
NL_OUT_MEAN	100.00	0.00	100.00
NL_LEG_MEAN	100.00	0.00	100.00
SL_KNEAREST8	100.00	0.00	100.00
NL_ANM_MEAN_MYP	94.43	37.50	62.50
NL_MEAN_RDAL	51.86	89.09	10.91
NL_PF_MEAN_MINING_R	50.15	19.53	80.47
NL_ANM_MEAN_AAU	50.00	13.11	86.89
NL_CPRM_POI_MEAN	50.00	30.31	69.69
NL_ANM_MEAN_AFS	37.50	45.40	54.60
NL_IBAMA_MEAN	33.90	12.37	87.63
NL_GAS	18.12	37.50	62.50

Summary of Multicollinearity			
Variable	VIF	Violations	Covariates
NL_ANM_MEAN_AAU	1.02	0	-----
NL_MEAN_RDAI	1.20	0	-----
NL_PF_MEAN_MINING_R	1.18	0	-----
NL_MEAN_MRI	6.19	0	-----
NL_ROADS_KM	1.13	0	-----
NL_ANM_MEAN_MYP	1.32	0	-----
NL_ANM_MEAN_AREA	6.24	0	-----
NL_OUT_MEAN	1.20	0	-----
NL_LEG_MEAN	1.25	0	-----
NL_ANM_MEAN_AFS	1.16	0	-----
NL_CPRM_POI_MEAN	1.03	0	-----
NL_GAS	1.20	0	-----
NL_IBAMA_MEAN	1.24	0	-----
SL_KNEAREST8	1.32	0	-----

Summary of Residual Normality (JB)							
JB	AdjR2	AICc	K(BP)	VIF	SA	Model	
0.000000	0.001103	-1376.733953	0.000956	1.000000	0.000000	+NL_PF_MEAN_MINING_R***	
0.000000	0.000032	-1340.291029	0.000052	1.000000	0.000000	+NL_MEAN_RDAl	
0.000000	0.001355	-1385.287978	0.000000	1.000000	0.000000	+NL_ANM_MEAN_AAU***	

Summary of Residual Spatial Autocorrelation (SA)

SA	AdjR2	AICC	JB	K(BP)	VIF	Model
0.000000	0.476162	-23307.208579	0.000000	0.000000	6.237421	-NL_MEAN_RDAI*** -NL_MEAN_MRI*** +NL_ROADS_KM*** -NL_ANM_MEAN_MYP*** +NL_ANM_MEAN_AREA*** -NL_OUT_MEAN*** -NL_LEG_MEAN*** -NL_ANM_MEAN_AFS -NL_IBAMA_MEAN +SL_KNEAREST8***
0.000000	0.476154	-23307.691180	0.000000	0.000000	6.157601	-NL_MEAN_RDAI*** -NL_MEAN_MRI*** +NL_ROADS_KM*** -NL_ANM_MEAN_MYP*** +NL_ANM_MEAN_AREA*** -NL_OUT_MEAN*** -NL_LEG_MEAN*** -NL_IBAMA_MEAN +SL_KNEAREST8***
0.000000	0.476152	-23305.559039	0.000000	0.000000	6.238652	-NL_ANM_MEAN_AAU -NL_MEAN_RDAI*** +NL_MEAN_MRI*** +NL_ROADS_KM*** -NL_ANM_MEAN_MYP*** -NL_ANM_MEAN_AREA*** -NL_OUT_MEAN*** -NL_LEG_MEAN*** -NL_ANM_MEAN_AFS -NL_IBAMA_MEAN +SL_KNEAREST8***

Model 1 Summary

Model No.	AdjR2	AIcC	Jarque-Bera (JB) p-value	Moran's I p-value	Max VIF	Significant Variables	Negative Variables	Positive Variables	Observations

Model 1	0.4762	-23307.208579	0.000000	0.000000	6.2374	NL_MEAN_MRI, NL_ROADS_KM, NL_ANM_MEAN_AREA, NL_OUT_MEAN, NL_LEG_MEAN, SL_KNEAREST8, NL_MEAN_RDAI, NL_ANM_MEAN_MYP, NL_ANM_MEAN_AFS, NL_IBAMA_MEAN	NL_MEAN_RDAI, NL_ANM_MEAN_MYP, NL_ANM_MEAN_AFS	NL_MEAN_MRI, NL_ROADS_KM, NL_ANM_MEAN_AREA, NL_OUT_MEAN, NL_LEG_MEAN, SL_KNEAREST8, NL_IBAMA_MEAN	Jarque-Bera p-value indicates non-normal residuals, possibly due to zero-inflated dependent variable or the relationship not being linear.

Model 1 was made with the original variables to test their performance, but issues have surged from non-normal residuals. Since a meaningful explanation power was obtained, the following models were going to explore this issue further.

Step 2. Exploratory Regression Model 2

Same as model 1, but only in cells where illegal mining was present.

Select positive cells

```
arcpy.management.SelectLayerByAttribute(
    in_layer_or_view="grid_analysis_lambert",
    selection_type="NEW_SELECTION",
    where_clause="nl_no_title_mean > 0",
    invert_where_clause=None
)
```

Run the regression

```
arcpy.stats.ExploratoryRegression(
    Input_Features="grid_analysis_lambert",
    Dependent_Variable="nl_no_title_mean",
```

```
Candidate_Explanatory_Variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;sl_knearest8",
Weights_Matrix_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\GIS\matrix\grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8.swm",
Output_Report_File="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Results\exploratory\regressions\report_er_2.txt",
Output_Results_Table="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_er_2",
Maximum_Number_of_Explanatory_Variables=14,
Minimum_Number_of_Explanatory_Variables=1,
Minimum_Acceptable_Adj_R_Squared=0.1,
Maximum_Coefficient_p_value_Cutoff=0.1,
Maximum_VIF_Value_Cutoff=10,
Minimum_Acceptable_Jarque_Bera_p_value=0.1,
Minimum_Acceptable_Spatial_Autocorrelation_p_value=0.1
)
```

***** Exploratory Regression Global Summary (NL_NO_TITLE_MEAN) *****

```
Percentage of Search Criteria Passed
Search Criterion      Cutoff Trials # Passed % Passed
Min Adjusted R-Squared > 0.10 16383 12288 75.00
Max Coefficient p-value < 0.10 16383 831 5.07
Max VIF Value < 10.00 16383 16383 100.00
Min Jarque-Bera p-value > 0.10 16383 0 0.00
Min Spatial Autocorrelation p-value > 0.10 43 0 0.00
```

```
Summary of Variable Significance
Variable      % Significant % Negative % Positive
NL_OUT_MEAN   100.00 0.00 100.00
NL_LEG_MEAN   100.00 0.00 100.00
SL_KNEAREST8  100.00 0.00 100.00
NL_ANM_MEAN_AREA 97.66 0.00 100.00
NL_ROADS_KM   92.88 0.00 100.00
NL_CPRM_POI_MEAN 70.51 43.99 56.01
NL_ANM_MEAN_MYP 65.08 78.38 21.62
NL_MEAN_MRI   64.31 12.50 87.50
NL_ANM_MEAN_AAU 50.12 0.00 100.00
NL_ANM_MEAN_AFS 33.28 20.70 79.30
NL_MEAN_RDAI  31.62 58.91 41.09
NL_PF_MEAN_MINING_R 27.53 44.87 55.13
NL_GAS        20.14 88.77 11.23
NL_IBAMA_MEAN 2.08 40.60 59.40
```

```
Summary of Multicollinearity
Variable      VIF Violations Covariates
NL_ANM_MEAN_AAU 1.03 0 -----
NL_MEAN_RDAI   1.26 0 -----
NL_PF_MEAN_MINING_R 1.21 0 -----
NL_MEAN_MRI    6.67 0 -----
NL_ROADS_KM    1.15 0 -----
NL_ANM_MEAN_MYP 1.28 0 -----
NL_ANM_MEAN_AREA 6.87 0 -----
NL_OUT_MEAN    1.26 0 -----
NL_LEG_MEAN    1.22 0 -----
NL_ANM_MEAN_AFS 1.13 0 -----
NL_CPRM_POI_MEAN 1.03 0 -----
NL_GAS         1.27 0 -----
NL_IBAMA_MEAN  1.34 0 -----
SL_KNEAREST8   1.24 0 -----
```

Summary of Residual Normality (JB)

```
JB  AdjR2  AICc  K(BP)  VIF  SA  Model
0.000000 0.000608 8635.061045 0.123729 1.000000 0.000000 +NL_PF_MEAN_MINING_R***
0.000000 -0.000056 8641.645115 0.000010 1.000000 0.000000 +NL_MEAN_RDAl
0.000000 0.004557 8595.773916 0.000000 1.000000 0.000000 +NL_ANM_MEAN_AAU***
```

Summary of Residual Spatial Autocorrelation (SA)

```
SA  AdjR2  AICc  JB  K(BP)  VIF  Model
0.000173 0.421523 3213.688237 0.000000 0.000000 1.238283 +NL_MEAN_MRl*** +NL_ROADS_KM*** +NL_OUT_MEAN*** +NL_LEG_MEAN*** +SL_KNEAREST8***
0.000159 0.422239 3201.393835 0.000000 0.000000 1.230035 +NL_ROADS_KM*** +NL_ANM_MEAN_AREA*** +NL_OUT_MEAN*** +NL_LEG_MEAN***
+SL_KNEAREST8***
0.000145 0.423092 3188.740110 0.000000 0.000000 1.469021 -NL_MEAN_RDAl +NL_ROADS_KM*** -NL_ANM_MEAN_MYP*** +NL_ANM_MEAN_AREA***
+NL_OUT_MEAN*** +NL_LEG_MEAN*** +SL_KNEAREST8***
```

Model No.	AdjR2	AICc	Jarque-Bera (JB) p-value	Moran's I p-value	Max VIF	Significant Variables	Negative Variables	Positive Variables	Observations
Model 2	0.422239	3201.393835	0.000000	0.000159	1.469021	+NL_ROADS_KM***, +NL_ANM_MEAN_AREA***, +NL_OUT_MEAN***, +NL_LEG_MEAN***, +SL_KNEAREST8***	-	+NL_ROADS_KM, +NL_ANM_MEAN_AREA, +NL_OUT_MEAN, +NL_LEG_MEAN, +SL_KNEAREST8	Jarque-Bera p-value indicates non-normal residuals, and AICc is high, possibly due to model misspecification or omitted variables.

Generalized Linear Models (GLM)

Step 1. Generalized Linear Model 1

Run the regression with the same variables of ER to compare results

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAl;nl_pf_mean_mining_r;nl_mean_MRl;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest8",
    output_features="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis.gdb\results_glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAl;nl_pf_mean_mining_r;nl_mean_MRl;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUANTILE FirstQuartile;THIRDQUANTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

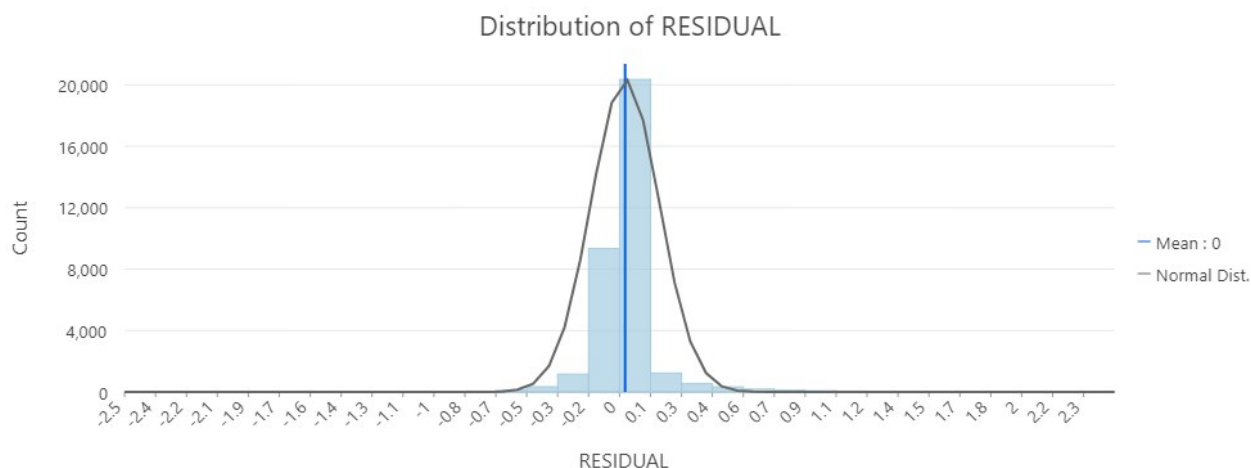
Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\GLR\glr_1_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Summary

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations

1	0.4761	-23299.94	Governance: nl_mean_RDAI (-0.01), nl_anm_mean_myp (-0.01); Place: nl_roads_km (0.01), nl_leg_mean (0.33); Control: nl_anm_mean_area (0.01), nl_out_mean (0.03); Spatial Lag: sl_knearest8 (0.16)	nl_urban_mean, nl_anm_mean_AFS, nl_ibama_mean, nl_gas, nl_anm_mean_AAU, nl_cprm_poi_mean, nl_pf_mean_mining_r	Explanation power (R^2 0.47) and model adjustment (AIC - 23299) are satisfactory. Legal mining seems to be the main driver of illegal mining in the vicinity. Spatial lag control is efficient (16%).



Step 2. Generalized Linear Model 2

Run the regression with the same variables as before, but with 16 neighbors

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_
mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest16",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_an_
m_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest16;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_2_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric_TableToExcel.xls
x",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations

2	0.4406	-21068.862	Governance: nl_mean_RDAI (-0.0087), nl_anm_mean_myp (-0.0051); Place: nl_roads_km (0.0086), nl_leg_mean (0.3602); Illegal Income: nl_mean_MRI (0.009); Control: nl_anm_mean_area (0.0094), nl_out_mean (0.035); Spatial Lag: sl_knearest16 (0.1564)	nl_anm_mean_AAU, nl_pf_mean_mining_r, nl_anm_mean_AFS, nl_cprm_poi_mean, nl_gas, nl_ibama_mean, nl_urban_mean	Model 2 exhibits a slightly reduced AdjR2 (0.4406) compared to Model 1 (0.4761), yet remains significant. Both models validate significant variables across Governance, Place, and Control, with Spatial Lag presenting a robust effect in both. Model 2 introduces Illegal Income as a significant aspect.

Step 3. Generalized Linear Model 3

Run the regression with the same variables as before, but with 50 neighbors

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest50",
    output_features="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest50;PREDICTED;RESIDUAL;STD_RESID",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberOfUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\GLR\glr_3_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric_TableToExcel.xls",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
3	0.3954	-18425.904	Governance: nl_mean_RDAI (-0.0109); Illegal Income: nl_mean_MRI (0.0123); Place: nl_roads_km (0.0094), nl_leg_mean (0.404); Control: nl_anm_mean_area (0.009), nl_out_mean (0.0529); Spatial Lag: sl_knearest50 (0.1534)	nl_anm_mean_AFS, nl_cprm_poi_mean, nl_gas, nl_ibama_mean, nl_urban_mean, nl_anm_mean_myp, nl_pf_mean_mining_r, nl_anm_mean_AAU	With the neighborhood expansion to 50 nearest neighbors, the model exhibits a decline in explanation power (R ² 0.3954) and model adjustment (AIC -18425.9037) compared to Model 1. The spatial lag effect is nearly consistent at 15.34%, emphasizing the persistent role of spatial factors. Legal mining continues to be a primary driver, albeit with a higher coefficient (0.404).

Step 4. Generalized Linear Model 4

Run the regression with the same variables as before, but with 250 neighbors

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_
mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest250",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_an
m_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_knearest250;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION
StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM
Sum;RANGE Range;INTERQUARTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION
CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_4_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric_TableToExcel.xl
sx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
4	0.3562	-16295.1489	Governance: nl_mean_RDAI (-0.012); Illegal Income: nl_mean_MRI (0.0163); Place: nl_roads_km (0.0101), nl_leg_mean (0.4444); Control: nl_anm_mean_area (0.0084), nl_out_mean (0.0824); Spatial Lag: sl_knearest250 (0.1377)	nl_anm_mean_AFS, nl_cprm_poi_mean, nl_gas, nl_ibama_mean, nl_urban_mean, nl_anm_mean_myp, nl_pf_mean_mining_r, nl_anm_mean_AAU	Model 4 further experiences a decline in both explanation power (R ² 0.3562) and model adjustment (AIC -16295.1489) compared to Models 1 and 3. Despite the decline, the role of legal mining as a main driver remains consistent with an elevated coefficient (0.4444). The spatial lag effect, albeit slightly reduced to 13.77%, continues to be a significant factor.

Assessment of K-Nearest Models

Explanation Power (Adjusted R²)

Model 1-8: 0.4761
Model 2-16: 0.4406
Model 3-50: 0.3954
Model 4-250: 0.3562

A progressive decline in R² values was observed as the k-nearest neighborhood size increased. This indicated that smaller neighborhood structures were more conducive to higher explanatory power. Model 1-8 emerged as the model with the highest explanatory capacity.

Model Fit (AICc)

Model 1-8: -23299.94
Model 2-16: -21068.86
Model 3-50: -18425.90
Model 4-250: -16295.15

Consistent with the R² values, the AICc also deteriorated as the neighborhood structure expanded. Model 1-8 was identified as having the most favorable model fit.

Variable-Specific Neighborhood Assessment

Governance (nl_mean_RDAI): The coefficient for this variable was most significant in Model 4-250 (-0.012), suggesting that larger neighborhoods captured governance effects more comprehensively.

Illegal Income (nl_mean_MRI): Model 4-250 displayed the highest significance for this variable, with a coefficient of 0.0163. This indicated that larger neighborhood structures were more effective in capturing the broader economic determinants of illegal income.

Place (nl_roads_km, nl_leg_mean): These variables were consistently significant across all models. The coefficient for legal mining (nl_leg_mean) was highest in Model 4-250 (0.4444), indicating that the impact of legal mining was more pronounced in larger neighborhoods.

Control (nl_anm_mean_area, nl_out_mean): These variables maintained their significance across all models. The control variable pertaining to mining tenement area (nl_anm_mean_area) was most significant in Model 1-8, with a coefficient of 0.0094.

Spatial Lag (sl_knearest): Model 1-8 displayed the highest coefficient (0.16), highlighting that smaller spatial scales were more effective in capturing spatial autocorrelation. In summary, Model 1-8 was identified as the most explanatory and best-fitting model overall. However, for capturing the nuances of specific variables, larger neighborhood structures, such as those in Model 4-250, offered valuable insights. The optimal k-nearest neighborhood size was found to be variable-specific, necessitating a nuanced approach for comprehensive analysis.

Non-Significant Variables

Governance:

nl_anm_mean_AAU: Nearest to significance in Model 4 (k-250)
 nl_anm_mean_AFS: Nearest to significance in Model 3 (k-50)
 nl_pf_mean_mining_r: Nearest to significance in Model 1 (k-8)
 nl_anm_mean_myp: Nearest to significance in Model 2 (k-16)

Place:

nl_cprm_poi_mean: Nearest to significance in Model 4 (k-250)
 nl_gas: Nearest to significance in Model 4 (k-250)
 nl_urban_mean: Nearest to significance in Model 3 (k-50)

The analysis revealed that the efficacy of a given k-nearest neighborhood size in capturing the significance of a variable was indeed variable-specific. Governance-related variables were generally closer to significance in larger neighborhoods (Model 4, k-250), with the exception of police-related variables, which were nearest to significance in smaller neighborhoods (Model 1, k-8). Place-related variables were consistently closer to the significance threshold in the largest neighborhood (Model 4, k-250). These insights have the potential to guide future model specification and refinement, thereby contributing to a more robust analytical framework.

Step 5. Generalized Linear Model 5

Run the regression with the same variables as before, but with a fixed distance of 25 km

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_fixdis25",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_fixdis25;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUARTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\GLR\glr_5_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
Model 5-Fixed Distance 25 km	0.3735	-17220.42	nl_mean_RDAI (-0.0116), nl_mean_MRI (0.0136), nl_roads_km (0.01), nl_anm_mean_area (0.0089), nl_out_mean (0.0648), nl_leg_mean (0.4294), sl_fixdis25 (0.1471)	nl_anm_mean_AAU, nl_pf_mean_mining_r, nl_anm_mean_myp, nl_anm_mean_AFS, nl_cprm_poi_mean, nl_gas, nl_ibama_mean, nl_urban_mean	The 25km fixed distance model revealed a moderate explanatory capacity, with a higher AdjR2 than Model 4-250 but lower than the smaller k-nearest models. In terms of variable significance, governance and place-related variables exhibited a mixed pattern across k-nearest models and the fixed distance model. However, it is noteworthy that the fixed distance model captured the significance of 'nl_mean_MRI' which aligns with its performance in larger k-nearest neighborhoods.

Step 6. Generalized Linear Model 6

Run the regression with the same variables as before, but with a fixed distance of 50 km

```
arcpy.gapro.GeneralizedLinearRegression(
```

```
input_features="grid_analysis_lambert",
dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",
```

```
explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_fixdis50",
output_features="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
in_table="glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50",

in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_fixdis50;PREDICTED;RESIDUAL;STD_RESID",
out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric",
group_by_field=None,
out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUARTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
Input_Table="glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric",
Output_Excel_File="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_6_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
Model 6 (50km fixed distance)	0.3497	-15951.287	nl_mean_RDAI (-0.0125), nl_mean_MRI (0.017), nl_roads_km (0.01), nl_anm_mean_area (0.0081), nl_out_mean (0.0879), nl_leg_mean (0.4521), sl_fixdis50 (0.1274), Intercept (-0.0908)	nl_anm_mean_AAU (0.5935), nl_pf_mean_mining_r (0.1057), nl_anm_mean_myp (0.0849), nl_anm_mean_AFS (0.3396), nl_cprm_poi_mean (0.4571), nl_gas (0.3317), nl_ibama_mean (0.3247), nl_urban_mean (0.3991)	The 50km fixed distance model presented moderate explanatory power, slightly inferior to the 25km fixed distance model but aligned with Model 4-250. It notably captured the significance of 'nl_mean_MRI', consistent with its performance in larger k-nearest settings.

Step 7. Generalized Linear Model 7

Run the regression with the same variables as before, but with an inverse distance of 25 km

```
arcpy.gapro.GeneralizedLinearRegression(
input_features="grid_analysis_lambert",
dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",

explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_inversedis25",
output_features="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
in_table="glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25",

in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_inversedis25;PREDICTED;RESIDUAL;STD_RESID",
out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric",
group_by_field=None,
out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUARTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Results\\GLR\\glr_7_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
Model 7 (Inverse 25km distance)	0.418	-19722.005	nl_mean_RDAI (-0.0083), nl_mean_MRI (0.0112), nl_roads_km (0.0097), nl_anm_mean_area (0.0087), nl_out_mean (0.0357), nl_leg_mean (0.3863), sl_inversedis25 (0.1993)	nl_anm_mean_AAU (0.3522), nl_pf_mean_mining_r (0.1303), nl_anm_mean_myp (0.2638), nl_anm_mean_AFS (0.0875), nl_cprm_poi_mean (0.9509), nl_gas (0.166), nl_ibama_mean (0.0825), nl_urban_mean (0.1046), Intercept (0.3735)	The inverse 25km distance model showed higher explanatory power (AdjR2) compared to both fixed distance and k-nearest models. It notably captured 'nl_mean_MRI' and 'nl_mean_RDAI', aligning well with larger k-nearest models.

Step 8. Generalized Linear Model 8

Run the regression with the same variables as before, but with an inverse distance of 50 km

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_inversedis50",
    output_features="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Analisis.gdb\\glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Analisis.gdb\\results_glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50",

    in_fields="nl_anm_mean_AAU;nl_mean_RDAI;nl_pf_mean_mining_r;nl_mean_MRI;nl_roads_km;nl_anm_mean_myp;nl_anm_mean_area;nl_out_mean;nl_leg_mean;nl_anm_mean_AFS;nl_cprm_poi_mean;nl_gas;nl_ibama_mean;nl_urban_mean;sl_inversedis50;PREDICTED;RESIDUAL;STD_RESID",
    out_location="E:\\OneDrive\\Academica\\1-Doutorado UFRN\\Tese\\1_research\\Analisis\\Analisis\\Analisis.gdb",
    out_tables="NUMERIC glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUANTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Results\\GLR\\glr_8_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric_TableToExcel.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
Model 8 (Inverse 50km distance)	0.3935	-18308.975	nl_mean_RDAI (-0.0089), nl_mean_MRI (0.0142), nl_roads_km (0.0103), nl_anm_mean_area (0.0078), nl_out_mean (0.0499), nl_leg_mean (0.4074), nl_ibama_mean (0.0281), sl_inversedis50 (0.2291)	nl_anm_mean_AAU (0.4353), nl_pf_mean_mining_r (0.3278), nl_anm_mean_myp (0.7043), nl_anm_mean_AFS (0.128), nl_cprm_poi_mean (0.7294), nl_gas (0.1961), nl_urban_mean (0.2356), Intercept (0.0103)	The inverse 50km model displayed lower AdjR2 compared to the 25km inverse distance model but higher than the fixed distance models. It also showed significance for 'nl_ibama_mean', which was not as prominent in other models.

Summary of Variable Significance Across Generalized Linear Regression Models

Explanation Power (Adjusted R²)

Model 1-8: 0.4761
 Model 2-16: 0.4406
 Model 3-50: 0.3954
 Model 4-250: 0.3562
 Model 5 (25km Fixed Distance): 0.3735

Model 6 (50km Fixed Distance): 0.3497
 Model 7 (25km Inverse Distance): 0.418
 Model 8 (50km Inverse Distance): 0.3935

A trend of declining R^2 values is evident as the k-nearest neighborhood size increases (Model 1-8 to Model 4-250). However, when considering fixed and inverse distance models, a more nuanced pattern emerges. Model 7 and Model 8, both inverse distance models, exhibit higher R^2 than their fixed distance counterparts (Model 5 and Model 6). Model 1-8 retains the highest explanatory capacity.

Model Fit (AICc)

Model 1-8: -23299.94
 Model 2-16: -21068.86
 Model 3-50: -18425.90
 Model 4-250: -16295.15
 Model 5: -17220.4222
 Model 6: -15951.287
 Model 7: -19722.0049
 Model 8: -18308.9745

Model 1-8 holds the best model fit, indicated by the lowest AICc. Among the fixed and inverse distance models, Model 7 has the most favorable AICc, followed by Model 8, Model 5, and Model 6. The AICc values corroborate the trends observed in the R^2 analysis.

Variable-Specific Neighborhood Assessment

Governance Variables

- Mining Fines (nl_anm_mean_AFS): The variable gained significance in Model 7, denoted by a p-value of 0.08750. This underscores the variable's increased impact in models that incorporate inverse distance metrics.
- Opportunities for Legal Income (nl_mean_RDAI): Across all models, this variable remained significant, with its highest impact being in Model 6, where the coefficient stood at -0.01.
- Environmental Fines Average Value (nl_ibama_mean): Model 8 marked the variable as significant, as indicated by a p-value of 0.03374, thus emphasizing its elevated importance in larger spatial configurations.

Place Variables

- Legal Mining Proxy Average Area (nl_leg_mean): Exhibiting significance in every model, the variable had its highest coefficient in Model 6, standing at 0.45.
- Roads Length in km (nl_roads_km): The variable remained significant across all models. Model 8 revealed the highest coefficient for this variable, recorded at 0.01.

Target Variable

- Opportunities for Illegal Income (nl_mean_MRI): This variable was consistently significant, exhibiting its highest impact in Model 6 with a coefficient of 0.02.

Control Variables

- Mining Tenements Area (nl_anm_mean_area): Consistently significant across all models, the variable had a consistent impact of 0.01. It could be discarded.
- Mining Proxy Outside Mining Tenements (nl_out_mean): Maintaining its significance throughout all models, this control variable exhibited its highest coefficient in Model 6, at 0.09.

Spatial Lag Variables

- The spatial lag variables were uniformly significant across all models, underscoring the importance of accounting for spatial autocorrelation. Model 8, incorporating a 50 km inverse distance, demonstrated the highest coefficient at 0.23, affirming the role of spatial scale in explanatory power.

Non-Significant Variables

Governance Variables

- Mining Administrative Infractions (nl_anm_mean_AAU): No model rendered this variable as statistically significant, thereby questioning its explanatory power in the context of governance across varying spatial lags.
- Police Closed Cases Related to Mining (nl_pf_mean_mining_r): With a p-value of 0.10574 in Model 6, the variable approaches significance, highlighting its relevance when the spatial structure is defined by fixed distances.

Place Variables

- Average Urban Area (nl_urban_mean): Closest to achieving significance in Model 2, as evidenced by a p-value of 0.05763, this variable suggests a nuanced influence in smaller neighborhood structures.
- Average number of CPRM POIs (nl_cprm_poi_mean): Always far from being significant (nearest 0.45).
- Gas stations number (nl_gas): Closest in Model 7, with p-value of 0.16595, under the inverse distance 25km neighborhood.

In summation, while certain models demonstrated a higher explanatory capacity and model fit, some variables became significant only under specific conditions or did not prove significant at all. In general, governance variables, showed increased significance in larger spatial structures, while place-related variables were more uniformly significant across varying scales. Controls and spatial lags were significant across all models.

Step 9. Generalized Linear Model 9

Model 9 used the best model (k-nearest 8), kept the consistently significant variables, but tested alternatives to nl_anm_mean_AAU, nl_anm_mean_AFS, nl_cprm_poi_mean, nl_gas, nl_ibama_mean, nl_mean_RDAI, nl_pf_mean_mining_r, nl_urban_mean.

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_fines;nl_anm_mean_myp;nl_cprm_dist;nl_gas_dist;nl_ibama_mean_value;nl_leg_mean;nl_mean_MRI;nl_mean_gdp;nl_out_mean;nl_
    _pf_sum;nl_roads_km;nl_urban_dist;sl_knearest8",
    output_features="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Analisis.gdb\\glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="E:\\OneDrive\\Academica\\1-Doutorado
    UFRN\\Tese\\1_research\\Analisis\\Analisis.gdb\\results_glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)
```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",

    in_fields="nl_anm_mean_fines;nl_anm_mean_myp;nl_cprm_dist;nl_gas_dist;nl_ibama_mean_value;nl_leg_mean;nl_mean_MRI;nl_mean_gdp;nl_out_mean;nl_pf_sum;nl_r
oads_km;nl_urban_dist;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
    out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_9_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
9	0.4758	-23282.3977	nl_mean_gdp (-0.0043), nl_mean_MRI (0.0261), nl_cprm_dist (0.0017), nl_roads_km (0.0101), nl_out_mean (0.0278), nl_leg_mean (0.3272), sl_knearest8 (0.1589), nl_urban_dist (0.0031)	nl_pf_sum, nl_anm_mean_myp, nl_ibama_mean_value, nl_anm_mean_fines, nl_gas_dist	Variables like nl_mean_MRI and nl_roads_km maintain their significance but with minor coefficient adjustments. Some variables like nl_anm_mean_myp lost significance. Overall, the model exhibits high explanatory power (AdjR2 0.4758) and model fit (AICc -23282.3977). GDP and Urban distance did not succeeded in improving legal income significance. CPRM distance shows promise.

Step 10. Generalized Linear Model 10

Dropping nl_gas_dist, nl_anm_mean_myp, nl_cprm_dist, nl_urban_dist, and choosing alternatives to nl_pf_sum and nl_ibama_mean_value.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_pf_sum_value_ca;nl_ibama_interdict_mean_value;nl_mean_RDAI;nl_anm_mean_fines;nl_mean_MRI;nl_roads_km;nl_out_mean;nl_leg_mean;sl_knearest8",
    output_features="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",

    in_fields="nl_pf_sum_value_ca;nl_ibama_interdict_mean_value;nl_mean_RDAI;nl_anm_mean_fines;nl_mean_MRI;nl_roads_km;nl_out_mean;nl_leg_mean;sl_knearest8;PR
EDICTED;RESIDUAL;STD_RESID",
    out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_10_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
10	0.4758	-23281.5278	nl_mean_RDAI (-0.0069); nl_mean_MRI (0.0257); nl_roads_km (0.0086); nl_out_mean (0.0277); nl_leg_mean (0.3269); nl_ibama_interdict_mean_value (0.0114); sl_knearest8 (0.1586); nl_anm_mean_fines (-0.0164)	nl_pf_sum_value_ca	Model 10 exhibits superior performance in terms of both AdjR2 and AICc compared to previous models. All variables except nl_pf_sum_value_ca are significant at the 90% confidence level.

Step 11. Generalized Linear Model 11

Maintaining the core explanatory variables from Model 10, while also introducing new variables to test for additional insights and control for potential confounders.

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

    explanatory_variables="nl_anm_mean_fines;nl_anm_mean_area;nl_anm_mean_myp;nl_ibama_interdict_mean_value;nl_ibama_mean;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest8",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)
```

Summarize statistics

```
arcpy.management.FieldStatisticsToTable(
    in_table="glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",

    in_fields="nl_anm_mean_fines;nl_anm_mean_area;nl_anm_mean_myp;nl_ibama_interdict_mean_value;nl_ibama_mean;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)
```

Export to Excel

```
arcpy.conversion.TableToExcel(
    Input_Table="glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\Analisis\Results\GLR\glr_11_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_headers="NAME",
    Use_domain_and_subtype_description="CODE"
)
```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
11	0.4763	-23314.7505	nl_mean_RDAI (-0.0067); nl_mean_MRI (0.0094); nl_roads_km (0.0088); nl_anm_mean_myp (-0.0068); nl_anm_mean_area (0.0086); nl_out_mean (0.0281); nl_leg_mean (0.3265); nl_ibama_interdict_mean_value (0.0107); sl_knearest8 (0.1587)	nl_anm_mean_fines (-0.0098); nl_ibama_mean (0.0106)	ANM and IBAMA fines insignificant. Only legal mining and IBAMA interdictions had a relevant impact.

Step 12. Generalized Linear Model 12

After 11 models, model 12 aggregated governance-related variables to test for significance.

Calculate aggregated variable for governance:

```
arcpy.management.CalculateField(
    in_table="grid_analysis_lambert_bkup",
    field="gov",
    expression="sum($feature.anm_fines,$feature.ibama_count,$feature.ibama_interdict_count,$feature.MEAN_mining_r)",
    expression_type="ARCADE",
    code_block="",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)

arcpy.management.JoinField(
    in_data="grid_analysis_lambert",
    in_field="OID_1",
    join_table="grid_analysis_lambert_bkup",
    join_field="OID_1",
    fields="gov",
    fm_option="NOT_USE_FM",
    field_mapping=None
)

arcpy.management.CalculateField(
    in_table="grid_analysis_lambert",
    field="nl_gov",
    expression="math.log(lgov! + 1) if !lgov! > 0 else -math.log(abs(!lgov!)) + 1 if !lgov! < 0 else 0",
    expression_type="PYTHON3",
    code_block="import math",
    field_type="FLOAT",
    enforce_domains="NO_ENFORCE_DOMAINS"
)
```

Run GLR

```
arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
```

```

dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",
explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest8",
output_features="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
in_table="glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
group_by_field=None,
out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
Input_Table="glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_12_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
12	0.476	- 23299.005	nl_mean_RDAI (-0.0071); nl_mean_MRI (0.0086); nl_roads_km (0.0087); nl_anm_mean_area (0.0078); nl_out_mean (0.0284); nl_leg_mean (0.3267); sl_knearest8 (0.1584); Intercept (-0.024)	nl_gov (0.0026)	The variable nl_gov did not reach the significance threshold in a k-nearest 8 neighborhood (p-value of 0.3035.)

Step 13. Generalized Linear Model 13

Same as model 12, but with a inverse 50km spatial lag.

```

arcpy.gapro.GeneralizedLinearRegression(
input_features="grid_analysis_lambert",
dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",
explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_inversedis50",
output_features="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
in_table="glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50",
in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_inversedis50;PREDICTED;RESIDUAL;STD_RESID",
out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
out_tables="NUMERIC glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric",
group_by_field=None,
out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
Input_Table="glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric",
Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_13_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis50_FieldStatisticsToTable_Numeric.xlsx",
Use_field_alias_as_column_header="NAME",
Use_domain_and_subtype_description="CODE"
)

```

Model No.	AdjR2	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
13	0.3932	- 18313.384	nl_mean_RDAI (-0.0102); nl_mean_MRI (0.0126); nl_roads_km (0.0108); nl_anm_mean_area (0.0082); nl_out_mean (0.0506); nl_leg_mean (0.4074); sl_inversedis50 (0.2282); Intercept (-0.0449)	nl_gov (0.0043)	Model 13 displayed a decrease in AdjR2 compared to Model 12, indicating less variability explained using a spatial lag of 50km inverse distance. The governance variable nl_gov remained below the significance threshold with a p-value of 0.1194.

Step 14. Generalized Linear Model 14

Same as model 12, but with a spatial lag of 25km inverse distance.

```

arcpy.gapro.GeneralizedLinearRegression(
input_features="grid_analysis_lambert",
dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",
explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_inversedis25",
output_features="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25",
)

```

```

input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_inversedis25;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_14_grid_final_aggregated_In_lambert_spatial_weights_matrix_inversedis25_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
14	0.4179	-19721.8565	nl_mean_RDAI: -0.0098, nl_mean_MRI: 0.0098, nl_roads_km: 0.0105, nl_anm_mean_area: 0.0084, nl_out_mean: 0.0365, nl_leg_mean: 0.3866, sl_inversedis25: 0.1985, Intercept: -0.0389	nl_gov: 0.0024	The governance variable (nl_gov) still did not meet the significance threshold.

Step 15. Generalized Linear Model 15

Same as model 12, but with a spatial lag of 25km fixed distance.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",
    explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_fixdis25",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_fixdis25;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_15_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis25_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
15	0.3737	-17228.0185	nl_mean_RDAI: -0.0115, nl_mean_MRI: 0.0123, nl_roads_km: 0.0105, nl_anm_mean_area: 0.0092, nl_out_mean: 0.0654, nl_leg_mean: 0.4295, sl_fixdis25: 0.1468, Intercept: -0.0534	nl_gov: 0.002	All variables except nl_gov were found to be statistically significant.

Step 16. Generalized Linear Model 16

Same as model 12, but with a spatial lag of 50km fixed distance.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",
    explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_fixdis50",

```



```

output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis.gdb\glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_fixdis50;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_16_grid_final_aggregated_In_lambert_spatial_weights_matrix_fixdis50_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
16	0.3498	-15957.412	nl_mean_RDAI: -0.0108, nl_mean_MRI: 0.016, nl_roads_km: 0.0101, nl_anm_mean_area: 0.0089, nl_out_mean: 0.0882, nl_leg_mean: 0.452, sl_fixdis50: 0.1278, Intercept: -0.0586	nl_gov: 0.0038	All variables except nl_gov were found to be statistically significant.

Step 17. Generalized Linear Model 17

Same as model 12, but with a spatial lag of k-nearest 16.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",
    explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest16",
    output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest16;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_17_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest16_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
17	0.4405	-21070.7404	nl_mean_RDAI: -0.0088, nl_mean_MRI: 0.0082, nl_roads_km: 0.0092, nl_anm_mean_area: 0.0087, nl_out_mean: 0.0355, nl_leg_mean: 0.3605, sl_knearest16: 0.156, Intercept: -0.0348	nl_gov: 0.0035	All variables except for nl_gov were statistically significant.

Step 18. Generalized Linear Model 18

Same as model 12, but with a spatial lag of k-nearest 50.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",

```

```

explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest50",
output_features="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest50;PREDICTED;RESIDUAL;STD_RESID",
    out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric",
    Output_Excel_File="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_18_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest50_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
18	0.3953	-18432.1747	nl_mean_RDAI: -0.0109, nl_mean_MRI: 0.0111, nl_roads_km: 0.0099, nl_anm_mean_area: 0.0089, nl_out_mean: 0.0534, nl_leg_mean: 0.4041, sl_knearest50: 0.1531, Intercept: -0.0464	nl_gov: 0.0023	All variables except for nl_gov were statistically significant.

Step 19. Generalized Linear Model 19

Same as model 12, but with a spatial lag of k-nearest 250.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",
    explanatory_variables="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest250",
    output_features="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250",
    in_fields="nl_gov;nl_anm_mean_area;nl_leg_mean;nl_mean_MRI;nl_mean_RDAI;nl_out_mean;nl_roads_km;sl_knearest250;PREDICTED;RESIDUAL;STD_RESID",
    out_location="r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric",
    Output_Excel_File="r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_19_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest250_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
19	0.3563	-16303.1376	nl_mean_RDAI: -0.0114, nl_mean_MRI: 0.0154, nl_roads_km: 0.0104, nl_anm_mean_area: 0.0091, nl_out_mean: 0.0829, nl_leg_mean: 0.4443, sl_knearest250: 0.1376, Intercept: -0.0587	nl_gov: 0.0025	All variables except for nl_gov were statistically significant.

Step 20. Generalized Linear Model 20

Same as model 12, but without the composite deterrent variable.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",

```

```

model_type="CONTINUOUS",
explanatory_variables="nl_anm_mean_area;nl_out_mean;nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;sl_knearest8",
output_features="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    in_fields="nl_anm_mean_area;nl_out_mean;nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_20_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
20	0.4761	-23306.77	nl_mean_RDAI (-0.0063); nl_mean_MRI (0.0087); nl_roads_km (0.0090); nl_anm_mean_myp (-0.0070); nl_anm_mean_area (0.0087); nl_out_mean (0.0286); nl_leg_mean (0.3266); sl_knearest8 (0.1586)		Adequate Fit

Step 21. Generalized Linear Model 21

Same as model 20, but without controls.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",
    dependent_variable="nl_no_title_mean",
    model_type="CONTINUOUS",
    explanatory_variables="nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km",
    output_features="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    input_features_to_predict=None,
    explanatory_variables_to_match=None,
    dependent_variable_mapping=None,
    output_predicted_features=None,
    coefficient_table="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    in_fields="nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;PREDICTED;RESIDUAL;STD_RESID",
    out_location="E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File="E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_21_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
21	0.3158	-14233.7472	nl_mean_RDAI (-0.0093); nl_mean_MRI (0.0225); nl_roads_km (0.0115); nl_anm_mean_myp (0.0085); nl_leg_mean (0.4985)	None	Still adequate fit, but with less explanatory power.

Step 22. Generalized Linear Model 22

Same as model 21, but with only spatial correlation control.

```

arcpy.gapro.GeneralizedLinearRegression(
    input_features="grid_analysis_lambert",

```

```

dependent_variable="nl_no_title_mean",
model_type="CONTINUOUS",
explanatory_variables="nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;sl_knearest8",
output_features=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
input_features_to_predict=None,
explanatory_variables_to_match=None,
dependent_variable_mapping=None,
output_predicted_features=None,
coefficient_table=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\results_glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8"
)

```

Summarize statistics

```

arcpy.management.FieldStatisticsToTable(
    in_table="glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8",
    in_fields="nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;sl_knearest8;PREDICTED;RESIDUAL;STD_RESID",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics=None
)

```

Export to Excel

```

arcpy.conversion.TableToExcel(
    Input_Table="glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado
UFRN\Tese\1_research\Analisis\Results\GLR\glr_22_grid_final_aggregated_In_lambert_spatial_weights_matrix_knearest8_FieldStatisticsToTable_Numeric.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Model No.	Adj. R-Squared	AICc	Significant Variables and Coefficients	Variables Below Significance Threshold	Observations
22	0.4744	-23198.59	nl_mean_RDAI (-0.0067); nl_mean_MRI (0.0227); nl_roads_km (0.0094); nl_leg_mean (0.3296); sl_knearest8 (0.1625); Intercept (0.0346)	nl_anm_mean_myp (-0.0037)	Myp loses significance.

Descriptive analysis

Step 1. Calculate grid statistics for analysis and save as xlsx.

```

arcpy.management.FieldStatisticsToTable(
    in_table="grid_analysis_lambert",

    in_fields="nl_anm_mean_myp;nl_mean_RDAI;nl_mean_MRI;nl_leg_mean;nl_roads_km;nl_anm_mean_area;nl_out_mean;nl_anm_mean_fines;nl_ibama_interdict_mean_val;nl_ibama_mean;nl_anm_mean_AAU;nl_anm_mean_AFS;nl_pf_mean_mining_r;nl_cprm_poi_mean;nl_gas;nl_urban_mean;MEAN_myp;MEAN_RDAI;MEAN_MRI;leg_mean;MEAN_roads_km;MEAN_area;MEAN_out;anm_fines;ibama_interdict_mean_value;MEAN_ibama;MEAN_sum_AAU;MEAN_sum_AFS;MEAN_mining_r;MEAN_cprm_poi;MEAN_gas;MEAN_urban;nl_no_title_mean;no_title_mean",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb",
    out_tables="NUMERIC variables_statistics",
    group_by_field=None,
    out_statistics="ALIAS Alias;COEFFICIENTOFVARIATION CoefficientofVariation;COUNT Count;FIELDNAME FieldName;FIELDTYPE FieldType;FIRSTQUARTILE FirstQuartile;INTERQUARTILERANGE InterquartileRange;KURTOSIS Kurtosis;LEASTCOMMON LeastCommon;MAXIMUM Maximum;MEAN Mean;MEDIAN Median;MINIMUM Minimum;MODE Mode;NULLS Nulls;NUMBEROFUNIQUEVALUES NumberofUniqueValues;OUTLIERS Outliers;RANGE Range;SKEWNESS Skewness;STANDARDDEVIATION StandardDeviation;SUM Sum;THIRDQUARTILE ThirdQuartile"
)
#Export as xlsx.
arcpy.conversion.TableToExcel(
    Input_Table="variables_statistics",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Results\variables_statistics.xlsx",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Step 2. Calculate original ANM statistics for descriptive analysis and save as xlsx.

```

arcpy.management.FieldStatisticsToTable(
    in_table="ANM_all_caatinga_municipalities_wgs",

    in_fields="QTAREAHA;SUBS;SUSE;SSN;NAME;P_TYPE;ANM_KEY;YEAR_PRO;LAST_EVE;ACTIVE;INACTIVE;EVENT;EVENT_CT;EVENT_TI;DTITLECA;TITLECTA;DTITLECT;TITLECT;AF S_SUM;AFS_2003;AFS_2004;AFS_2005;AFS_2006;AFS_2007;AFS_2008;AFS_2009;AFS_2010;AFS_2011;AFS_2012;AFS_2013;AFS_2014;AFS_2015;AFS_2016;AFS_2017;AFS_2018;AFS_2019;AFS_2020;AFS_2021;AFS_2022;AUTO_SUM;AAU_2003;AAU_2004;AAU_2005;AAU_2006;AAU_2007;AAU_2008;AAU_2009;AAU_2010;AAU_2011;AAU_2012;AAU_2013;AAU_2014;AAU_2015;AAU_2016;AAU_2017;AAU_2018;AAU_2019;AAU_2020;AAU_2021;AAU_2022;LEDSUM;LED_2003;LED_2004;LED_2005;LED_2006;LED_2007;LED_2008;LED_2009;LED_2010;LED_2011;LED_2012;LED_2013;LED_2014;LED_2015;LED_2016;LED_2017;LED_2018;LED_2019;LED_2020;LED_2021;LED_2022;CFEM2003;CFEM2004;CFEM2005;CFEM2006;CFEM2007;CFEM2008;CFEM2009;CFEM2010;CFEM2011;CFEM2012;CFEM2013;CFEM2014;CFEM2015;CFEM2016;CFEM2017;CFEM2018;CFEM2019;CFEM2020;CFEM2021;CFEM2022;CFEM;OP_YEAR;UT_PER;TAH",
    out_location=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb",
    out_tables="NUMERIC ANM_all_caatinga_municipalities_wgs_FieldStatisticsToTable_Numeric",
    group_by_field=None,
    out_statistics="FIELDNAME FieldName;ALIAS Alias;FIELDTYPE FieldType;NULLS Nulls;MINIMUM Minimum;MAXIMUM Maximum;MEAN Mean;STANDARDDEVIATION StandardDeviation;MEDIAN Median;COUNT Count;NUMBEROFUNIQUEVALUES NumberofUniqueValues;MODE Mode;LEASTCOMMON LeastCommon;OUTLIERS Outliers;SUM Sum;RANGE Range;INTERQUARTILERANGE InterquartileRange;FIRSTQUARTILE FirstQuartile;THIRDQUARTILE ThirdQuartile;COEFFICIENTOFVARIATION CoefficientofVariation;SKEWNESS Skewness;KURTOSIS Kurtosis"
)
arcpy.conversion.TableToExcel(
    Input_Table="ANM_all_caatinga_municipalities_wgs_FieldStatisticsToTable_Numeric",
    Output_Excel_File=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\descriptive_analysis\summary_anm_tenements_caatinga_selected.xls",
    Use_field_alias_as_column_header="NAME",
    Use_domain_and_subtype_description="CODE"
)

```

Step 3. Calculate original ANM legal mining statistics for descriptive analysis.

Merge all layers

```
arcpy.management.Merge(
    inputs=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2010";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2011";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2012";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2013";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2014";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2015";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2016";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2017";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2018";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2019";E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_wgs_2020";
    output=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\anm_legal_2010_2020_Merge",
    field_mappings="process \"process\" true true false 12 Text 0 0,First,#;add_source \"add_source\" true true false 8 Text 0 0,First,#",
    add_source="NO_SOURCE_INFO"
)
```

Delete identical

```
arcpy.management.DeleteIdentical(
    in_dataset="anm_legal_2010_2020_Merge",
    fields="process",
    xy_tolerance=None,
    z_tolerance=0
)
```

Calculate geometry attributes

```
arcpy.management.CalculateGeometryAttributes(
    in_features="anm_legal_2010_2020_Merge",
    geometry_property="area_ha AREA_GEODESIC",
    length_unit="",
    area_unit="HECTARES",
    coordinate_system=None,
    coordinate_format="SAME_AS_INPUT"
)
```

Step 4. Calculate original legal exploration statistics for descriptive analysis.

Merge all layers

```
arcpy.management.Merge(
    inputs=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2010";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2011";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2012";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2013";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2014";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2015";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2016";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2017";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2018";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2019";E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2020";
    output=r"E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis\Analisis.gdb\anm_legal_exploration_2010_2020_Merge",
    field_mappings=r"Id \"Id\" true true false 4 Long 0 0,First,#;E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2010,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2011,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2012,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2013,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2014,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2015,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2016,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2017,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2018,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2019,Id,-1,-1,E:\OneDrive\Academica\1-Doutorado
    UFRN\Tese\1_research\GIS\thesis\thesis.gdb\legal_exploration_wgs_2020,Id,-1,-1",
    add_source="NO_SOURCE_INFO"
)
```

Calculate geometry attributes

```
arcpy.management.CalculateGeometryAttributes(
    in_features="anm_legal_exploration_2010_2020_Merge",
    geometry_property="area_ha AREA_GEODESIC",
    length_unit="",
    area_unit="HECTARES",
    coordinate_system=None,
    coordinate_format="SAME_AS_INPUT"
)
```

Step 5. Calculate correlation matrix

```
# Load required libraries
```

```
library(arcgisbinding)
```

```
library(apaTables)
```

```
library(car)
```

```
# Set ArcGIS binding
```

```
arc.check_product()
```

```
# Define the path to the geodatabase and feature class
```

```
feature_class_path <- "E:\OneDrive\Academica\1-Doutorado UFRN\Tese\1_research\Analisis\Analisis.gdb\grid_analysis_lambert"
```

```
# Read the feature class into an R data frame
```

```
data_df <- arc.open(feature_class_path) %>% arc.select() %>% arc.data2df()
```

```

# Extract only the variables required for the collinearity assessment
data_subset <- data_dff[, c(
  "nl_no_title_mean",
  "nl_anm_mean_AAU",
  "nl_anm_mean_AFS",
  "nl_anm_mean_area",
  "nl_anm_mean_myp",
  "nl_cprm_poi_mean",
  "nl_gas",
  "nl_ibama_interdict_mean_value",
  "nl_ibama_mean",
  "nl_leg_mean",
  "nl_mean_MRI",
  "nl_mean_RDAI",
  "nl_out_mean",
  "nl_pf_mean_mining_r",
  "nl_roads_km",
  "nl_urban_mean"
)]

# Generate APA 7 style correlation table
# Here, the function saves the table in the APA format. You can specify a filename if you want to save it.
apa.cor.table(data_subset, filename = NULL, table.number = 1)

# Calculate the correlation matrix for saving as a CSV
cor_matrix <- cor(data_subset)

# Write the correlation matrix to a CSV file in the specified directory
write.csv(cor_matrix, file = "E:/OneDrive/Academica/1-Doutorado UFRN/Tese/1_research/Analisis/descriptive_analysis/correlation_matrix.csv")

```

Appendix J Distribution Graphs

