FEDERAL UNIVERSITY OF CEARÁ
CAEN
GRADUATE PROGRAM IN ECONOMICS
MASTER DEGREE IN ECONOMICS

PEDRO REIS LIMA

ANALYZING CRIMINAL FACILITY LOCATION OF ILLEGAL AIRSTRIPS IN THE AMAZON

FORTALEZA
2025

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Dissertation submitted to the Graduate Program in Economics of the CAEN of the Federal University of Ceará, as a partial requirement for obtaining the title of Master in Economics. Concentration Area: Economics

Advisor: Prof. Dr. José Raimundo de Araújo Carvalho Júnior

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Dados Internacionais de Catalogação na Publicação
Universidade Federal do Ceará
Sistema de Bibliotecas
Gerada automaticamente pelo módulo Catalog, mediante os dados fornecidos pelo(a) autor(a)

L71a Lima, Pedro Reis Lima.
Analyzing criminal facility location of illegal airstrips in the Amazon / Pedro Reis Lima Lima. – 2025.
83 f. : il. color.

Dissertação (mestrado) – Universidade Federal do Ceará, Faculdade de Economia, Administração, Atuária e Contabilidade, Programa de Pós-Graduação em Economia, Fortaleza, 2025.
Orientação: Prof. Dr. José Raimundo de Araújo Carvalho Júnior.

1. Location choice. 2. Microeconomia. 3. Pistas de Pouso Ilegais. I. Título.

CDD 330

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Dedico este trabalho ao meu amigo Jimmy.

ACKNOWLEDGEMENTS

Primeiramente, agradeço aos meus pais, que me deram as condições necessárias para chegar até este momento e continuar meus estudos na vida adulta. Este trabalho, por exemplo, jamais teria sido escrito em inglês sem os anos de investimento que fizeram na minha formação. Se eu tivesse trabalhado pelo menos 10% do que eles trabalharam até minha idade, talvez já tivesse concluído um doutorado — quem sabe até dois.

Aos meus irmãos que são grandes exemplos, Bruno e André que se doaram a suas respectivas áreas, na frente acadêmica, profissional e artística.

Agradeço aos meus amigos Cacimbinhas, Inácio, Rômulo, Pedro e Clara que sempre estiveram do meu lado e tanto me fizeram rir ao longo dos anos. Em especial ao Davi e Daniel, que conheço há tantos anos e até hoje me ajudam nos desafios do dia-a-dia.

Dos colegas da graduação, Italo, Natanael, Deoclécio e Sávio, que estiveram comigo nos momentos mais difíceis desse querido curso.

Também tenho muita gratidão a todos os colegas que fiz no CAEN, Aline, Amanda, Fillipe, Jamylle, João Victor, Roberto, Wesley, Leonardo, Lyanna, Pedro Luiz, Pedro Machado e Yuri. Nunca imaginei ter uma turma tão colaborativa, dividimos todas as dores dos semestres com boas doses de ironia.

Agradeço a CAPES, que financiou minha pesquisa e tornou possível que eu pudesse sair do mercado de trabalho para me dedicar à academia. Aos funcionários do CAEN, que fazem o curso acontecer, Cleber, Jonathan e Carmem.

Agradeço aos professores da UFC que me marcaram durante minha formação. O prof. Guilherme Irffi, que sempre foi um destaque em didática e atenção aos alunos. À profa. Georgeana Silveira, que me orientou na graduação e me mostrou como é ser um acadêmico profissional. Ao prof. Ivan Castelar, que toda aula nos ensinava econometria com boas pitadas de filosofia.

Agradeço a banca, ao prof. Victor Hugo de Oliveira pela sua colaboração, ao prof. Diego de Maria André que esteve nas primeiras reuniões onde esse trabalho surgiu. E, em especial, ao Prof. José Raimundo Carvalho, que foi uma das minhas inspirações já no meu primeiro semestre de faculdade e hoje posso dizer que é o orientador da minha dissertação.

Por fim, à minha companheira Marina Soares, que sempre esteve do meu lado e nunca me deixou esquecer o impacto que podemos ter no mundo com nosso cuidado e dedicação.

ABSTRACT

Throughout 2021 and 2022, environmental and national defense reports identified over 1,200 illegal airstrips in the Brazilian Amazon - surpassing the number of legalized airstrips in the region. This study investigates the spatial decision making of transnational criminal organizations when selecting locations for these runways in the Brazilian legal Amazon by means of a microeconometric approach. Using precisely georeferenced spatial data provided by the Centro Gestor e Operacional do Sistema de Proteço da Amazônia - CENSIPAM/Ministry of Defense, the entire Amazon area was discretized and runway occurrences were modeled using discrete counting models such as Poisson and Negative Binomial, as well as zero-inflated and hurdle models to account for excess zeros due to the vastness of the study area. The analysis is grounded in economic location theory such as facility location and residential choice modeling; as well classical criminology theories such as rational choice, routine activity, and crime pattern theories to reflect the strategic nature of illegal airstrip placements as key infrastructure to support the flow of criminal procedures; mainly drugs, illegal gold, and timber. Our results highlight the economic rationality with which these organizations have operated in recent years, suggesting that they strategically position airstrips at optimal distances to minimize detection risk while ensuring access to critical public infrastructure, including roads, waterways, ports and legitimate airports.

Keywords: Location choice. Microeconomics. Illegal Airstrips.

RESUMO

Ao longo de 2021 e 2022, relatórios ambientais e de defesa nacional identificaram mais de 1.200 pistas de pouso ilegais na Amazônia Brasileira – superando o número de pistas legalizadas na região. Este trabalho investiga a tomada de decisão espacial de organizações criminosas transnacionais ao selecionar locais para essas pistas na Amazônia Legal brasileira por meio de uma abordagem microeconométrica. Utilizando dados espaciais precisamente geo-referenciados fornecidos pelo Centro Gestor e Operacional do Sistema de Proteção da Amazônia – CENSIPAM/Ministério da Defesa, toda a área da Amazônia foi discretizada e as ocorrências de pistas foram modeladas utilizando modelos de contagem discretos, como Poisson e Binomial Negativa, bem como modelos zero-inflacionados e hurdle para contabilizar o excesso de zeros devido à vastidão da área de estudo. A análise está fundamentada em teorias de localização econômica, como a localização de instalações e o modelo de escolha residencial, bem como em teorias clássicas da criminologia, tais como a escolha racional, atividade de rotina e teorias de padrão de crime, para refletir a natureza estratégica do posicionamento das pistas de pouso ilegais como infraestrutura-chave para apoiar o fluxo de procedimentos criminosos – principalmente drogas, ouro ilegal e madeira. Nossos resultados destacam a racionalidade econômica com que essas organizações têm operado nos últimos anos, sugerindo que elas posicionam estrategicamente as pistas a distâncias ótimas para minimizar o risco de detecção enquanto garantem acesso a infraestrutura pública crítica, incluindo rodovias, hidrovias, portos e aeroportos legítimos.

Palavras-chave: Location choice. Microeconomia. Pistas de Pouso Ilegais.

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LIST OF ABBREVIATIONS AND ACRONYMS

AIC	Akaike Information Criterion
ANAC	Agência Nacional de Aviação Civil - National Agency for Civil Aviation
Censipam	Centro Gestor e Operacional do Sistema de Proteção da Amazônia
CPT	Crime Pattern Theory
CV	Comando Vermelho
FDN	Família do Norte
IBGE	Instituto Brasileiro de Geografia e Estatística
IVD	Intentional Violent Deaths
NB	Negative-Binomial
PCC	Primeiro Comando da Capital
QGIS	Quantum Geographic Information System
RAT	Routine Activities Theory
RCP	Rational Choice Perspective
TOC	Transnational Organized Crime
ZI	Zero Inflated

CONTENTS

1 INTRODUCTION

1.1 The Recent Violence & Homicide Underworld of the Legal Amazon Region

Transnational Organized Crime (TOC) is constantly adapting, as any other industry, by adjusting to the market and developing new crimes and methods. In this context, Brazil faces a growing influence of the country's criminal organizations in the Amazon Region, driven by factors such as its enormous dimensions, low population density, and proximity to the world's largest cocaine-producing countries: Colombia, Peru, and Bolivia (UNODC, 2023).

In this sense, Brazil witnesses an oligopoly of drug traffickers, with its main representatives being Primeiro Comando da Capital (PCC) and Comando Vermelho (CV). The "split" between PCC and CV in 2016, which represented the end of a 20-year truce between factions (MANSO; DIAS, 2017), resulted in a territorial dispute throughout the country for control of trafficking routes. This dispute led to new alliances between criminal organizations and caused violent consequences for the country, as it ignited a violent war between factions that affected, in particular, the northern and northeastern regions of Brazil (CERQUEIRA; BUENO, 2023).

Despite this, the scope of criminal activities continues to grow in the country, even with difficulties such as the COVID-19 pandemic in 2020. In this specific case, one of the main routes for trafficking, Rota do Solimes in the Amazon region, is observed to intensify on the air transport front, both in terms of number of flights and duration during the pandemic (CARVALHO, 2023). These data show a worrying adaptation of drug supply networks to economic shocks, even in environments with low road infrastructure and high geographic complexity, such as the Amazon region.

From the perspective of organized crime, the Amazon region shows great potential for the expansion of illegal activities. According to Instituto Brasileiro de Geografia e Estatística (IBGE) (IBGE, 2024), the state of Amazonas alone has 1.5 million km² and the lowest population density in the country. Therefore, it is a relatively remote region, with less state presence, several unsupervised river routes, and proximity to cocaine-producing countries such as Colombia and Peru. This is further aggravated for indigenous territories as they face stricter legal requirements for police enforcement and higher budget costs, only in March 2024 a provisional measure of R$ 1 billion was published to support a specific indigenous community (GOV, 2024; BRASIL, 2024).

Furthermore, the Amazon Region is seen as an opportunity to diversify markets, as it has other activities such as illegal deforestation, illegal mining, and wildlife trafficking. A route already used plus new resources to explore further strengthened the transnational power of these organizations. Furthermore, the war between PCC and CV also made this possibility even more viable, as it caused CV to ally with Família do Norte (FDN), the third largest faction in the country, and this strengthened the criminal commercial structure in the Amazon region (BERG, 2021).

In this context, the Brazilian homicide rate has shown a consistent upward trend since 1980, by 2019 it had increased by 85%, while in the northern region, for the same period, an increase of 260,3% was registered (SANTOS *et al.*, 2024). In 2023, one of the victims of the escalating violence was the native tribes of the legal Amazon. In response, federal police initiated an operation to combat illegal mining on the lands of the Yanomami Native Tribes (G1, 2023). It is estimated that 59% of the rivers inhabited by Yanomami tribes are affected by criminal activities (VITOR *et al.*, 2023). There is an evident need for more robust measures from the public security in the northern region, particularly in the legal Amazon region.

However, due to the magnitude and complexity of the state of Amazonas, its socioeconomic, geographical, physical, and structural characteristics, combined with the evolution of crimimal methods, combating TOC becomes a challenge for the public authorities. Records indicate that illicit drug planes take 5 minutes from landing to unloading all their content (ABREU, 2017).

Therefore, it is necessary to develop the national defense literature on the fight against drug trafficking, especially with regard to evidence-based public policies. In this scenario, it is justified to study the choice of crime location, to enable greater intelligence on trafficking within Amazonas, a region that is difficult to monitor.

The ongoing disputes between factions of criminal organizations over drug routes in the Amazon region contribute to the increase in Intentional Violent Deaths (IVD) in legal Amazon states. Naturally, many of the environmental crime hotspots are also the locations with the highest violence rates. The intersection between environmental crime and violence is evident in the numbers and demonstrates how the crime dynamic differs from the rest of the country.

In fact, at least since the 2000s, there has been a growth in the internalization of violence: crime that used to be concentrated in large urban centers has spread to the intersection zones of smaller towns and rural areas. This change in the dynamics of crime is especially observed in the Legal Amazon region, see FBSP (2022). Although in other regions of Brazil 79%

of IVD are committed in urban areas, in the Amazon region, this percentage falls to 66%. This indicates that a higher proportion of homicides occur in rural municipalities and intermediary areas.

However, both the Legal Amazon and the rest of the Brazilian states experienced a reduction in lethal violence within urban areas between 2018 and 2020. However, rural areas in the Amazon region experienced an increase of 9.2% in homicide rates between 2018 and 2020, contrary to the trend in the rest of the country, which saw a decrease of 6.1%. This pattern also occurs in intermediary zones between urban and rural centers.

Strengthening the correlation with environmental crimes, a specific mapping conducted by the Brazilian Forum on Public Safety proposed the disaggregation of homicide rates by the 'level' of deforestation (FBSP, 2022). In 2020, deforested zones recorded 34.6 and non-forested zones recorded 29.7 intentional violent deaths per 100,000 inhabitants. The presence of land disputes becomes even more evident when one observes that the zones under pressure from deforestation are the ones with the highest rates, reaching 37.1.

Hence, land conflicts and economic interest in deforestation have been changing and intensifying the dynamics of lethal violence in this part of the country. As will be discussed in the Literature Survey section, the absence of the state as a protective authority is one of the main factors that contributes to the repeated targeted 'victimization' of this region. Acre, for example, has only 80 police chiefs to handle incidents throughout the state, although the presence of international trafficking organizations in the area is well known (FBSP, 2022). In practice, in terms of effective duty, they have around 20 police chiefs per shift.

1.2 The Drugs-Illegal Mining-Crime Nexus in The Amazon Region

In 2020, Brazil lost 24 trees per second and 95% of the deforested area showed signs of illegality, either due to lack of authorization or because it occurred in protected areas (MAPBIOMAS, 2021). Since 1978, a cooperative effort to protect the Amazon has been in place through the Amazon Cooperation Treaty Organization, with the objective of uniting Amazonian countries to preserve the world's richest biodiversity. An aspect of this objective that deserves more attention is combating the crime nexus in the Amazon.

These criminal organizations not only intensified deforestation, but also accelerated the spread of other types of crime, such as corruption, tax evasion, indigenous land invasions, sexual assault, human trafficking, and illegal wildlife trafficking. Furthermore, illegal activities are perpetuated not only by well-known criminal groups but also by political actors. Activities such as issuing illegal licenses and falsifying the origin of timber and gold are carried out by high-ranking officials (UNODC, 2021).

With regard to drug trafficking, this activity has a direct impact that cannot be overlooked; when referring to cocaine, 300 liters of gasoline are needed to produce 1 kilogram of the drug (UNODC, 2021). However, agricultural production of coca, the base plant of cocaine, is more concentrated in neighboring countries, partly due to legal restrictions, such as in Colombia and Peru, which are more commonly used for traditional culture. Regarding cannabis, in a single operation, the Federal Police reported more than 200 tons of cannabis cultivated in deforested areas in 2020 in Pará (G1, 2020). Although drug production has a direct impact, the bigger one resides in its indirect reverberations.

Figure 1 – Yanomami indigenous children play on the wreckage of a Brazilian Air Force aircraft

Source: Frazão, Fernando (2023).

In that sense, the so-called Narco-Deforestation is one of the indirect impacts, for the purpose of reinvesting drug money or laundering money, whether criminals acquire land legally or not. That land might be used for cattle pasture, agricultural plantations, and even the construction of illegal landing airstrips (HOWARD, 2014). Furthermore, there are negative externalities caused in the surrounding areas when the land is seized by criminals, such as local tensions that escalate to violence, especially when near indigenous land (G1, 2021).

In addition, illegal lumbering and drug trafficking are so intertwined that between

2017 and 2021, Pública (2021) estimated that at least 16 major cocaine seizures occurred, the drug disguised in international shipments of timber, destined by sea to various European countries.

Another pillar of this crime nexus, in addition to drugs, is illegal mining. Especially concentrated in Pará (MCCOY; TRAIANO, 2020) and the triple frontier in Roraima (UNODC, 2021), this activity generates toxic residues that contaminate the riverside communities and the miners themselves. In fact, the uncontrolled use of mercury in this activity has been generating increasingly worrying consequences. A recent study, sampled from eight different communities in the Tapajós Basin, concluded that 75.6% of the tested adults had levels higher than the safe limit of mercury concentration in their blood.

1.3 Trafficking Routes and Modals

As we have discussed, transnational crime in Latin America has evolved over the years, with changes in its routes, transportation modalities, consumer markets, and agents themselves. Colombia has historically dominated South American routes, but more recently, Brazilian criminal groups have gained prominence. In fact, PCC has expanded its members to other South American, African and European countries, although there is still some fragmentation of power among different Brazilian criminal organizations. To put it simply, this presence was developed mainly due to two different important trafficking routes: (1) the Solimões Route and (2) the "Caipira" Route (BERG, 2021; CARVALHO, 2023). For the scope of this research, most of the focus will be on the Solimões route.

The highest profit targets for Brazilian criminal factions reside not in national land, nor in neighboring countries, but in other continents, such as North America and Europe. This led criminal groups to explore and study which means of transport should be exploited and through which routes they should be taken. This is no simple feat, as moving between different storage points (sometimes in different countries), different actors, and different supply and demand chains can be challenging, especially when dealing with public security surveillance.

For that reason, the chosen path is usually the least 'resistance', making criminal routes highly volatile to law enforcement measures. Furthermore, the main types of transport modalities, as they are called, are air, sea, land, and, generally to a lesser extent, postal/mail (UNODC, 2023). The pandemic apparently resulted in an increase in air modalities as opposed to land trafficking (CARVALHO, 2023). In fact, crime demonstrates great innovation in transport modalities; recently, cocaine destined for North Africa was apprehended in São Paulo, hidden in the hull of a ship below the waterline (G1, 2024).

As mentioned above, two different routes dominate drug trafficking throughout the country. The Caipira Route is located in the southeast and central-west regions of the country, being fed by Bolivia and Paraguay. This route takes advantage of the extensive highway infrastructure, access to suppliers, and even the regenerative capacities of the biomes, which are used to hide landing strips and drug hotspots (ABREU, 2017). Therefore, its origins involve air transport, while most of the movement on national ground occurs by land.

On the other hand, the Solimões Route, the most interesting when it comes to the Amazon region, also uses air transport but also employs the rich river system that the Amazonian land provides. In fact, the Amazon rivers connect Peru and Colombia to Brazil and also penetrate deeply into different states. After the 'Racha' (split) between PCC and CV, when they became enemies, a great dispute erupted over the control of the routes. With increased domestic competition, criminal organizations also intensified their disputes to control the Atlantic Ocean outlet, ultimately turning the capitals of the Northeast into centers of violent criminal conflicts (SULLIVAN, 2022).

Thus, the importance of access to means of transportation serves as a guiding pillar for this research. To understand criminal choices for airstrip locations, one must recognize that the desired characteristics are not related only to the air modality, as many modalities are involved in criminal activities. Moreover, as mentioned, they are motivated not only by drugs, but also by other illegal activities.

1.4 The Role of Illegal Airstrips in The Traffic Network

Of all modalities, aircrafts stand out as the main source of drug supply from foreign agents. Although water routes play an enormous role in national transportation, air transport remains the preferred method of transport in a dense forest (MISTLER-FERGUNSON, 2021). To make illegal mining feasible on the scale that "garimpeiros" (as illegal miners are called in Brazil) operate, specialized equipment is required. Thus, not only do aircraft serve as the origin of drug products, but they are also the most reliable transportation for criminal equipment.

Therefore, the illegal airstrip itself can be seen as illegal equipment, or perhaps a facility, fundamental to different types of criminal activity. In 2022, it was reported that there were 1,269 unauthorized runways used between 2021 and 2022, more than the number of legally recognized airstrips (UOL, 2022; Potter, Hyury, 2022).

Figure 2 – Seized aircraft for environmental crimes on Yanomami indigenous land inside the Federal Police yard

Source: Fernando Frazão (2023)

Agência Nacional de Aviação Civil - National Agency for Civil Aviation (ANAC) regulates the authorization of new runways, as stated in the Brazilian Aeronautical Code (ANAC, 2021). Interestingly enough, even though hundreds of illegal runways were recognized, only six fines were issued by ANAC for the irregular construction of runways between 2016 and 2021, none of which were located in the Amazon region. In addition, various media outlets argue that the Bolsonaro government was complacent with the situation, especially with respect to illegal mining (MISTLER-FERGUNSON, 2021), (Potter, Hyury, 2022), and (MCCOY; TRAIANO, 2020). In fact, there is a growing political group that advocates for mining agendas, seeking to further legitimize the practice (VEJA, 2020).

Therefore, the air mode gains prominence not only as an effective means of transportation but also for being somewhat successful in recent history in avoiding state interventions. Moreover, there are records that the destruction of dirt airstrips was a very expensive expense, as was done by implosion (ABREU, 2017). The fact that small aircraft are the most commonly used, modified to be lighter and enable shorter runways, coupled with how many airstrips are registered, shows how accessible they are as a tool for offenders.

In this sense, the classic field of criminology on a crime location choice proves to be a useful intelligence tool. Why is an airstrip built at one location and not at the other? A fundamental concept is that, for crime to occur, a motivated offender must find an appropriate target in a vulnerable situation (COHEN; FELSON, 1979). Identifying what makes an appropriate target for the offender and which regions have a lower public security presence can be the key to combating drug trafficking in this region.

1.5 Objectives

The objective of the dissertation is to analyze and econometrically model the socioeconomic, geographical, physical, and structural determinants of the locational choices for building illegal landing airstrips in the Amazon region made by organized criminal organizations as a facility to feed transnational illicit supply networks.

As specific objectives, the aim is to: (1) build a georeferenced database in the Legal Amazon with socioeconomic, geographical, physical, structural data and the location of landing strips from "unidentified flights"; (2) develop a hexagonal grid as the spatial standard for the state of the Legal Amazon based on census grids IBGE (IBGE, 2021); (3) conduct a literature review on the topic of residential location choice; (4) estimate a spatial discrete model of crime location choice.

2 LITERATURE SURVEY

To develop a theoretical framework capable of assessing illegal airstrip activity in the Amazon region, a literature survey was conducted. To assess classical criminology theory, its modern developments, and other complementary approaches that prove useful for this specific question, this section is divided into three parts. First, a discussion of environmental criminology, its roots, founders, ramifications, and different conceptions. Second, moving toward an empirical method of testing theory, the section presents how to unravel target location selection. Third, a new perspective is proposed, drawing from two fields not typically associated with criminology: residential choice and facility location.

2.1 Crime and Places

In the early 1800s, two researchers in the field of moral statistics produced what is considered the first instance of crime mapping theory (GUERRY, 1832). Back then, they were already able to show that crimes were not uniformly distributed across the different regions of France. Subsequently, Fletcher also produced maps showing the rates of male incarceration in the Journal of Moral and Educational Statistics of England and Wales, discussing its causes (FLETCHER, 1849).

After that spark, many criminal theories emerged to address crime distribution. Specifically, in the 1970s, the criminology literature changed its focus and began to emphasize more the importance of *place* (HUNT, 2019; RUITER, 2017). Lawrence Cohen and Marcus Felson developed the Routine Activities Theory (RAT) that describes how the routine of offenders affects the choice of the location of the crime (COHEN; FELSON, 1979); Clarke and Cornish introduced a Rational Choice Perspective (RCP), with a microeconomic basis, to the problem of choosing the location (CLARKE, 1983; CORNISH; CLARKE, 1985) and then Crime Pattern Theory (CPT) surged as a ramification trying to merge RAT and RCP (BRANTINGHAM, 1978; BRANTINGHAM; BRANTINGHAM, 1984; BRANTINGHAM, 1981).

2.1.1 Routine Activity Theory

Cohen and Felson (1979) argue that, based on a human ecology perspective, each successfully completed violation minimally requires an offender with both criminal inclinations and the ability to carry out those inclinations, a person or object providing a suitable target for the offender, and the absence of guardians capable of preventing violations, and they emphasize that the lack of any of these elements will normally be sufficient to prevent such violations, see Figure 4.

In this sense, the legal Amazon region seems vulnerable to suitable and vulnerable factors. These factors may normally go unnoticed as the absence of violations hides their susceptibility, creating a security blind spot. An element that is usually neglected in the literature is the guardianship of ordinary citizens (COHEN; FELSON, 1979), which is expected to be less effective in the Amazon biome, due to its less dense population and the presence of native communities, endowed with less capacity to defend themselves, as seen in the Yanomami tragedy.

Moreover, the agent's daily routine would be the thread uniting an offender to its selected crime location, when a motivated offender stumbles in the suitable scenario in the course of their routine, then crime is likely to occur. Because each individual has a different coverage pertaining to his characteristics, crime is not uniformly distributed over space and time. This line of thought constructs a framework for assessing crime location choice.

However, the routine approach cannot account for premeditated crimes that many offenders opt for their usual path. This is in direct dialogue with our research theme, because illegal airstrips in the Amazon are constructed by large criminal structures, requiring several motivated and planned criminals. In addition, an illegal airstrip is just a means and not an end in itself. It is built to facilitate the flux of illegal goals. How would building illegal airstrips be an opportunity in anyone's routine? This requires further theoretical foundation to be explored; see 2.1.2 and 2.3.2.

2.1.2 Rational Choice

Cornish and Clarke define that The Rational Choice Perspective to Offending "assumes that when criminals offend, they do so because crime provides the most effective means of achieving desired benefits" Cornish and Clarke (2002, p. 41). This theory treats offenders as other rational economic decision-makers pondering risks and rewards, cost, and expected profit. And after that evaluation, choose what maximizes or at least brings them closer to their goals.

The usual criticism of that approach is that it requires too much abstract effort in deliberation and planning and ignores the effect of impulsivity of the offender's behavior (CORNISH; CLARKE, 2002). Furthermore, it requires a very narrow experiment design, which requires additional auxiliary assumptions to be of any use.

Because of this logical foundation, parallels with environmental biology and ethology emerged as a way to enrich rational choice theory. Target selection regarding animals behavior for diet, foraging and time spent in territory seen fit for comparison. From that perspective came the term environmental criminology, the study of the role of the environment in crime patterns (JEFFERY, 1971; BRANTINGHAM, 1981). The behavioral ecology foraging theory was used as a supplement to many researches (COHEN; FELSON, 1979). In fact, this comparison was similar to the War in Attrition, originally used to study animal conflicts for scarce resources that ended up serving as a model for game theory on natural monopoly (a duopoly conflict for scarce resources) (DUTTA, 1999).

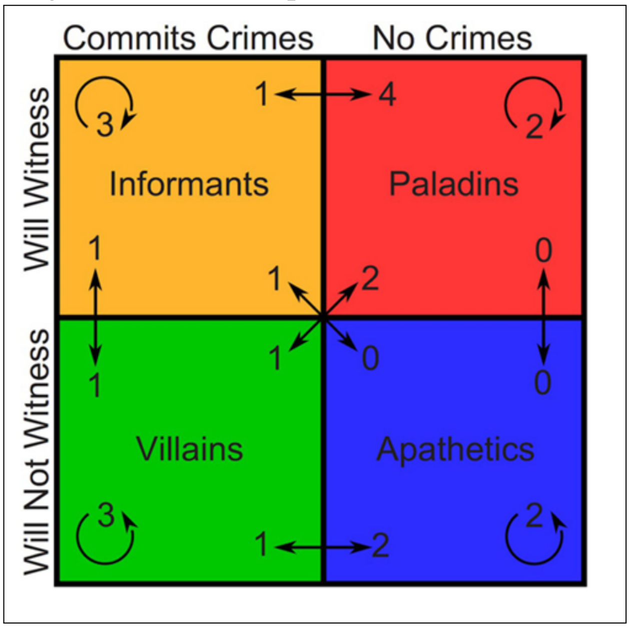
The discipline of economics has developed many contributions to the study of criminology. One of its pioneers was Gary Becker (1968), who developed a rational model for criminal behavior introducing imprisoning costs, opportunity costs, moral costs, income, and illegal income that influenced Cornish and Clarke (CORNISH; CLARKE, 2002). This utility maximizing agent is the foundation for rationalizing the behavior of criminal organizations as they act as rational agents as firms, aiming to maximize their profit. They consider factors such as the human capital needed for drug transport through airships and the expected risk of apprehension. Such is their concern with efficiency that there are records indicating, as referred to before, that it can take just 5 minutes for an illegal airplane transporting cocaine to land, a truck has to load its contents and then accelerates and resumes flight (ABREU, 2017).

More recently, another important contribution has been the study of crime as a social dilemma described by evolutionary game theory. Of the many possible game cases for study, the most famous is the prisoner's dilemma, where the Nash equilibrium is not socially optimal, as there is an incentive to defect from the common interest (GIBBONS, 1992). Although the prisoner's dilemma may not fit the project objectives, it shows another useful perspective for the problem description.

In fact, there have been efforts to study the evolution of crime within the framework of social dilemmas. In that sense, social order can be considered as a common good (the social pay-off) that is threatened by criminal activities, with competition between criminal agents and those acting against it. Agents have the power to witness the crime and collaborate to punish it while also being able to commit (or not) the crimes themselves. The possible players then become: (I) informants, who commit crimes and cooperate with authorities; (V) villains, who commit crimes and do not cooperate; (P) Paladins, who do not commit crimes and will cooperate;

and (A) apathetics, who will neither commit crimes nor cooperate (SHORT *et al.*, 2010).

Figure 3 – Game Depiction



Source: citeshort2010cooperation.

There can be built two scenarios, a low-crime equilibrium (cooperation-dominated) and high-crime (defection-dominated). The authors of the model argue that under the circumstance where crime is very prolific, there will be less incentive to collaborate with authorities because of fear of retaliation (SHORT *et al.*, 2010). Fear might be so ingrained that social norms change to benefit hiding criminal activities from legal authorities. These behaviors are usually related to crime organizations such as the Italian mafia, street gangs, drug cartels, and in Brazil's case, the criminal faction. This contributes to the sense that the Amazon region is even more fragile for the defection scenario, as lower-density communities with fragile connection to authorities are faced by large presence of crime organizations.

2.1.3 Crime Pattern Theory

Crime Pattern Theory brings a broad explanation of crime, applying features from the perspective of routine activity and rational choice (BRANTINGHAM, 1978; BRANTINGHAM; BRANTINGHAM, 1984). They propose that offenders have a learned template of characteristics of what makes a proper crime location, and suitable targets are identified in those proper scenarios.

Furthermore, offender search is not random and occurs in their "awareness space" reminiscent of the routine activity, but more relaxed in that it does not pertain to his daily routine directly, but to the spatial knowledge they obtained from it. The attractiveness of certain targets may be understood as an influence of the rational choice utility support. Crime pattern theory then affirms that crime occurs where targets are attractive enough to intersect with the criminal's awareness space.

2.1.4 The Synthesis from Environmental Criminology

The different theories of criminology could be seen as competing explanations of crime determination, but they are more useful if they are seen as complements to each other. Routine Activity relies on individuals behaviors, while Crime Pattern demand places characteristics to define crime risk. These differences can lead to different conclusions, but also could be valid for different contexts and different experiment designs. Crime-specific research could show some theory that is more effective depending on the topic.

In summary, Routine Activity, Crime Pattern, and Rational Choice theories build ground to empirical research in Crime Location. In fact, most of the research on the development of criminology had focused on why certain individuals commit crimes; it is only after the theories cited developed a framework that explains crime, not the criminals themselves (ECK; WEISBURD, 1995).

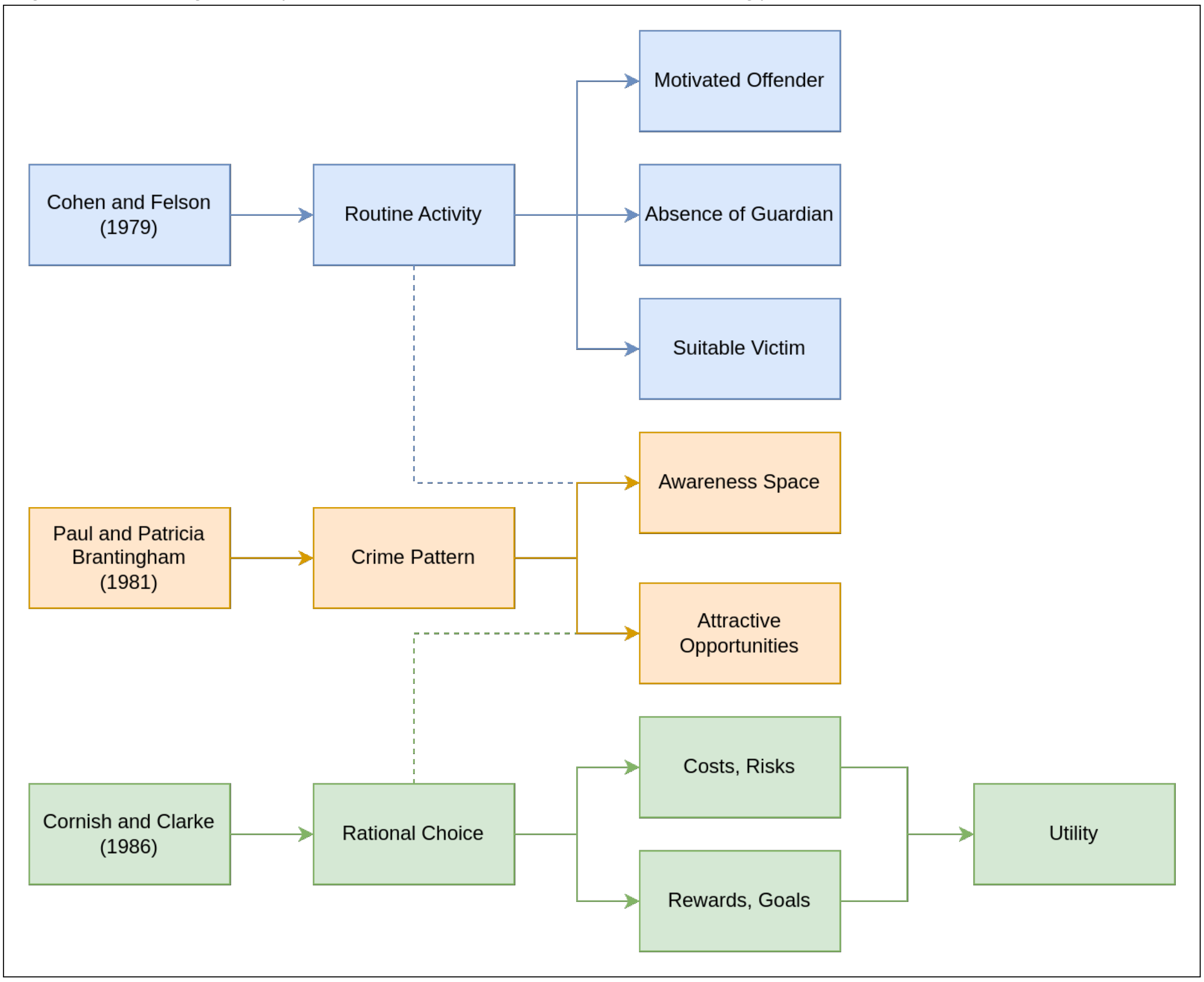
2.2 Crime Location Choice

So far, we have discussed three perspectives (RAT, RCP and CPT), able to explain how space relates to crime. However, it is necessary to be more precise and consider crime location as a choice of purpose. Hence, crime location choice theory refers to the analysis of where offenders commit their offenses and why they specifically commit them there rather than in other locations, and what logic lies behind this criminal behavior.

2.2.1 From Macro to Micro Specific Locations

Crime mapping started with a country as a sample, a macro approach, Guerry (1832) found that France had a nonuniform distribution of crimes. After that, studies looked at smaller scales such as regions, states, cities, communities, and neighborhoods. However, it still lacked the ability to examine the places themselves (ECK; WEISBURD, 1995). What is the reason a certain bus stop is a higher target for victimization among many in the same community, what

Figure 4 – Diagram Synthesis of Environmental Criminology



Source: author elaboration.

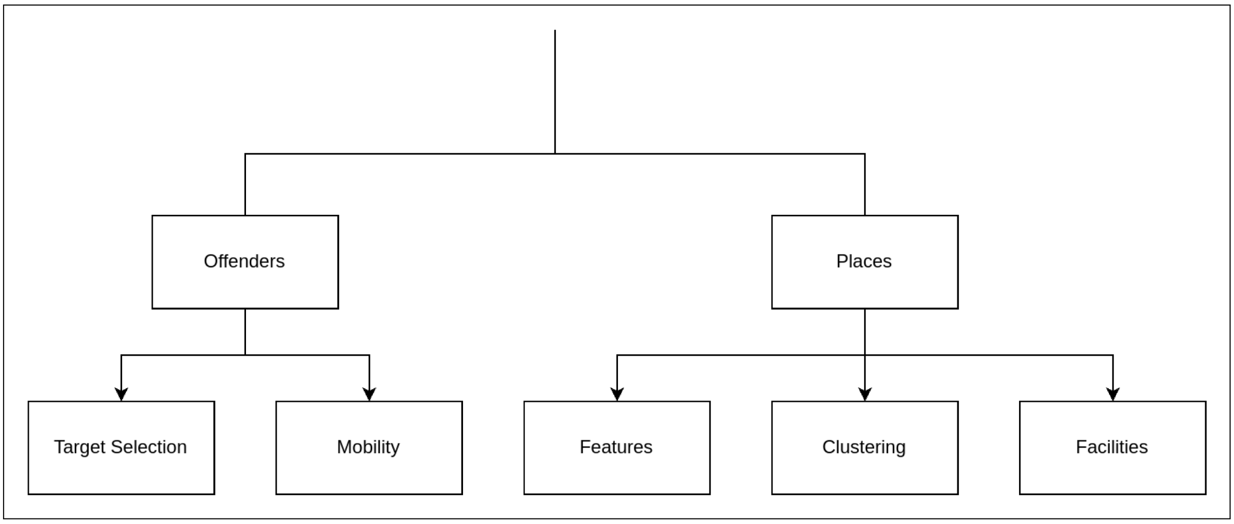
makes certain alleys more suitable for drug trafficking - these questions can only be answered by a micro lens.

Countries, cities, and neighborhoods do not have consistent rules to delimit their limits. Borders are arbitrary lines that do not guarantee any type of representativeness, there are larger and smaller states, cities with high and lower heterogeneity of characteristics (ARBIA; ARBIA, 1989). For that reason, analyzing discrete crime in that type of scope can lead to misinterpretation.

Eck and Weisburd (1995) categorizes 3 types of empirical evidence regarding places; see Figure 5. First, define facilities as structures with specific purposes. Those can be schools, stores, housing, and universities. Places show an effect on the increase or decrease in crime in their immediate surroundings, regions where offenders went to school have an increased probability of being targeted(RUITER, 2017; BERNASCO, 2010b). When studying the London 2011 Riots, Baudains *et al.* (2013) found that the effects of school presence were stronger for juveniles than for adult offenders.

Another possible problem for conducting research is that often the density of crime and the risk of victimization are not used accordingly (WIKSTRÖM, 1995). Burglary rates are normally calculated by dividing the number of burglary events by population, but to calculate risk, they should be divided by the number of buildings in the area. Even when considering the number of buildings, resident characteristics can play a big role. Take a house with childless adults that spend the day working or an area with retired couples, both can show different risks for the same population and houses.

Figure 5 – Places Features Diagram



Source: adaptation of Eck and Weisburd (1995, p. 8).

The second category is clustering. At every level of aggregation, some areas may contain fewer crime rates than others (BRANTINGHAM; BRANTINGHAM, 1982). Successful crime prevention efforts have taken the approach of identifying small clusters of crime "hot spots". The third one is site features; these relate to a variety of physical and social characteristics of places that can be related to the attractiveness to offenders. It can be related to the lack of guardianship from Cohen and Felson (1979).

2.2.2 Random Utility Maximization and Discrete Choice

Although criminal choice location had already become a classic area of study in the criminology literature, it was only in recent years that discrete modeling became introduced as a tool for its analysis (BERNASCO; NIEUWBEERTA, 2005). In fact, the discrete choice framework emerged from the field of microeconomics, with the intention of formulating econometric models of population choice, the multinational logit model was developed (MCFADDEN, 1972) and, over the years, many variations and extensions of the model proliferated.

Historically, there have been three common approaches to examine the choice of criminal location (BERNASCO; NIEUWBEERTA, 2005), each differing in the dependent variable analyzed. The first is offender-based, where its focus is on the length of the journey to crime from the offender to the victim. This strategy aims to explain the criminal choice, after it has taken place, so it disregards other factors such as why not other locations. Furthermore, it does not take into account the profit and risk related to particular targets. Complementarily, the second approach is based on a target, relates to the victimization rate, and what affects its attractiveness to offenders. This is useful to compare regions and see why some areas may be less affected by crime. But lacking the offender characteristics, it fails to control for its characteristics, hiding a potential bias for a location susceptibility.

The third option, trying to merge the first two, used the number of victimizations from one neighborhood to another as dependent variables and added the factors of 'push' and 'pull' as covariates, indicating what factors make a region 'produce' burglars and what 'attracted' them in the other. This gravity model, derived from geography, lacked because it required aggregate data from crime trips, losing the individual offender analysis aspect. That's when discrete modeling proved itself as an opportunity, usually used for urban housing demand studies, and it exploded as a tool to combine the three mentioned approaches.

The paper responsible for introducing discrete spatial choice to the study of criminal location choice used the model to explain how residential burglars select target areas (BERNASCO; NIEUWBEERTA, 2005). They applied the model in the city of The Hague in the Netherlands, using data not only for victimized residences, but also from the burglars themselves. Therefore, their approach describes target selection by the victims' characteristics and by the offender's characteristics simultaneously. In general, they found that the proximity to the offender's home, that 'availability' of the targets (residential density) and the percentage of single-family dwellings all increased the chance of offense.

To first summarize, the discrete choice framework is constructed on a set of assumptions regarding any individual choice behavior (BEN-AKIVA; BIERLAIRE, 1999):

1. Decision makers: The one responsible for opting for a choice.
2. Alternatives: The decision maker must choose one alternative from a set of choices. That is, a set of countable alternatives that are mutually exclusive and contain all possible

choices.

3. Attributes: Alternatives have each characteristic that makes them attractive or unattractive to the decision maker, the decision maker themselves can have attributes. All alternatives are evaluated by the decision maker.
4. Decision rule: According to RUM, the decision maker chooses the alternative that maximizes the expected utility function.

Evidently, the discrete spatial choice model is derived from microeconomics principles, having much of its application developed from McFadden (MCFADDEN, 1972), so much that it made him one of the 2000's Nobel laureates "for his development of theory and methods for analyzing discrete choice" (NOBELPRIZE.ORG, 2000). The problem may be expressed as the utility function U of the decision maker i, which is evaluated for the expected utility regarding profits and risks for a discrete location j:

$$U_i(z_{ij}) = z_{ij}\beta + \varepsilon_{ij} \tag{2.1}$$

Let z_{ij} be a set of attributes related to both the location j and the decision maker i, so that the explanatory variables may include the attributes of the location and the agent. β is the column vector of population parameters that measure the effects of each variable on the utility of the agent. The ε represents the unmeasured effects, for the relevant unobserved variables, as well as the error. Then the problem of discrete choice may appear as a problem of individual agent utility maximization.

Ruiter (2017, p. 6) breaks down the discrete choice framework when applied to the choice of location of the crime by identifying the decision maker as the offender and the alternatives as the target locations in a study area. Recalling the environmental criminology theories described, sets of attributes can be derived. Offenders will target areas with attributes with the highest reward (RE), requiring the least effort (EF), and minimal risks (RI). Visualizing these abstractions in the utility function:

$$U_{ij} = \beta_{RE}RE + \beta_{EF}EF + \beta_{RI}RI + \varepsilon_{ij} \tag{2.2}$$

RE could be the sources of availability for gold mining, EF the effort to build the airstrip at the location, and RI the distance to the nearest city center. The expected magnitudes of the parameters then would be expected to be respectively positive, negative and negative to the agent's utility. One could further expand this linear function to include many more variables just by adding. This shows how to build a theoretical framework and McFadden (1972) demonstrates that, under specific assumptions, it can be directly translated into a conditional logit model.

Therefore, in order to estimate this theoretical model of discrete spatial choice, the usual method of estimation is the conditional logit model (MCFADDEN, 1972; GREENE, 2011). The purpose of this method is to describe the probability that an offender i will choose an alternative j given their characteristics.

$$Prob(Y_i = j|z_{ij}) = \frac{exp(z'_{ij}\beta)}{\sum_{j=1}^{J} exp(z'_{ij}\beta)} \tag{2.3}$$

Where Y_i is the choice to victimize the location j by the offender i. z_{ij} being the set of attributes that may vary between individuals and locations. e^{β} may be interpreted as a non-linear marginal effect of an increase in some of the covariates. One important assumption of this model is the independence of irrelevant alternatives (IIA), it states that adding or removing alternatives from the choice set will not change the probabilities associated with existing alternatives.

Although the literature on crime location choice has focused on assessing the effects of criminal agent characteristics on crime, another common assumption made, present in the conditional logit model, is that offenders are homogeneous in their crime location preferences. However, recent research has found evidence that offenders vary in decision-making factors (TOWNSLEY *et al.*, 2016; FRITH *et al.*, 2017; LONG *et al.*, 2018). To encompass this component new models, such as mixed and conditional logit, have been adopted. These models would enable researchers to assume a combination of different distributions of preferences among offenders.

In fact, this assumption can be disruptive to common conclusions in the literature. Frith (FRITH, 2019) conducted a comparison of the fit of the model to account for heterogeneity and found that, for the latent class logit model, some classes of criminals were severely deterred by having to travel longer distances while for others the estimation showed to have no effect. Therefore, although the average effect of a variable may indicate a certain magnitude, its effect can vary significantly or even differ in direction between offender classes.

Regarding illegal landing zones in the Amazon, the literature is clear on the combination of drug traffic, illegal mining, and deforestation involved in criminal operations (BERG, 2021). Evidently, each of these activities may carry a different set of preferences that could contribute to heterogeneity. Furthermore, the role of criminal organizations and their territories might also influence offenders' preferences, whether by avoiding enemy territory or by specializing in certain type of crime. Therefore, this aspect warrants consideration in this project, as even similar sets of characteristics may carry different preferences sets.

In fact, the choice of the location of the crime is within a scholarly tradition approach inaugurated by the book by Paul and Patricia Brantingham (1981) in which 'environmental criminology' was defined as the study of the 'discrete location in time and space... in which a criminal event occurs'; see (BRANTINGHAM, 1981). Notwithstanding the seminal contribution brought by Cohen and Felson (1979), ((BRANTINGHAM, 1981), and authors like (Deutsch, J., Hakim, S., & Weinblatt, J. (1987)), (Weisburd D, Bernasco W, Bruinsma GJN (eds) (2009)), (Bernasco W (2010a) Modeling micro-level crime location choice: application of the discrete choice framework to crime at places), (Bernasco, W., Ruiter, S. (2014)), and Ruiter (2017); this environmental criminology approach has neglected so far how criminals choose geographic location of accessory facilities to commit crimes.

2.2.3 Awareness Space and Timing

Although pattern theory brought the idea of awareness spaces in a more general term, most crime location choice studies focus on limited information of the offender's knowledge variables. Taking the recurring conclusion that offenders commit crimes near their home areas, it is important to note that the location of the home is considered at the time of the misdeed. Therefore, past experiences that build the individual awareness space can go unnoticed.

In fact, homeless individuals can commit crimes; therefore, the current house does not aggregate any information. This type of crime behavior can be related to drug addiction, which is concentrated in drug sales areas (RENGERT, 2004). Canter and Larkin (2017) on their study of serial rapists, make two categories of criminals: marauders and commuters. The marauders use their home as a center of operation and commit crimes near it. Commuters, as the name implies, commit crimes outside their home range. In their study, serial rapists fit the marauder profile the best.

In 2010, two studies tested the hypothesis that offenders would also be more likely to target areas near where they used to live (BERNASCO, 2010c; BERNASCO; KOOISTRA, 2010). They found out it was the case, not only they targeted areas they currently lived near, but also their past housing areas. Furthermore, it was found that the longer an offender lived in an area, the stronger the effects in target selection that fit the expected behavior by pattern theory.

2.3 New Perspectives

It is evident from the previous sections that there is a significant intersection between criminology and other fields, such as economics and environmental biology. Therefore, this section further examines the possibilities of interdisciplinarity to enrich the analysis of illegal airstrip locations by discussing the literature on residential location choice and facility location choice.

2.3.1 Residential Location Choice

Hence, we searched for the theoretical and applied tradition of location choice that could support our present efforts to econometrically model the location of accessory facilities to commit crimes. A thoroughly developed framework is residential location choice based on the early developments of Mcfadden discrete modeling for residential location choice, by the author himself (MCFADDEN, 1978). In fact, the choice of residential location captures many of the variables of interest in these objectives of the project, as it has developed the mathematical model for different scenarios that involve georeferenced data for rational consumer choice. The use of utility in a locational sense gave the model the ability to predict the probability of the location choice explained by a multitude of location factors.

One of the possible explanatory variables examined by the location of the residential choice is accessibility (PAGLIARA *et al.*, 2010). It is feasible to imagine that when an agent chooses a residence he will take into consideration factors such as what is close to it, is it close to his work, to shopping malls, to his children's schools, and many other important routine facilities. These activities are constrained by a time budget, similarly to the usual microeconomic budget constraint (PAGLIARA *et al.*, 2010). Higher utility will be granted to locations close to important dependencies, not only in pure distance, but in accessibility, that may come from the lack of traffic or the quality of the road infrastructure. Beyond that, many activities will occur in succession, some activities require one to carry another, there will be cases where activities are close substitutes, and so on. There is a need to optimize the path to the activities.

The relation to crime location choice is evident, criminals also face a time constraint. They need to coordinate the time the airship takes from the cocaine producer to the illegal airstrip in the amazon, this is influenced by weather, be it the air currents or the rain forecast for the chosen path. Not only does aerial transport influence the decision, they have to collect the drug through terrestrial or fluvial transportation, so they need decent road tracks to follow or rivers capable of supporting cargo-carrying boats. These factors need to be precisely coordinated so that authorities cannot follow their tracks; it seems reasonable to use these factors to predict the choice of landing zone location. This collaborates with the criminal location choice literature, which indicates that criminals act near their own residence, minimizing travel distance to the crime scene.

2.3.2 Facility Location

One specification of this project is its interest in the location of airstrips from criminal organizations, and that subtly it is not referring to the crime scene itself, but to one of the means to it. In this regard, crime facility is a more appropriate term that, by itself, sheds light in another literature that should be considered, the facility location choice. This branch of knowledge investigates where to settle facilities in order to minimize the cost of satisfying a set of demands subject to a set of constraints. Hence, an intersection of this knowledge and the other mentioned areas seems useful to face the discrete modeling of the location choice of airport facilities (HALE; MOBERG, 2003).

The study of facility location can be allegorically traced back to Pierre Fermat in the 17th century when he enunciated the question: "given three points in a plane, find a fourth point such that the sum of its distances to the three given points is minimum", which was answered by one of Galileo’s students, Evagelistica Torricelli (KRARUP; VAJDA, 1997). In more formal terms, the literature began in 1929 when Weber studied how to position a single warehouse to minimize the sum of distances to all its customers (WEBER, 1929). It was later generalized to what would be called "median problems".

Imagine an airport needs to be constructed to feed a network of other airports that demand routes to certain locations, the position at which the new facility will be located must minimize travel distances. Another more generalized example would be P number of factories that must supply a number of i warehouses. The warehouses may demand different quantities, giving them a certain amount of demand. This type of problem can be mathematically formalized as a P-median problem (OWEN; DASKIN, 1998) with the following notation:

Inputs:

- i: index of demand node
- j: index of potential facility site

- h_i: demand at node i
- d_{ij}: distance between demand node i and potential facility site j
- P: number of facilities to be located
- X_j: 1 if a facility is located in site j, 0 otherwise
- $Y_i j$: 1 if demand at node i is satisfied by a facility j, 0 if not

Based on these definitions, the objective of the problem is to minimize the distance between customers and facilities weighted by demand subject to a number of P facilities, where all Y_i are served by some X_j. For further theoretical descriptions of the problem, see Owen and Daskin (1998).

This formulation provides a way to determine the best placement that values the demand-weighted distance between custumers and facilities at a finite set of potential sites. A downside of this approach is that only distance is taken into account, and other attributes, which could affect production, are abstracted from consideration. For instance, some factories require access to road infrastructure and other, as is the case for some data centers developing artificial intelligence models, require a really high supply of water.

To illustrate, Sakai *et al.* (2020) argues that although a large number of studies emerged to assess the distribution of logistics facilities, studies that analyze factors that influence location choice at the individual facility level show to a lesser extent and there is very limited research that focuses on the differences between different types of activity. Therefore, adding variables other than distance could benefit more specific facility location models.

Hence, another formal definition of the problem can be described, very similar to the discrete modeling used in criminal choice. Let V_i be the utility function of the company i and $w_i j$ a observed set of characteristics of location j:

$$V_i(w_{ij}) = w_{ij}\gamma + \varepsilon_{ij} \tag{2.4}$$

Therefore, the parameter γ will describe the effects of location characteristics in the company utility. Recalling the p-median problem (OWEN; DASKIN, 1998), if w assumed the distance to a demand node, the expected magnitude of γ would be negative. That is, the greater the distance, the less utility that location would suffice for a facility. The question remains as to what other factors should be taken into account in the decision-making utility.

Concerning this, Heragu (1997) describes in his book "Facilities Design" that for single-facility location problems, there can be two scoring methods. The first one is based on a

Qualitative Analysis, focused on abstracting what factors matter and in what order. Although this method outputs a final score that can be used as a decision-rule, the values were created subjectively. Therefore, a formal decision requires to take into account objective measures based on a Quantitative Analysis. Thus, in recovering the P-median problem, the distance to demand is an objective measure.

However, the quantitative approach does not allow the incorporation of unquantifiable factors that can impact the location decision (MORADI; BIDKHORI, 2009; HERAGU, 1997). Therefore, a hybrid solution can be formulated by classifying the objective and subjective factors addressed as

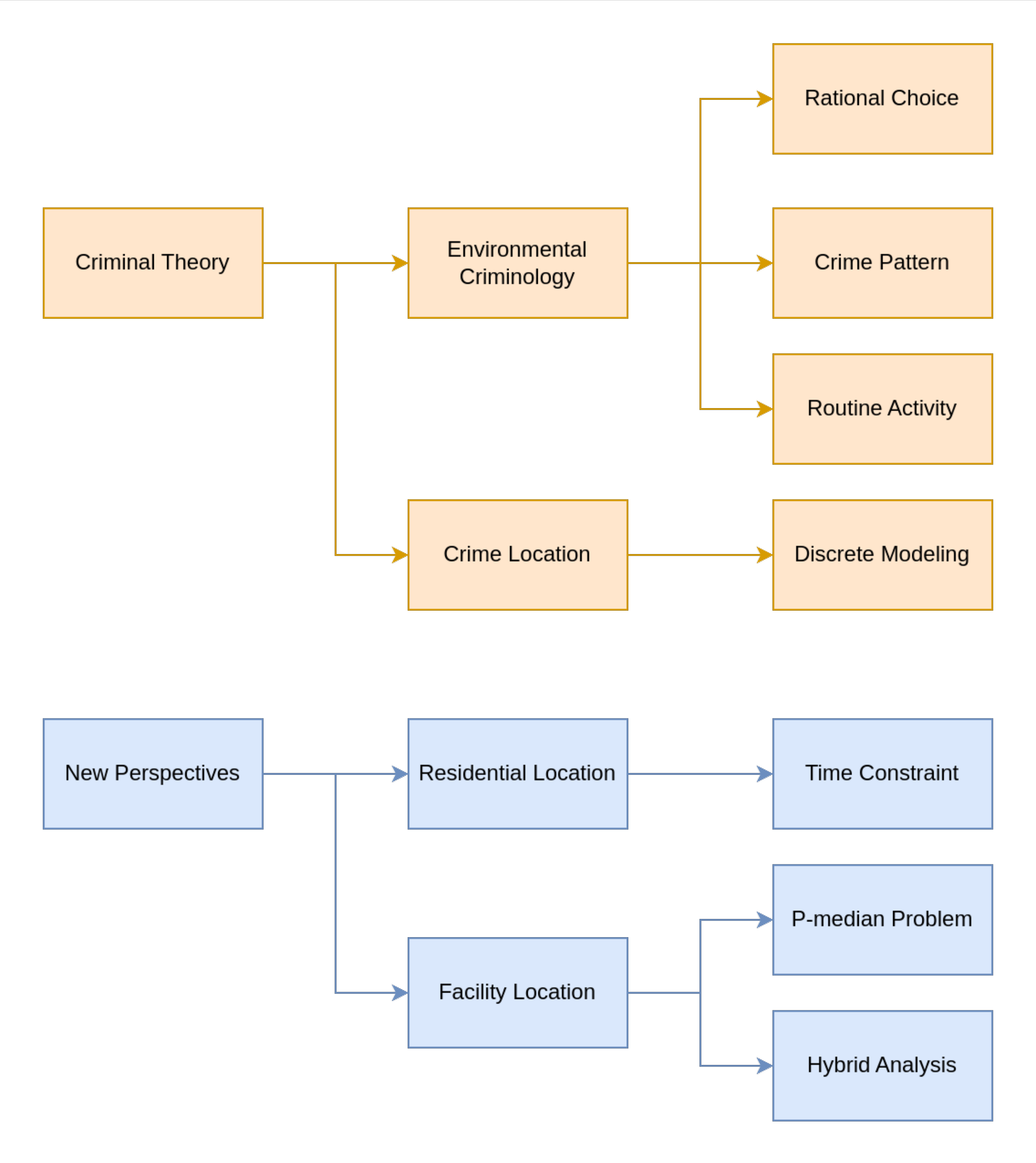
- Critical: essential factors that make it considerable for further evaluation. Taking the flow of water for a hydroelectric plant, without access to it, the location is not even considered.
- Objective: quantitative factors.
- Subjective: qualitative factors.

Finally, we illuminated our search for alternative approaches to fill up that knowledge gap about crime facility location by looking at a promising literature on crime location studies called 'illegal dumping'. The literature on the prediction of illegal dumping has many similarities to our objective of analysis. In fact, illegal dumping is a criminal offense that impacts not only the local economy but also the local health of surrounding residents. It is a challenging crime to monitor, as their offenders intentionally work towards hiding the chosen locations. Public monitoring can be expensive, especially in vast regions with a lower population density.

In fact, most techniques for monitoring illegal dumping by the state require investments in physical capital and security intelligence. Because illegal dumping is highly correlated with road infrastructure (TASAKI *et al.*, 2007), as it requires vehicles to transport waste, initiatives such as roadside surveillance or drone use. However, these methods are highly dependent on the monitoring network and the density of installations in monitored areas, which is usually not high. These methods are limited in scope, especially when focusing on an area like the legal Amazon, which would require too high of a budget for sufficient facilities capable of monitoring the whole territory. As an additional barrier, not only are ground vehicles associated with illegal airstrips, aquatic and aerial routes are also explored and introduce many more dimensions to the problem.

In this regard, one of the solutions proposed in the literature on the choice of illegal dumping is to develop procedures to identify and predict high-risk areas for illegal dumping by analyzing geographic information (DU *et al.*, 2023). This approach enables public authorities to invest in monitoring equipment for high-risk regions, reducing costs and increasing the efficiency of such installations. Another useful similarity of this field is the importance of studying the effects of different vegetation or terrain on the probability of illegal dumping. There is evidence that different roadside vegetation, being species, number of size, may have effects in the probability of the offense (JOO; KWON, 2015). In the Brazilian 'Caipira' route of drugs, it is known that in the plains of cities in São Paulo, farther from the state capital, criminals prioritize sugarcane-vegetation regions to build runways (ABREU, 2017). When the plant is short in height, it is easy for offenders to detect a police operation, and when its taller it can camouflage the airships and makes it harder for the law enforcement to locate the exact spot of landing amidst the vegetation.

Figure 6 – Diagram Foundational Theories for Criminal Facility Location



Source: author elaboration.

3 METHODOLOGY

The adopted methodology for the project will be quantitative, with an econometric scope, focusing on Crime Location Choice models utilizing empirical data. This study aims to analyze data on illegal airstrips identified in the Amazon region between 2021 and 2022, employing discrete models to explain the choices of criminal locations based on socioeconomic, geographical, physical, and structural variables.

3.1 Space discretization

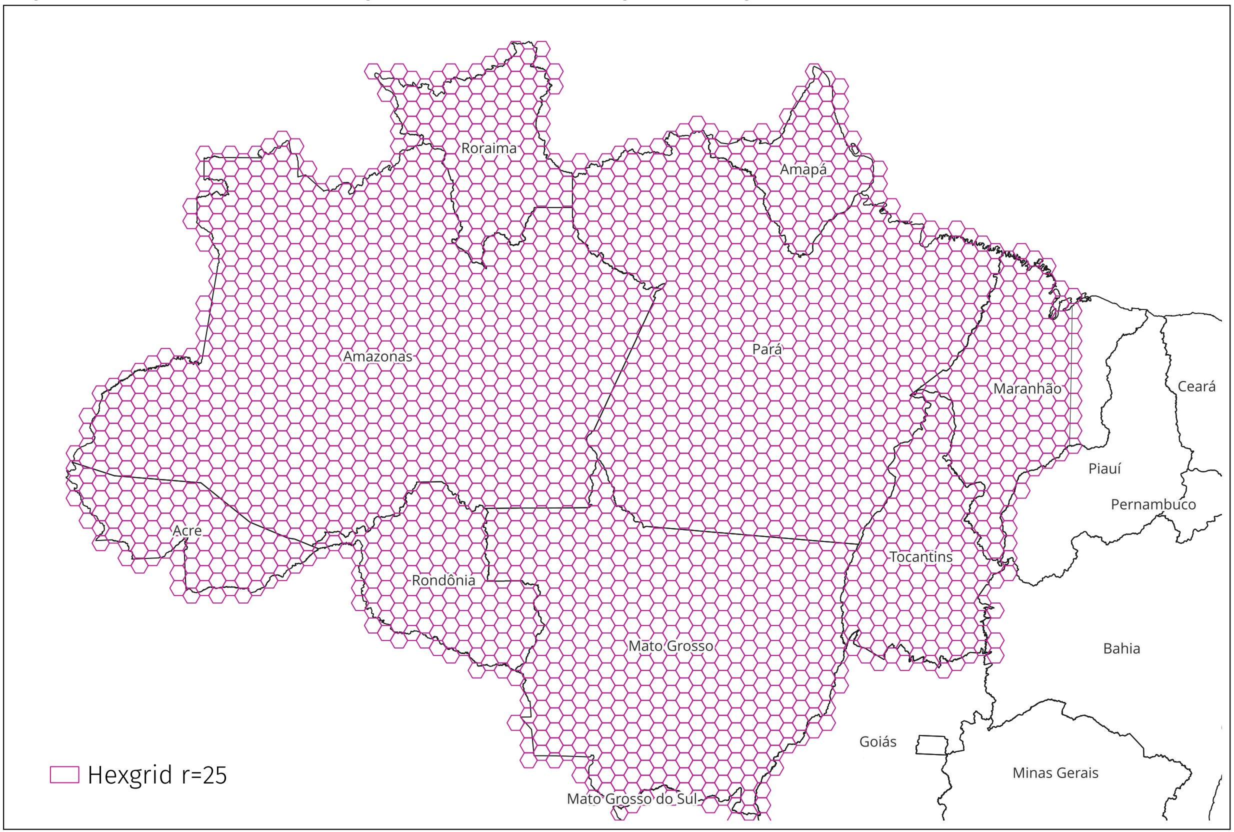
For the data discretization process, a regular hexagonal grid was created using Quantum Geographic Information System (QGIS) Research Tools. This process is very important to mitigate the modifiable areal unit problem (OPENSHAW, 1984; ARBIA; ARBIA, 1989). When aggregating data by area, the zones usually used aren't unbiased, they usually reflect a historical process that may be correlated to the problem of interest. For example, if inequality is evaluated, there may be a conclusion when aggregating by states and another when using cities instead. These may be two different conclusions for the same space, but with different arbitrary area definitions.

To limit the sample area, only hexagons that intersect the area within the legal limits of Amazon (IBGE, 2022a) are selected to compose the sample, as can be seen in Figure 7. This means that there are nine states in the area of study: Acre (22 cities), Amapá (16), Amazonas (62), Mato Grosso (141), Pará (144), Rondônia (52), Roraima (15), Tocantins (139) and part of Maranhão (181, with 21 partial cities included), totaling 772 cities.

Evidently, one of the challenges of working with maps is that every map has some sort of distortion, as one cannot depict a 3D image in 2D without loss. For these reasons, there are many coordinate reference systems (CRS) for different projections that aim to minimize area, angles, or distance distortions (PROJECT, 2024). For the scope of the project, SIRGAS 2000 21S was selected to minimize the distortion of the area centered on the Amazon region. In fact, there is still distortion; the hexagonal areas vary, but this is minimized by the selected CRS. The selected projection is used for the entire project for consistency.

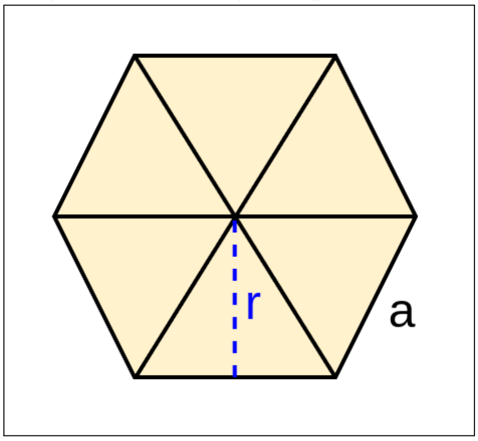
The size of the hexagon is calculated by vertical distances between the centroids of the hexagon, call it V, which can be simplified to double the apothem of the hexagon r as seen in Figure 8. This is useful for understanding the hexagonal area in the study; its determination

Figure 7 – Illustrative Hexagon Grid Intersecting with Legal Amazon Limits for $r = 25$



Source: author elaboration

Figure 8 – Hexagon Apothem



Source: author elaboration.

will be discussed in the explanatory analysis, as it is key to avoid ecological fallacy. Taking advantage of the notion that a regular hexagon is composed of six isosceles triangles, the area may be calculated from the apothem as:

$$HexagonArea = \frac{a^2 * 3 * \sqrt{3}}{2} = \frac{(\frac{2r*\sqrt{3}}{3})^2 * 3 * \sqrt{3}}{2} = 2 * r^2 * \sqrt{3} \tag{3.1}$$

Discretization is a core aspect of this project's goals; it provides for a feasible method for estimating georeferenced statistics. However, there are difficult choices to be made; there needs to be a defined area of discretized points. There are 3 main aspects for this: (1) there need to be good reasoning and theory behind the size to avoid ecological fallacy (empirical conclusions about higher levels of aggregation can produce misleading conclusions for smaller units) (JARGOWSKY, 2005); (2) there needs to exist enough information for a model to be viable for estimation and (3) it is of the projects interest that the area of study is of practical use for public police intelligence, so it needs to be specific.

Table 1 – Area by Apothem

Apothem (r)	Area
10 km	346.4 Km²
5 km	86.6 Km²
2.5 km	21.65 Km²

Source: author elaboration.

Regarding the first aspect, it can be seen in Table 1, by calculating the area by apothem *r*, it is evident that the area can grow exponentially. According to our data, the average airstrip has proportions of 860 meters in length by 23.6 meters, that is 20,296 m² or 0,02 km². That means that if every km² could be used, there would be approximately 50 airstrips per km2. That would be respectively 17,320; 4,330 and 1,082 for the calculated hexagon areas.

Of course, that is not what is observed; in fact, the maximum number of airstrips registered in the biggest hexagonal example is 24, see Table 2. This evidence shows that even though there are grouped points of airstrips, they are not compact enough to require too small of an area for discretization, with the apothem equal to 10 km, we observe that 75% of the hexagons containing airstrips only contain one road.

The second and third points are directly connected, there is a trade-off between information and specification. The smaller the area, the smaller the number of events that will be counted and the larger the sample size. On the one hand, a smaller area decreases autocorrelation with unit area and increases the X covariate variance (ARBIA; ARBIA, 1989), but on the other hand it diminishes the regressand Y variance. So, there is a risk of diluting the event information when analyzing tiny spaces, so it is not feasible to estimate it (JARGOWSKY, 2005).

According to ANAC (ANAC, 2024) the basic track length required for the smallest of airships is less than 800 meters. In fact, the data from Censipam showed that the mean track length was around 860 meters (see the Methodology Section); it can be seen in its histogram that the size of the airstrips can be very compact. With its 5 million km² in Brazil, the legal Amazon represents 59,93% of the Brazilian territory. These dimensions show how delicate it

Table 2 – Illegal Airstrips Distribution by Hexagon Apothem (r)

	r = 10 km		r = 5 km		r = 2.5 km	
Number of Airstrips	Freq.	Rel. Freq.	Freq.	Rel. Freq.	Freq.	Rel. Freq.
0	14039	92.64%	58430	97.75%	247942	99.10%
1	869	5.73%	1226	2.05%	2175	0.87%
2	174	1.15%	100	0.17%	75	0.03%
3	38	0.25%	14	0.02%	9	0.00%
4	23	0.15%	2	0.00%	2	0.00%
5	8	0.05%	2	0.00%	2	0.00%
6	0	0.00%	1	0.00%	0	0.00%
7	0	0.00%	0	0.00%	0	0.00%
8	0	0.00%	1	0.00%	0	0.00%
9	0	0.00%	0	0.00%	0	0.00%
10	1	0.01%	0	0.00%	0	0.00%
13	1	0,01%	0	0.00%	0	0.00%
24	1	0,.01%	0	0.00%	0	0.00%
Total	15154	100,00%	59777	100,00%	250205	100,00%

Source: author elaboration.

is to determine the spatial unit of analysis. As the spatial unit decreases, the variation within units decreases, which makes for more precise measurements, while the number of units and the variation between then increases. It can be seen as if the sample size can be arbitrarily selected, but on the other hand there might not be variables described in such small units.

In that sense, when $r = 2.5$, the event "has at least one airstrip" is 0.9% which might be too low. As the Y event gets rarer, the null hypothesis is harder to not accept as the expected value approaches zero. There is not only a loss in decreasing the hexagon size by losing information but also an exponential computational cost for the increasing number of hexagons. After increasing to $r = 5$, there is a significant increase in at least 1 airstrip to 3.32%, but the distribution is still really concentrated in zeros and ones.

For these reasons, the unit of choice was $r = 10$, as it seems small enough to accurately absorb the independent variables and large enough to contain information on the preferences of the offenders. Furthermore, the relative frequency of $r = 10$ is more distributed to higher values, better fitting count models as well. As such, the data set ended up with 15,154 hexagons, 1,115 of them with airstrip presence for the years 2021 and 2022.

3.2 Econometric Modeling

For the purposes of this study, two approaches were considered: (1) dichotomous models and (2) count models. In dichotomous models, the presence of illegal airstrips can be observed or not, thus receiving a value of 0, or 1, when airstrips are present. This binary framework is addressed using the Probit and Logit models, which are applied with a certain degree of equivalence.

Logit models can be derived from random utility models, similar to what was described in Section 2.2.2. If we consumer i makes choice j, we can assume that among all J choices, U_{ij} is the highest utility among J. Hence, the statistical model is driven by the choice j has been made (GREENE, 2011):

$$\text{Prob}(U_{ij} > U_{ik}) \forall k \neq j \tag{3.2}$$

To make the model operational, there needs to be a choice for distribution. For simplicity, take the logistic distribution so that it leads to the conditional logit model:

$$\text{Prob}(Y_i = j) = \frac{exp(z'_{ij}\theta)}{\sum_{j=1}^{J} exp(z'_{ij}\theta)} \tag{3.3}$$

In terms of the second approach, each region can be understood as having a positive integer number of airstrips, ranging from 0 to a potentially large number, denoted $j = 0, 1, 2, 3, \ldots J$. An initial perspective is the Poisson distribution, able to account for not only the presence or absence of the airstrip but the magnitude of it. In other words, identify not only locational targets but also most "victimized" targets, which could illustrate a new range of characteristics preferred by criminals when choosing their criminal facility location.

In this regard, the Poisson model is useful for analyzing the risk of victimization by incorporating a dimension that the dichotomous approach does not capture. As will be discussed, the Poisson model has known limitations in the literature when used in isolation (GREENE, 2011; CAMERON; TRIVEDI, 2005), so it will serve as an initial step in analyzing the phenomenon. In this way, the primary equation for the model can be described as follows.

$$Prob(Y = y_i|x_i) = \frac{e^{-\lambda}\lambda_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, ... \tag{3.4}$$

For simplicity, the most common formulation for Lambda is the log-linear model:

$$\ln \lambda_i = x_i'\beta \tag{3.5}$$

Taking a Poisson distribution, it is easily demonstrated that the implicit assumption that variance of Y is equal to its expected value holds.

$$\mathbb{E}[y_i|x_i] = Var[y_i|x_i] = \lambda_i = e^{x_i'\beta} \tag{3.6}$$

Since the model in its basic form is not a linear regression, one way to estimate it is by log-likelihood:

$$\ln L = \sum_{i=1}^{n}[-\lambda_i + y_i x_i'\beta - \ln y_i!] \tag{3.7}$$

That way, first-order conditions may provide the β estimators by an iteration algorithm such as Newton's method (GREENE, 2011).

In fact, one common tool to deal with overdispersion is to use a Negative Binomial distribution, which can arise as a gamma mixture of Poisson distributions. One formulation of its density is (ZEILEIS *et al.*, 2008; GREENE, 2011; CAMERON; TRIVEDI, 2005):

$$f(y_i|x_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(\theta + y_i)\Gamma(\theta)} r_i^{y_i}(1 - r_i)^{\theta}, \text{ where } r_i = \frac{\lambda_i}{\lambda_i + \theta} \tag{3.8}$$

Again, the negative binomial model can be estimated by maximum likelihood.

Beyond the overdispersion problem, excess zeros are a common limitation for Poisson Models in Social Sciences, for which both Hurdle and Zero Inflated (ZI) models are frequently proposed as solutions. The Hurdle model assumes the existence of two distributions, one for assessing non-zero discrete values and the other is for estimating zero values (the hurdle model itself) - see equation 3.10. ZI also combines two distributions for estimation, one Poisson or Negative Binomial for counting, this time including zeros, and another to estimate the zero-inflated observations (see more in equation 3.9). ZI sees zeros in two ways: structural (inflated) or non-structural, meaning there are two possibilities for the "failure" of the event to occur (CAMERON; TRIVEDI, 2005; ZEILEIS *et al.*, 2008).

$$f_{\text{zeroinfl}}(y;x,z,\beta,\gamma) = f_{\text{zero}}(0;z,\gamma) \cdot I_{\{0\}}(y) + (1 - f_{\text{zero}}(0;z,\gamma)) \cdot f_{\text{count}}(y;x,\beta), \tag{3.9}$$

$$f_{\text{hurdle}}(y;x,z,\beta,\gamma) = \begin{cases} f_{\text{zero}}(0;z,\gamma) & \text{if } y = 0, \\ (1 - f_{\text{zero}}(0;z,\gamma)) \cdot \frac{f_{\text{count}}(y;x,\beta)}{(1 - f_{\text{count}}(0;x,\beta))} & \text{if } y > 0 \end{cases} \tag{3.10}$$

Assessing which approach is the most suitable for a model is an ongoing topic in the recent literature, especially present in the health sciences (LOEYS *et al.*, 2012; HOFSTETTER *et al.*, 2016; FENG, 2021). Although the predicted values of the models are quite similar, making them very comparable in terms of predictive power, the estimators carry distinct interpretations, which affects the inference process (LOEYS *et al.*, 2012). The structural design of the research data is the fundamental factor in deciding the model.

Consider a researcher who wants to understand the demand for bike rental services in parks. Participants will be asked how many times they rented bikes in the last month. Some may report never renting because they own a bike, while others may just prefer other activities. There are two types of zeros; one type of individual is not a viable customer due to bike ownership, and the other decided that they prefer other activities. This distinction process suits the zero-inflated structure for inference purposes. However, if the research design changed to exclude bike owners, the hurdle model could be more appropriate, as the hurdle component would estimate the probability of an agent choosing to rent bikes and the count component of the model would estimate, after deciding to rent, how many occurrences would take place.

This theoretical exercise might seem inadequate, as including bike owners seems counter-intuitive, but for this project's scenario, it is an interesting comparison where it is not possible to identify who is a structural zero beforehand. There are factors that will fundamentally make some locations ineligible for airstrips. For example, there cannot be airstrips in unsuitable terrain such as water. These aspects that eliminate locations from consideration are called critical factors in the facility location literature (MORADI; BIDKHORI, 2009). Before calculating which location minimizes distances from suppliers and main roadways, it must be a suitable location.

Another aspect to take into consideration is that there are locations suitable for specific criminal activities, as it implies that there are locations that have not been targeted but that might one day observe illegal airstrips. In addition, there might be locations where there will never be airstrips because no known illegal activity is associated with these characteristics. In the case of illegal mining, gold deposits close by are needed for the activity, and for drug traffic there needs to be access to international suppliers to outflow its input onto highways.

For these reasons, the ZI model was understood as more appropriate. While there are cases of structural zeros - zones that would never be used as airstrips - there are also locations in the Legal Amazon that have not yet observed criminal facilities but could become targets under

Table 3 – Model interpretation by component

Model	Component	Coefficient	Interpretaion
ZI	Count	β_{ZI}	Corresponds to how many expected airstrips would increase by an additional unit of x, **given that the observation is not a structural zero.**
	Zero	γZI	Estimates the probability of the observation **being a structural zero given** z. Higher coefficients indicate a higher probability of a structural zero.
Hurdle	Count	β_{Hurdle}	Corresponds to how many expected airstrips would increase by an additional unit of x, **given that the event occurred at least once.**
	Zero	$\gamma Hurdle$	Estimates the probability of the observation **not being zero** given z. Higher coefficients indicate a higher of the event ocurring at least once

Source: author elaboration.

certain conditions. Conditions such as shifts in criminal organization strategies, advances in technology, formation of new alliances, or reduced government surveillance in less populated regions, as seen in the indigenous tribes case. There is a need to understand which areas that, although not currently targeted by criminals, exhibit characteristics that the model associates with potential criminal activity.

When inspecting the coefficients themselves, there is a difference between γ_{ZI} and γ_{hurdle}, the coefficients of the dichotomous component, described in table 3. The hurdle coefficients will indicate the probability that organized crime does not use the location, while the ZI coefficients will translate to the probability that the location is not suitable for criminal consideration. The γ_{ZI} therefore predicts regions that require the least surveillance, which is more useful information, as the hurdle model might not consider these gray areas that are not yet targeted but show indications of being suitable for criminal organizations. On the other hand, the betas from the count component also have a distinction. The β_{hurdle} estimatives will shed light on where, after the criminal agent decides to make an airstrip, there will be a greater presence. The β_{ZI} will describe the regions in which organized crime might act, indicating which hexagons will have a presence or more.

For further explanation of the difference between Hurdle and Zero Inflated, see the discussion in the appendix A.

3.3 Data set

To perform the modeling of this research, empirical geointelligence data was obtained from Centro Gestor e Operacional do Sistema de Proteção da Amazônia (Censipam) on the monitoring of illegal aerial activities and airstrips. These data form the background for our analysis. It covers the period from 01/01/2021 to 12/31/2022 and includes information on identified illegal airstrips in the Legal Amazon region.

Furthermore, regional data from IBGE will be utilized to obtain covariates for the model such as socioeconomic, geographical, physical, and structural data referred to in previous topics. In addition, the information from the IBGE census tracts will be combined with a manually constructed hex grid to discretize the variables regarding their location.

3.3.1 Socioeconomic, Geographical, Physical, and Structural Variables

The data set used by the project was constructed from socioeconomic, geographical, physical, and structural variables for the Legal Amazon Region. One of its challenges is to have enough georeferenced disaggregation to fit into the discretization scope. There are no data that directly translate into the created hexagonal grid, as it is an arbitrary space division.

The decided approach to this problem was to calculate the intersection of the hexagonal grid with the most disaggregated georeferenced data available. When the intersection is not one-to-one, that is, when there is more than one unit intersecting with the hexagon, there would be two methods to incorporate those data: (1) with regard to qualitative variables, the most representative unit variable would be taken as the corresponding hexagon variable. However, (2) quantitative data would be calculated using a weighted mean, with the weights being each unit ratio of the intersection. This process is described in Figure 10.

To formalize this method, let:

$$\mathscr{H} = \{H_j \mid H_j \text{ is a hexagon, } j = 1, 2, \ldots, J\} \tag{3.11}$$

$$\mathscr{C} = \{C_i \mid C_i \text{ is an IBGE Census Tract, } i = 1, 2 \ldots, I\} \tag{3.12}$$

For any H_j, there are two possible cases:

1. **Single Census Tract Containment**: There exists a unique Census Tract C_{i^*} such that $H_j \subset C_{i^*}$.

Table 4 – Variable Dictionary

Source	Category	Variable	Description
2022 Census IBGE (2022b)	Socioeconomic	t_households	Weighted total households by hexagon intersection divided by 1000
	Socioeconomic	t_population	Weighted total population by hexagon intersection divided by 1000
IBGE Cartography Base IBGE (2023)	Structural	d_highway	Distance to closest highway
	Structural	d_highway_fed	Distance to closest federal highway
	Structural	d_highway_est	Distance to closest state highway
	Structural	d_waterroute	Distance to closest waterway route
	Structural	d_city	Distance to closest city
	Structural	d_cport	Distance to closest port complex
	Structural	d_cairport	Distance to closest airport complex
	Structural	d_extmine	Distance to closest mineral extraction point
	Geographical	uf	State dummies, the base is the Amazonas state
	Physical	landform	Landform dummies for the majority of hexagon, the base is water landform
CENSIPAM	Geographical	indigenous	Dummy indicating if inside legal indigenous territories

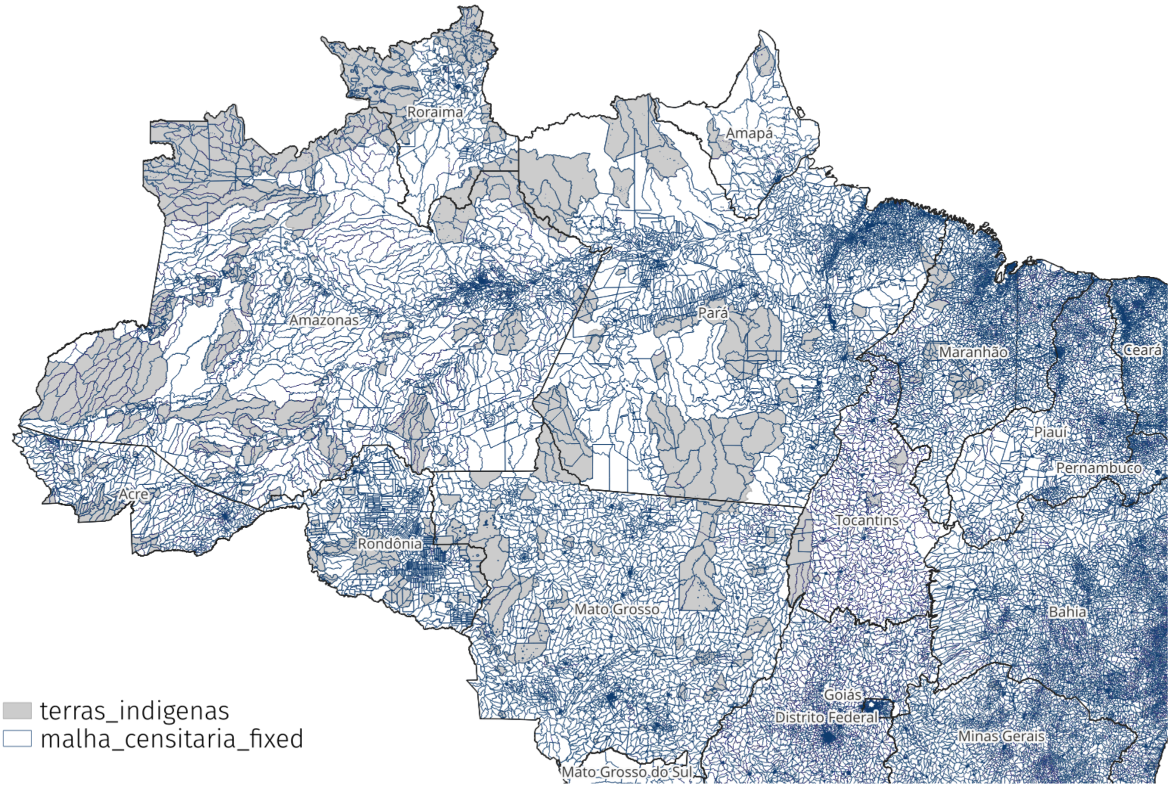
Source: author elaboration.

2. **Multiple Census Tracts Containment**: There exist multiple Census Tracts $C_{i_1^*}, C_{i_2^*}, \ldots, C_{i_k^*}$ such that

$$H_j \subset C_{i_1^*} \cup C_{i_2^*} \cup \cdots \cup C_{i_k^*}.$$

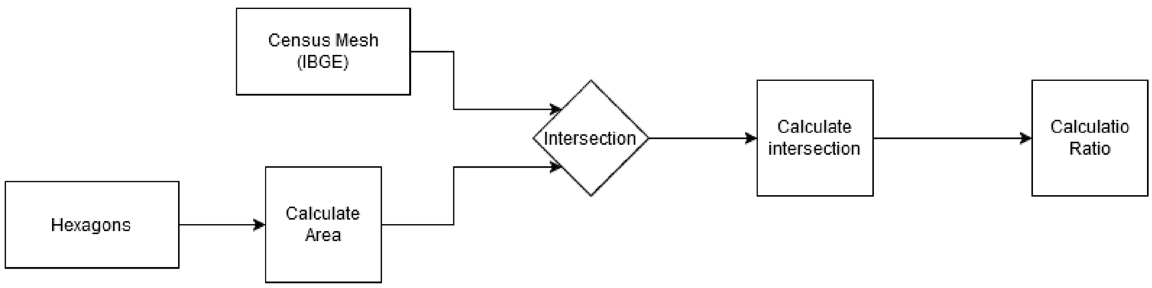
In the first case, assigning a value is straightforward as hexagons simply inherit the IBGE data directly. In contrast, in the second case, quantitative data are assigned based on the weighted mean of the IBGE values, where the weight corresponds to the proportion of each Census Tract C_{ik} within the hexagon. For qualitative data, the most representative C_{ik} determines the value; for example, when assigning a state variable, the state that covers the largest area within the hexagon is selected, as the qualitative attributes cannot be combined.

Figure 9 – IBGE Census Tracts



Source: author elaboration.

Figure 10 – Identify Hexagon Intersections



Example Result

After the process, there will be a row for each hexagon divided by its intersections with the Census Mesh. Each entry will contain the percentage of the ratio between the areas.

Hexagon ID	Hexagon Area	Intersection Area	Ratio	Census Unit
HEX1	10	7	70%	U1
HEX1	10	2	20%	U2
HEX1	10	1	10%	U3

Source: author elaboration.

Although quantitative data primarily include demographic indicators such as total population, it has also been applied to measure the prevalence of landforms (e.g., mountains, valleys, and plains).

In addition to demographic data, distances were an important point of the data frame.

Distances to highways (state or federal ones), to water routes, to airports, to ports, to cities, etc. To calculate distance, the hexagonal centroid was used as basis coordinates and the function used was v.distance from the GRASS module integrated to QGIS (GRASS, 2024). That way, all distances are absolute values and correspond to the smallest "line" to the desired polygon or vector. Null values occur if they intersect with the destination, that is, if a centroid occupies the space of a road it will output zero distance. The program outputs the distance in meters, but most of the analysis was performed using kilometers for simplicity.

Most of the constructed data set comes from IBGE, mainly from IBGE's "Base Cartográfica Contínua" 2023, with a range of territorial maps with different themes. Demographic information was recovered from the preliminary census from 2022 (IBGE, 2022b), as its full version disaggregated by census grid was not yet published at the time of this project's development. Censipam provided not only the independent variable, illegal airstrip locations, but also the map for "Terras Indígenas", legally demarcated Indigenous Terrains based on the Constitution (Título VIII, Da Ordem Social, Capítulo VIII, Dos Índios) (BRASIL, 1988).

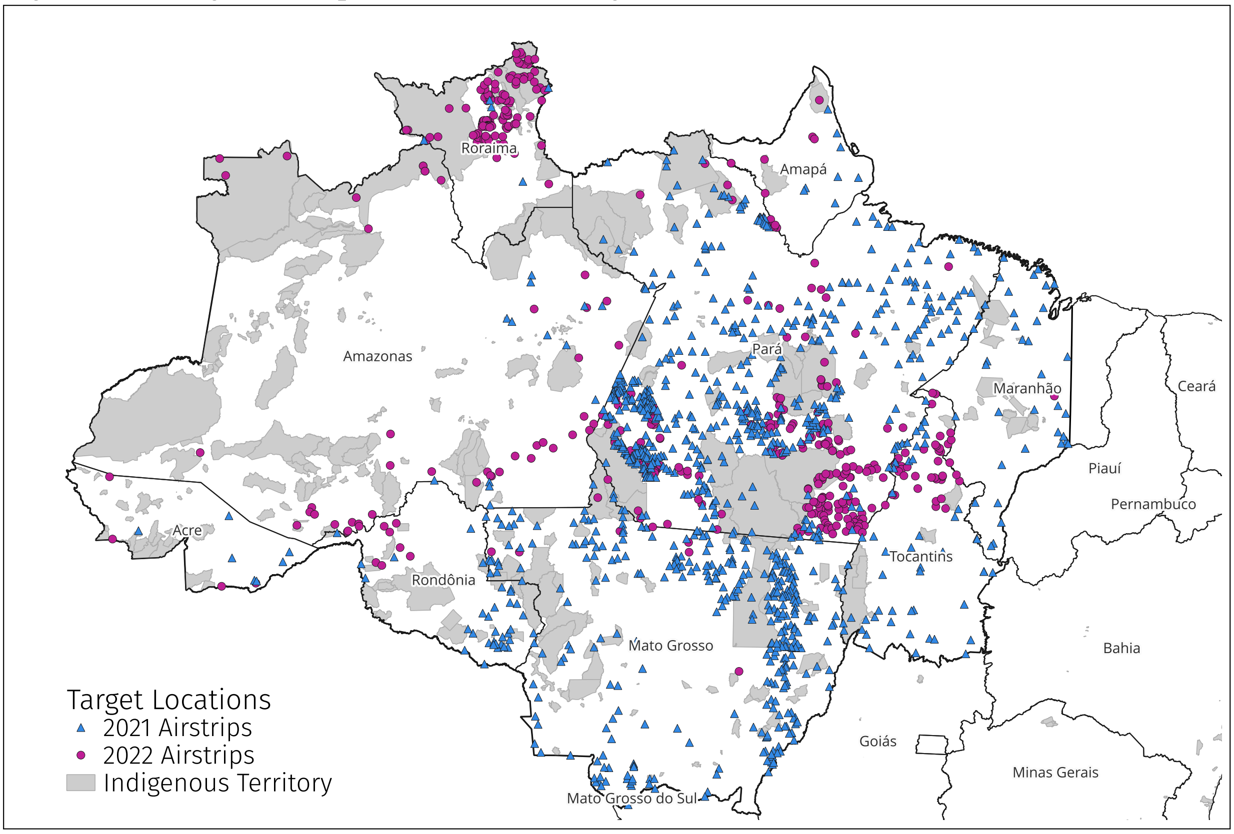
3.3.2 The (Illegal) Airstrips

For a general geospatial visualization of the variable of interest, see Figure 11. The projection shows the airstrips detected by satellite images from Censipam and indigenous territories in the legal limits of the Amazon. It is easy to recognize the known illegal occupation of the Yanomami's lands in Roraima (YANOMAMI; YE'KWANA, 2021; VITOR *et al.*, 2023). The lower density of points in the north-west region is compared with the state of Roraima. There are signals of other invaded territories, but the south-west of Roraima is clearly the most critical situation at hand. Even if other territories are not occupied, it may be valid to investigate the effect of the surrounding indigenous territories. The disincentive to live near native tribe lands can show itself as a guardianship void for illegal activities to occur.

Regarding the states, it can be seen in table 5 the distribution of airstrips by state. As was also observable from the map visualization, Pará stands out with 49.93%. It may be correlated by the fact that Pará is the state with the highest number of mineral extraction points in the Legal Amazon according to IBGE cartography maps, with 60,51% of them(IBGE, 2023). The intersection between traffic and illegal mining may be a factor in the higher concentration in the state.

Mato Grosso follows with 23,11% of the total illegal airstrips. With a lower repre-

Figure 11 – Illegal Airstrips Location in the Legal Amazon



Source: author elaboration.

sentation in the mining industry, the border with Bolivia may explain its significance for the total number of airstrips. As one of the reasons for the strengthening of the Caipira route, Bolivia has become an important route and, most importantly, a cocaine producer (BERG, 2021). Joined by Paraguay, Bolivia is an option for a substitute for the heavily controlled triple border with Colombia and Peru. This may also justify the Rondônia spot as the fourth with the most illegal airports.

Table 5 – Illegal Airstrips by State

UF	Frequency	Relative Frequency
PA	754	43,93%
MT	349	23,11%
RR	150	9,93%
TO	89	5,89%
AM	64	4,24%
RO	41	2,72%
MA	39	2,58%
AP	14	0,93%
AC	10	0,66%
Total	1510	100%

Source: author elaboration.

Furthermore, Censipam's data also brought light for the criminal facility infrastructure regarding the road terrain, seen in Table 6. The vast majority of roads are made of dirt. This could indicate rudimentary conditions, but also may be interpreted as a preference for mobility by the criminal organizations. There is evidence of criminals matching seasonal vegetation with quick improvised dirt roads to confuse authorities (ABREU, 2017). The choice of quantity over quality may also be explained by the historical difficulty of the federal police to destroy existing airstrips, as Abreu said Abreu (2017, p.17, our translation):

> "The Narcotraffic CPI [Parliamentary Commissions of Inquiry] at the Legislative Assembly of the State of São Paulo recognized, in the early of 2000, 32 illegal airstrips in the northwest of São Paulo, most of which were used for cocaine transportation. The Commission went so far as to order the implosion of those airstrips, but the federal government denied the request, alleging high costs. In 2010, I found that 19 of them were still active. In 2013, the federal police counted at least 200 in the rural area of the "interior paulista" [minor cities of the state of São Paulo]".

Table 6 – Illegal Airstrips by Terrain

Terrain	Frequency	Relative Frequency
Dirt	1901	80,21%
Grass	237	10,00%
Gravel	179	7,55%
Asphalt	40	1,69%
Dirt/Grass	12	0,51%
asphalt/Grass	1	0,04%
Total	2370	100%

Source: author elaboration.

Although the structures are somewhat simple, the variance in terrain shape fits different regulation categories by ANAC (2021). The length range is classified into 4 categories that range from less than 800 meters to more than 1800 meters; see Table 7 and Figure 12. This classification takes into account factors such as weight and wingspan and shows some indication of the plane aspects involved in the illegal activities. Longer roads could be motivated to supply bigger airships or perhaps to compensate for excess weight in smaller ships.

This is the right point to make some remarks about variables that will be included in the econometric models, for further details, see the variable dictionary in Table 4. First, for computational reasons, all distances were first expressed in kilometers and then divided by 1,000 to improve numerical accuracy[1].

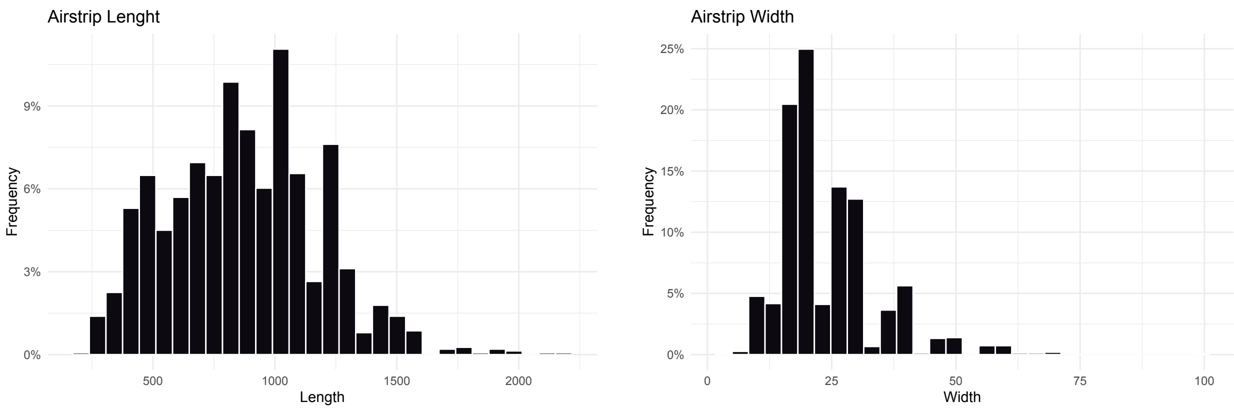
[1] When using kilometers directly, we faced non numeric numbers as a result of errors estimating the covariance

Table 7 – Airstrip Lenght distribution by Anac Classification

Code Number	Count	Rel. Freq.
1	950	40,08%
2	1059	44,68%
3	347	14,64%
4	14	0,59%

Source: author elaboration.

Figure 12 – Airstrips Length and Width Histogram



Source: author elaboration.

Second, the population and number of households would inform the characteristics of the target location and its surrounding (ECK; WEISBURD, 1995; BRANTINGHAM, 1978). Furthermore, a smaller number of residents would indicate the absence of guardians / protectors (SHORT *et al.*, 2010; COHEN; FELSON, 1979). Although households may act as a proxy for the level of urbanization and public infrastructure, better roads, access to highways, fresh water, and gas could be valuable strategically.

Third, another important factor is distance, a pillar of criminal theory, especially in empirical research on criminology, residential location, and facility location literature (MCFADDEN, 1978; HALE; MOBERG, 2003; BERNASCO, 2010a; BERNASCO; KOOISTRA, 2010; PAGLIARA *et al.*, 2010). It is expected by Routine and Crime Pattern theory that criminals will act in a finite awareness space, so they will probably act near other required structures such as Highways, Water routes and legal airports.

Fourth, indigenous land is one of the qualitative variables; if most of the hexagon resides in a marked territory, it assumes 1 and 0 if not. This variable is interesting not only for recent attacks against traditional tribes (YANOMAMI; YE'KWANA, 2021; G1, 2021), but also because it also represents a level of urbanization, access, and anonymity. The delimitated

matrix. This probably occurred because of the magnitude of the largest distances. Another possible solution tested was the standardized distance, but that would hinder the interpretation of the model.

territory has less state presence, less infrastructural features that are necessary for certain crimes. The state dummies are an important control variable, especially taking into account that each state has historically faced different natures of crime, the influence of illegal mining in Pará being one of them.

Fifth, it is worth saying that the merit of a second specification lies in the inclusion of the variable l_p norm distance, used to describe a combined spatial distance, formally expressed as the pth root of the sum of the norms of the distances (MORADI; BIDKHORI, 2009):

$$l_p = [\sum_{i=1}^{p} |u_i - v_i|^p]^{1/p} \tag{3.13}$$

A regular business would aim to minimize this distance, assuming a demand constant between nodes, to maintain the least distance to all important nodes. This variable then tests how similar the criminal decision tactics are to what the facility location describes. The variables used to create the l_p-norm were: $[d\_highway\_fed, d\_highway\_est, d_city]$. They represent access to land modalities and important infrastructure used by criminals. In fact, the second specification scores the lowest Akaike Information Criterion (AIC) (8549.2), but does so by a very small margin. Although they perform very similar, this is an interesting result, as it could be a step in a new tool to predict crime activity.

3.4 Exploratory Data Analysis

To better understand the applicability of criminal theories and the contributions of new perspectives, an exploratory analysis was performed. The process began with an examination of the primary subject of interest - the airstrips - followed by an analysis of the independent variables used to describe them.

3.4.1 Dependent Variable

As previously stated, our sample covers the years 2021 and 2022, during which 1,510 airstrips were validated by CENSIPAM — a figure comparable to contemporary media reports. For example, in 2022, illegal miners reported that 1,269 airstrips were used in the Amazon (UOL, 2022; Potter, Hyury, 2022). The number of landing strips increased in 2021, a trend consistent with the findings of Carvalho (2023), who identified a higher frequency of flights during the pandemic. A subsequent decline in these numbers is observed in 2023; however, this aspect falls beyond the scope of this study and will not be further explored.

The first step in analyzing the nature of the event of interest is to determine whether its spatial distribution is purely random or exhibits spatial autocorrelation (WATERS, 2017). Tobler's First Law of Geography states that "everything is related to everything else, but near things are more related than distant things" (TOBLER, 1970, p.1), suggesting that the presence of airstrips is unlikely to be random, as their location depends on both the site where they are built and their surroundings. Furthermore, a simple visual inspection of Figure 11 suggests that it is reasonable to assume that the airstrips are not randomly distributed, as certain clusters are clearly visible.

However, to formally test this spatial distribution, Moran's I is the statistic of choice for geographical analysis (MORAN, 1950; BIVAND; WONG, 2018). The standart representation of the measure is as follows:

$$I = \frac{N}{W} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \tag{3.14}$$

where:

1. N is the number of spatial units indexed by i (hexagons) and j (neighbors);
2. x is the variable of interest (airstrip count) and $\bar{x}$ its mean.
3. w_{ij} are elements of a matrix of spatial weights
4. W is the sum of all w_{ij}

One might find Moran's measure similar to a correlation measure, but weighted by a matrix of weights based on distance. w_ij is 0 whenever $i = j$ as they occupy the same space, in practice making the principal diagonal entirely of zeros.

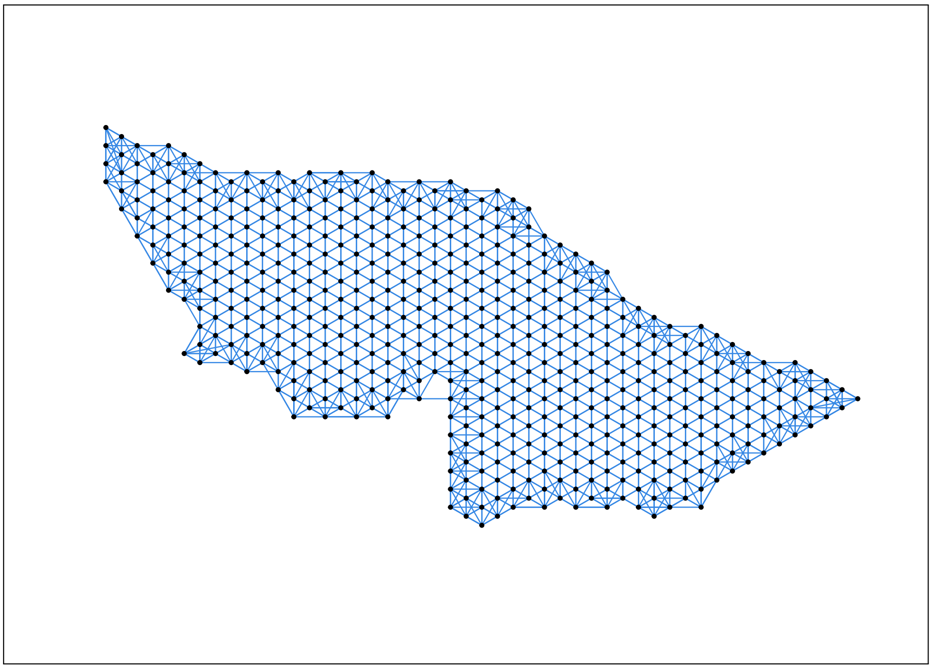
The chosen method for calculating the global Moran's I indicator involved assigning weights to the k-nearest neighbors. Specifically, the k nearest hexagons were used for the calculation. For example, with $k = 6$, each point would represent 6 neighboring elements to sum, one for each of its nearest neighbors. Since the hexagonal grid ensures a consistent distance between neighbors, the k-nearest neighbor method will be consistent for most hexagons (excluding corner cases).

To do this, the R package *sdpep* was used to construct the weights for the *moran.test* function. The global test used $k = 6$ and $k = 60$. Each hexagon has 6 immediate neighbors, those neighbors have 12 additional neighbors, etc. This forms an arithmetic sequence with a common ratio of 3, and its sum indicates how many neighbors a hexagon has as the distance expands to include them. Consider the apothem described in Figure 8; it can be reimagined as the radius of an inscribed circle within the hexagon. Therefore, the distance from the centroid of one hexagon to another is twice the radius. Thus, a distance of two hexagonal radius (20 km) would correspond to the 6 nearest neighbors, etc.

For that reason, the test was carried out with 6 and 60 neighbors, roughly 20 and 80 kilometers of radius, respectively, used to test spatial autocorrelation. That way, a different range of neighbors based on the discretization process can be accessed. One approach would emphasize first order neighbor while the second uses second and higher while both utilize fixed distance for calculation (with exception of corner hexagons) (ANSELIN, 2013). In this dissertation, no spatial weights were directly used for modeling, so no radius was chosen as basis over another or evaluated for model robustness.

The visualization of k-nearest neighbors for $k = 6$ is demonstrated in Figure 13, where there are some points of inconsistency in the corner regions. Border hexagons tend to further seek neighbors, but these inconsistencies are assumed to be not significant enough to affect the test, as border hexagons do not constitute the majority of the sample.

Figure 13 – K-nearest neighbor visualization for the state of Acre and K=6



Source: Fernando Frazão (2023)

The results of the tests for both k-values show extremely low p-values, as expected.

This indicates that the null hypothesis, which assumes that the values being analyzed are randomly distributed, is highly unlikely in both cases. There is evidence of autocorrelation between zones, suggesting a nonrandom factor that influences the distribution of events.

Table 8 – Moran I

k-value	Moran I Statistic	P-value	Expectation	Variance
6	0.287	2.220446e-16	-6.6e-05	2.104e-05
60	0.143	2.220446e-16	-6.6e-05	2.08e-06

Source: author elaboration.

It is important to recognize that the sample region is so extensive that there probably could still be clusters of airstrip events that have simply not been valued by Moran I as it is a single-value output. For that, local Moran's I_i statistic can evaluate each component of the global counterpart and define clusters (ANSELIN, 1995):

$$I_i = \frac{x_i - \overline{x}}{m_2} \sum_{j=1}^{N} w_{ij}(x_j - \overline{x}) \tag{3.15}$$

Where:

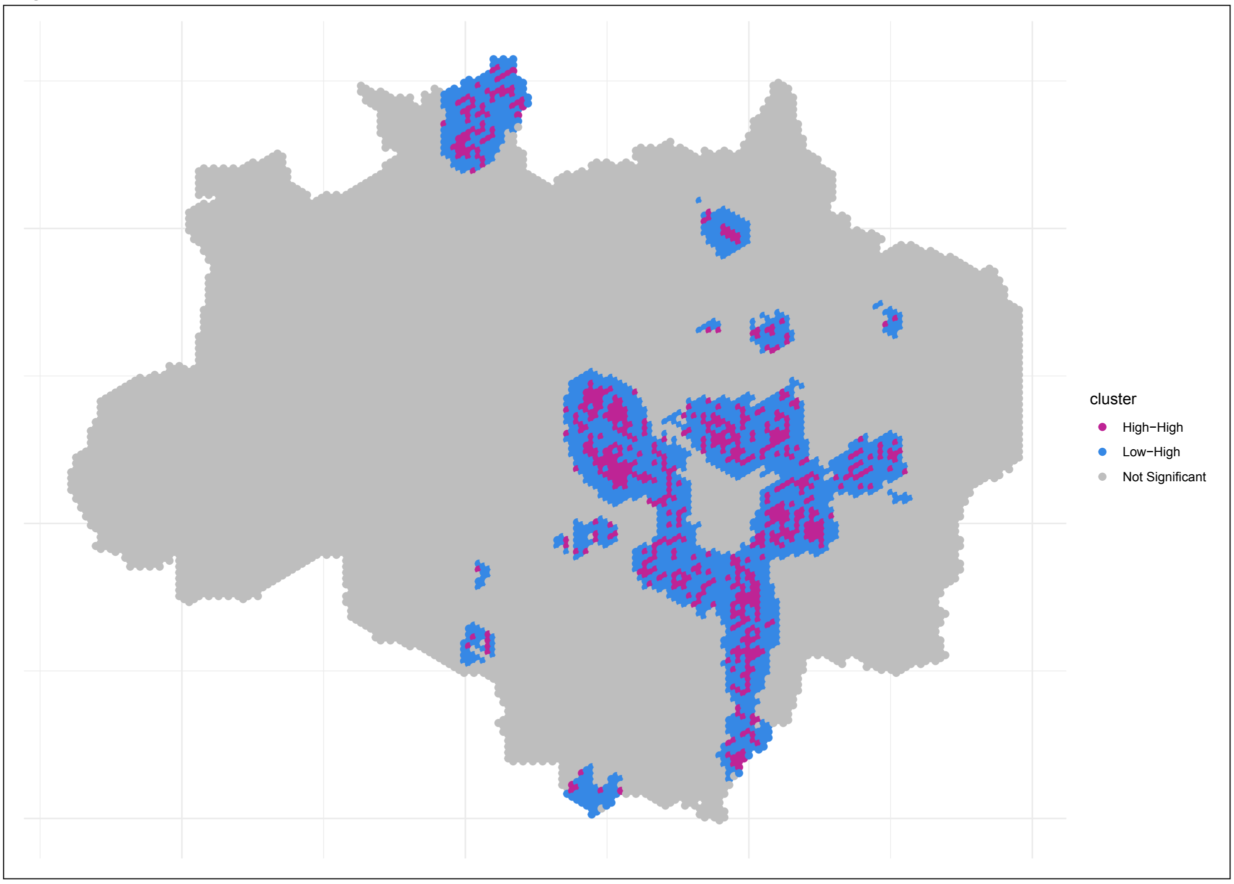
$$m_2 = \frac{\sum_{i=1}^{N}(x_i - \overline{x})^2}{N} \tag{3.16}$$

As a result, Figure 14 provides a more detailed examination of the clusters, analyzing each hexagon and the autocorrelation between neighboring zones — in this case, for $k = 60$. It is clear that the clusters in purple highlight areas with a high concentration of airstrips, and, as a consequence, the surrounding regions, with a lack of airstrips, exhibit negative values due to their deviation from the positive mean concentrated in these areas. Most of the land is not statistically significant as their neighbors show values close to zero, meaning that there is no meaningful effect to evaluate.

As observed in the section on airstrips in Table 5 and confirmed by Moran I_i, higher clusters of events were found in Pará, Mato Grosso and Roraima. In this regard, the distribution of clusters is not homogeneous over time; it actually changes between the two years, as shown in the heatmap comparison in Figure 15. Most of the recorded airstrips in Roraima were only detected in 2022. However, the presence in Pará changed from west to east, following the shape of (the federal highway) BR-165 to BR-158, as seen in Figure 16.

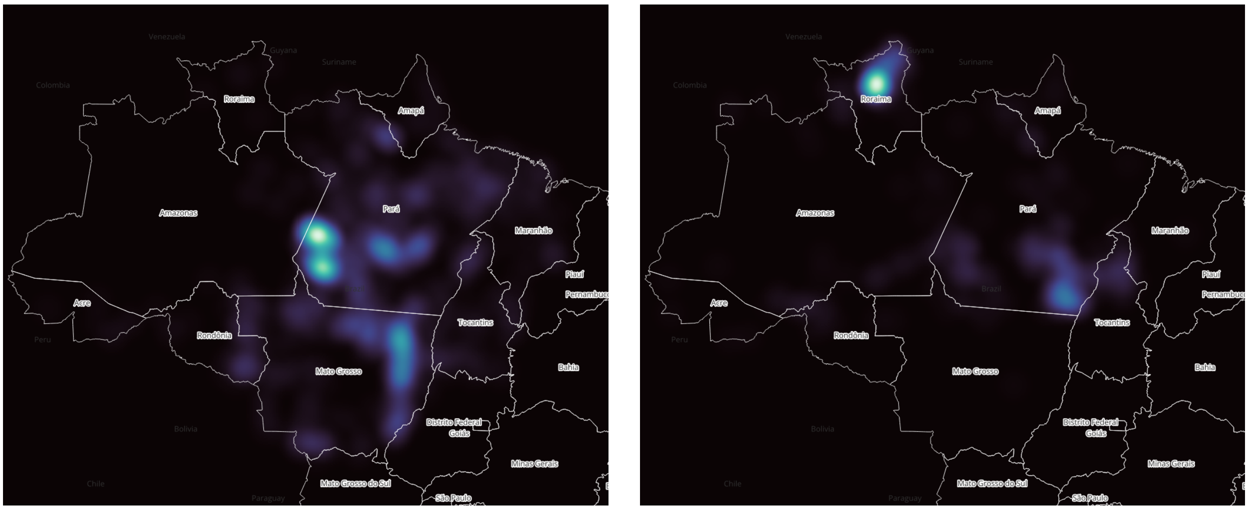
The importance of access to federal highways was expected by the environmental criminology literature (COHEN; FELSON, 1979; CORNISH; CLARKE, 2002; BRANTING-

Figure 14 – Local Moran for $k = 60$



Source: author elaboration.

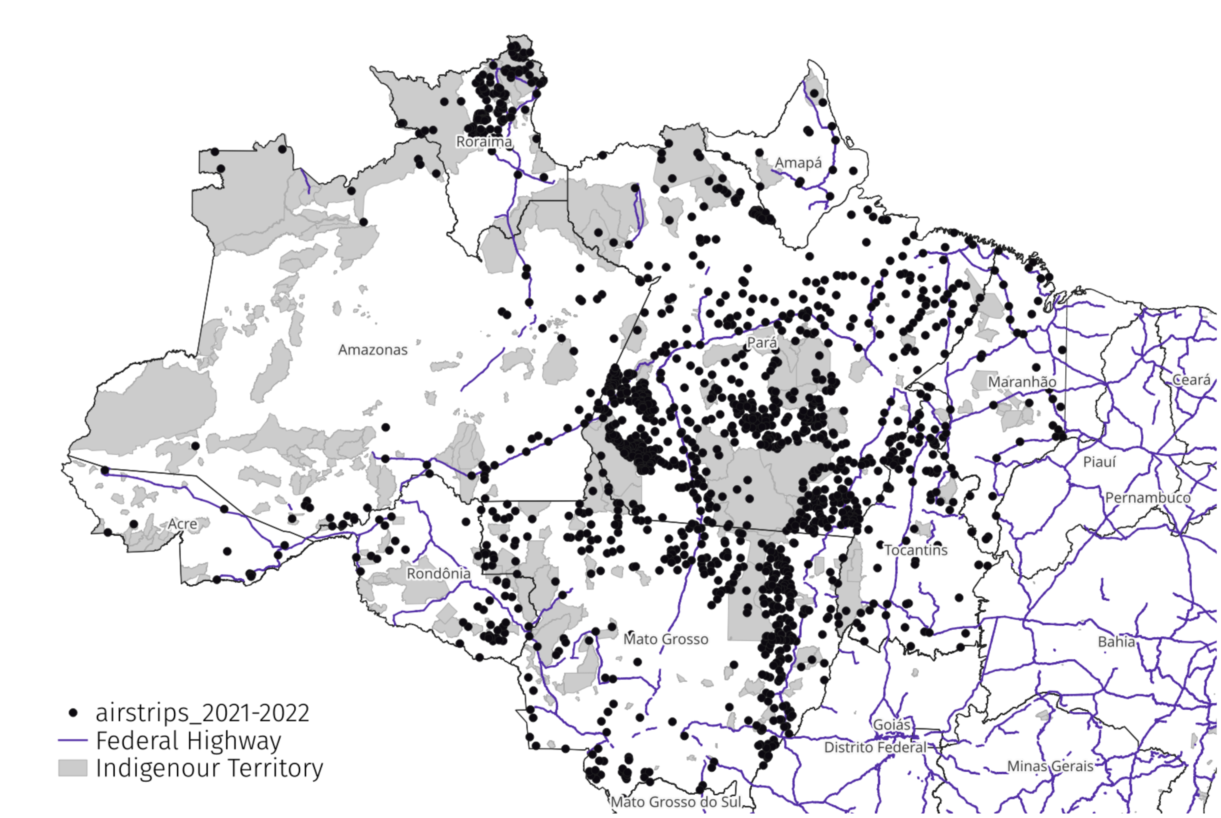
Figure 15 – Airstrip Presence Heat Map for 2021 and 2022 respectively



Source: author elaboration.

HAM, 1978), showing the importance of not only distance but also environmental characteristics that facilitate travel (ECK; WEISBURD, 1995). Visually, most exceptions are concentrated in Pará between the cited highways and are surrounded by indigenous land.

Figure 16 – Airstrips and Federal Highways



Source: author elaboration.

3.4.2 Independent Variables

The independent variables are intended to describe the determinants of criminal behavior in light of the literature survey. In fact, certain variables reflect multiple concepts discussed earlier. One such variable is the distance from the road infrastructure, which can be traced back to Routine Activity Theory (COHEN; FELSON, 1979) and the findings of Bernasco and Nieuwbeerta (2005), which suggest a relationship with proximity. However, proximity in this context may not align with its original application, where it was measured from the offender's home, nor with the location of the offense, as the target here is to build a criminal facility.

In that sense, the literature on illegal dumping has a particular analysis to this effect (TASAKI *et al.*, 2007). The dumping targets are expected to be accessible but not vulnerable to the offenders themselves, so there would be an optimal installation distance. Therefore, distance is a measure of access to travel capabilities, but also to guarantee fewer paladins (SHORT *et al.*, 2010). In parallel, there is also a relation of distance to the time constraint of the choice of residential location.

In addition, there are many other distance measures to different transport features, such as (legal) airports, port complexes, minor roads, and water routes. There can be a degree of diversification in order to minimize risk or maximize different advantages for each type of crime. Another parallel to be made is the location of the facility (HALE; MOBERG, 2003), because there may be more than one distance to minimize to make the most profit.

In this regard, Figures 16 and 17 show that although federal highways are an important factor in airstrip clusters, there is some scarcity of federal highways in the Amazon region. Therefore, the effect of state highways cannot be neglected as they are more present in less developed locations.

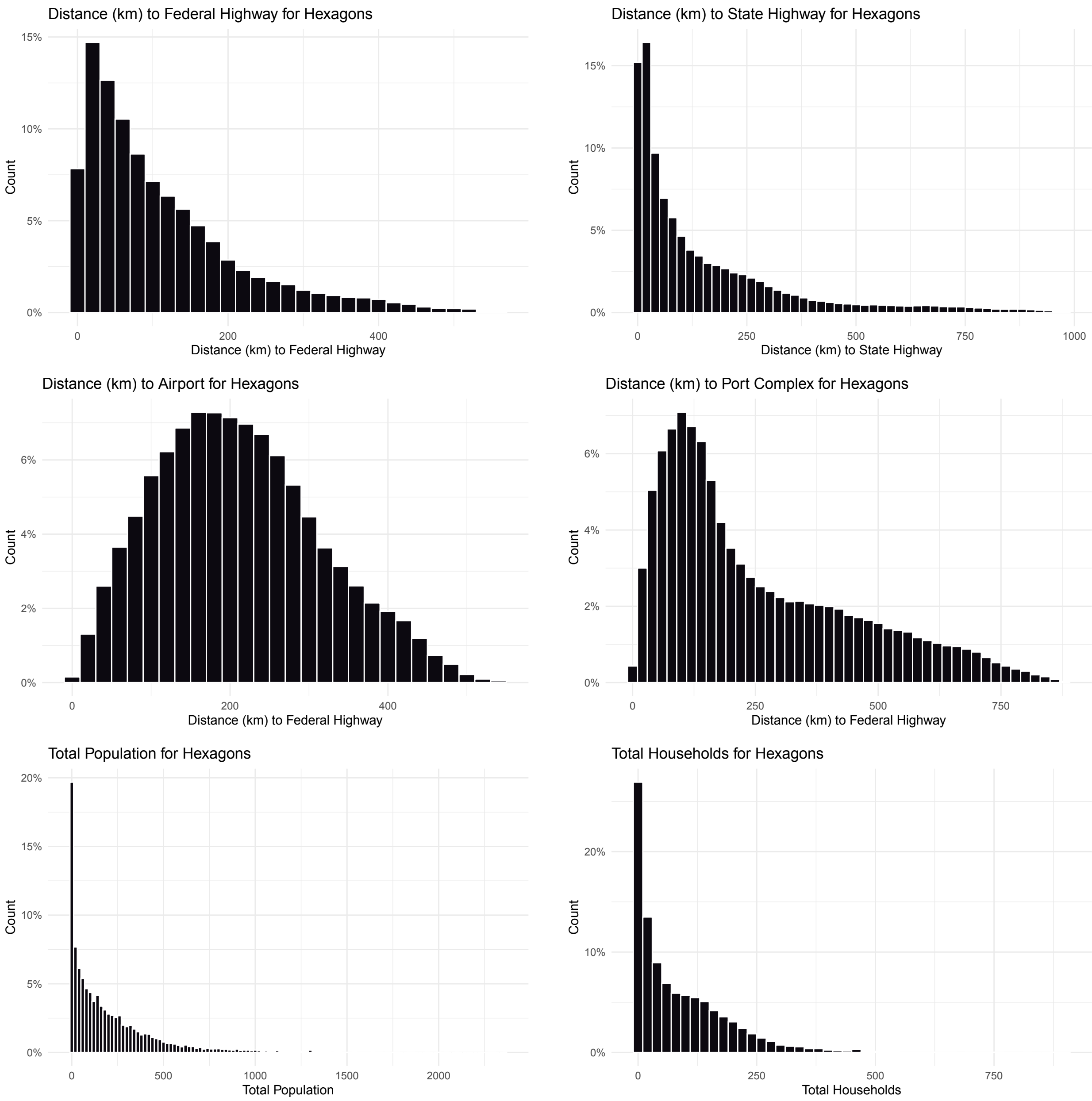
The absence of a guardian or a paladin can be measured not only by distance, but by demographic factors such as population and households from the IBGE census (IBGE, 2022b). Locations with fewer households probably contain fewer state apparatuses for criminals to worry about, and less population makes it harder to draw attention and be recognized by civilians.

Evidently, the cumulative histograms in Figure 18 support the assumption that criminals are indeed seeking to build facilities in areas with lower population density and household density. However, there is a clear tendency for airstrip locations to be closer to federal highways. It is possible that the differences in the magnitude of avoiding exposure and accessing transportation methods could be better understood by modeling these variables.

For categorical values, the states appear to have a focus, as described in Table 5, which likely aligns with the nature of the crime most prevalent in the region. Regarding indigenous territories, with the exception of Roraima, it seems that criminals tend to avoid direct contact with them. One reason for this may be the lack of infrastructure to support their activities. Another possibility could be the state's efforts to preserve the boundaries of the reserves. At the same time, one might argue that surrounding oneself with indigenous land could be a strategy to increase anonymity. Thus, there may be an optimal strategy for constructing facilities near indigenous territories while avoiding their direct invasion.

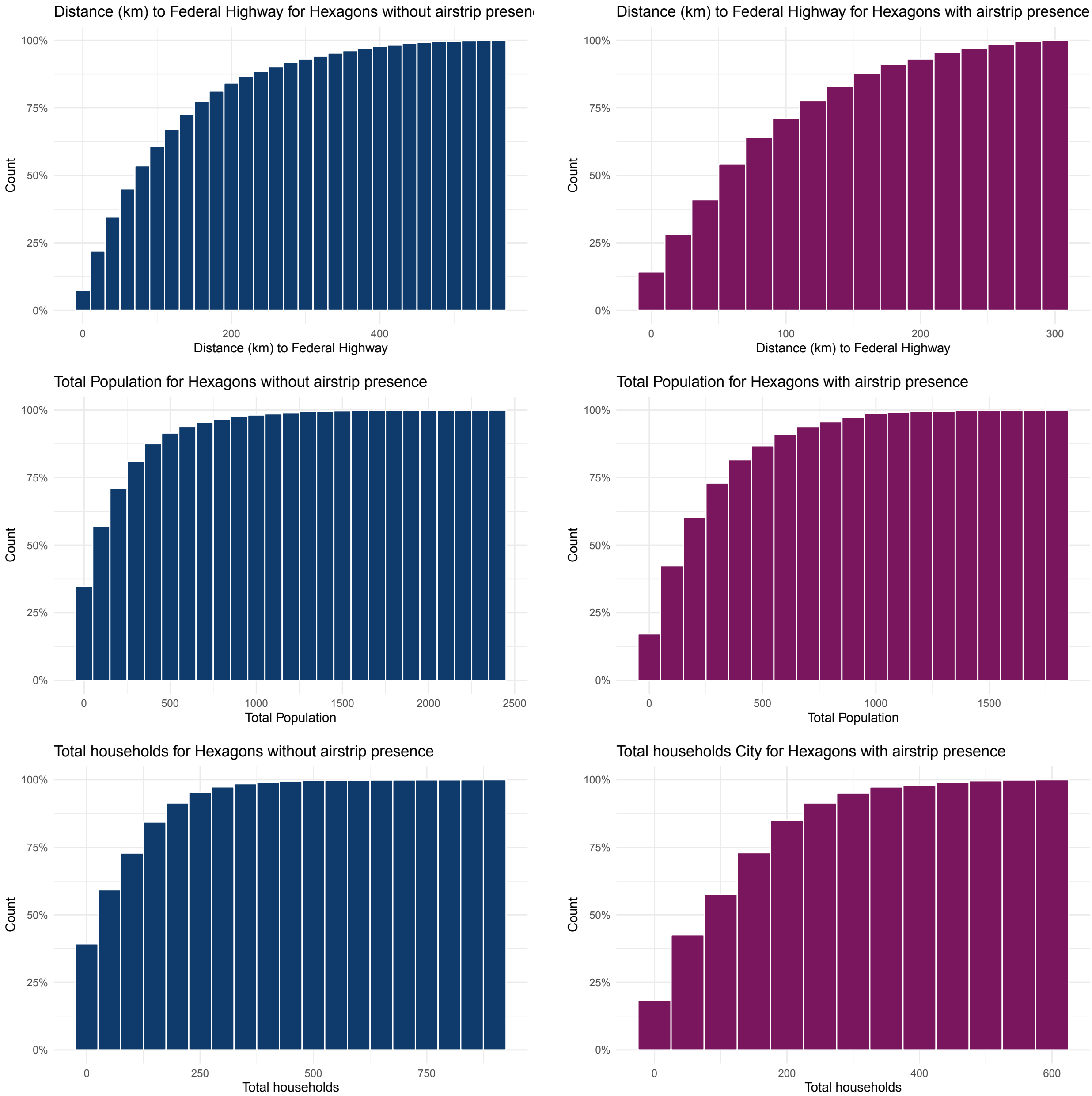
When inspecting the landforms, most of the hexagons were concentrated in depressions, terraces, and highlands, according to IBGE cartography (IBGE, 2023). The highlands exhibited the highest concentration of airstrips, with a presence of 18.48% within the biome. In fact, this analysis could benefit from more technical knowledge in aviation; for example, the mean altitude of the location might offer more insight than simply considering the general landform.

Figure 17 – Independent Variable Histograms



Source: author elaboration.

Figure 18 – Cumulative Histograms For Independent Variables Without and With Airstrip presence



Source: author elaboration.

4 RESULTS

To analyze how organized crime plans where to build their illegal facilities, different regression models have been used. As a first step, three baseline models were fitted: Logit, Poisson, and Negative-Binomial. Logit models stand as a formality, a residual from the first exploration of the data. It cannot be compared to count models that have a different distribution and, for that reason, deal with a different Y. The second and third models will serve to benchmark the results of the zero handling model. As the second step, and focus of this section, zero handling models were fitted: Zero Inflated and Hurdle.

Furthermore, all details about the variables used are described in Chapter 3. Distance calculations were based on the hexagon centroids, demographic information was calculated as a weighted mean using hexagon intersection weights, and qualitative variables were determined by the most representative hexagon area. It is important to reiterate that the variables used to construct the l_p-norm were [$d\_highway\_fed$, $d\_highway\_est$, d_city]. Consequently, they were omitted from the model in which the l_p-norm was used as a parameter, as their inclusion could introduce redundancy and hinder interpretation.

Furthermore, it is important to recall the different interpretations between the ZI and Hurdle models; for consultation, see Table 3. In summary, when referring to ZI, the Zero component refers to the probability that the target is a Structural Zero. Therefore, as stated, when discussing model parameters, for the following analysis the ZINB will be discussed by default, unless specified.

For the interpretation of the different components, it seems reasonable to rely on Moradi's formulation of the hybrid approach (MORADI; BIDKHORI, 2009). The zero component of ZI can be understood as critical factors; without them, location should not be considered for the construction of an airstrip. When a point has sufficient critical characteristics, that is, scores a high probability of not being a structural zero, other objective factors should be addressed. The objective factors can be derived from the count component; the more appropriate locations will have an increased probability of a higher airstrip count.

For another clarification, it is worth describing that the marginal effects for a zero-inflated model, a combination of distributions, is given by the sum of their respective marginal effects in this case. For the zero component side, the average marginal effects was used by default [1].

$$\frac{\partial E(Y)}{\partial X} = p \cdot \frac{\partial E(Y_{zero})}{\partial X} + (1-p) \cdot \frac{\partial E(Y_{Count})}{\partial X} \tag{4.1}$$

In Appendix B we present the logit, Negative-Binomial (NB), and Poisson models estimated merely for illustrative purposes, since, as mentioned earlier, the zero-inflated count models are the most suitable for our dataset. In this regard, Table 9 presents the four estimated zero-inflated models.

Although two models were estimated with two specifications (referred to as $S1$ and $S2$) Zero-Inflated and Hurdle models, as discussed in the Methodology, zero-inflated models were judged to be a better fit for the situation. Therefore, we will only discuss the results of the zero-inflated models, that is, the first two columns from Table 9. In fact, by AIC, both hurdle models were less parsimonious than their ZI counterparts, enhancing the choice of the model. For simplicity, all count components from the zero handling models were made with Negative-Binomial distributions, as it performed better, as expected by the assumption of over-dispersion. From now on, we will discuss the results of the zero-inflated model.

With respect to demographic variables, referring to the zero component, a contrast is evident. The number of households contributes to the probability that the observation is not a structural zero, significant at $p < 0.001$ for both specifications. In return, the population positively contributes to the probability of structural zero.

The opposite signs in this case could be understood by the routine theory lens (COHEN; FELSON, 1979), and the optimal forager, because a higher number of residents could indicate a higher level of crime awareness as a community. Given that reasoning, one could expect the same behavior from households; however, what is probably happening is that the availability of housing indicates the structural conditions of the location. That way, the offender would require a lower population density, but at higher levels of urbanization, so that the necessary features for their criminal activity to be accessible.

Another element of the zero component, and probably one of the research findings, is the distance to federal highways and its squared. The expected behavior based on the literature (BERNASCO, 2010a; DU *et al.*, 2023; TASAKI *et al.*, 2007) is that the criminal has a preference to minimize the distance to the crime location. Given that the land modality is fundamental for

[1] for calculation of marginal effects, the margins package for R was used, see Leeper *et al.* (2024).

different criminal activities, at least as an intermediary, the agent is expected to assign it to be a facility near those roads.

In this sense, for having a quadratic term, its marginal effect involves two coefficients. In Table 10, the marginal effect of each 1000 km to the nearest federal highway is approximately -0.097 for S1 and -0.022. Meaning that, as expected, on average, each kilometer more distant from federal highways increases the probability that the hexagon is a structural zero, nonviable for criminals to settle. But another aspect of its coefficients is that the marginal effect in this case is described as:

$$(\beta_i + 2 * X_i * \beta_j) \cdot E(Y_{zero}) \tag{4.2}$$

we then have:

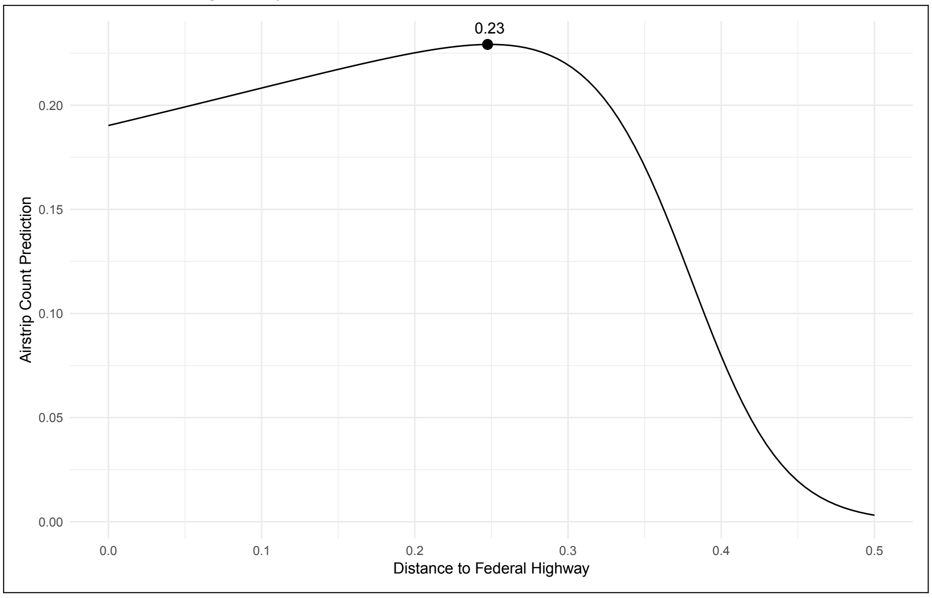
$$E(Y_{zero}) = \exp(X_i \beta_i + X_i^2 * \beta_j + ...) \tag{4.3}$$

Thus, given that $beta_j$ is positive, there exists a distance X_i^* such that the marginal effect is its lowest. Again, because it refers to the zero component, criminals have a selection criteria for distance to highways not too distant, nor too close, an optimal point balancing exposure and transportation access. This interpretation matches the rational choice theory in terms of risk and reward (CORNISH; CLARKE, 2002).

In fact, by computing the first specification predictions, we can tell what the optimal distance is from federal highways for the best probability of a higher airstrip count. To do so, the mean value of each observation was used with the exception of *indigenous* and UF, which were, respectively, 0 (not in indigenous land) and Pará. Then it reaches an expected count of 0.23 airstrips when located approximately 250 kilometers from a federal highway. After that point, the marginal effect is negative.

In addition, two other distances were valued. First, distance to capital was used as the benchmark models showcased the negative effect in the expected number of airstrips. In fact, when looking at both zero components from ZI specifications, the distance to capital decreases the probability of structural zero as it reaches higher values. That is, criminals are supposedly not concerned with building airstrips too close to large urban centers. It goes in the opposite direction of distance to the city (any city that is), where the closer the target is, the higher expected number

Figure 19 – Predicted value by ZI S1 model for Distance to Federal Highways



Source: Author elaboration (2025).

of illegal runways. This again matches the expectation of required infrastructure features versus the avoidance of a higher population and higher public surveillance.

The last zero component to be taken into account is the mentioned l_p-norm. The higher the value of this variable, the more this combined distance is, the higher the probability that the observation is a structural zero. This can be interpreted as an interest of criminals to reside near a variety of structures: highways, federal and state ones, and cities. The city component may represent the need for urban resources such as housing, fresh water, food, and other components of daily life. Another aspect might be the need for labor force; criminal factions require active recruiting. After all, from RAT it is expected that criminals commit their offense near their residence.

Now, focusing more on the terms on the count side, some stand out. It should be noted, again, that these comments do not refer to the entire sample but to the non-structural zero subset. For the state dummies, Roraima has the highest intercept, followed by Pará and then Tocantins, this is true for both specifications. That closely relates to the exploratory analysis but shows how Roraima airstrip incidence is more concentrated than other states, as much as it does not have the highest absolute one. On the other hand, the state with less expected number of airstrips is Amapá for the first specification and Acre for the second, both close to Amazonas, the omitted dummy.

For that aspect, it is important to recognize that each state has a distinct criminal logic. Acre, as a border state, has better infrastructure than Amazonas, making it more suitable as an import route for transnational trafficking. However, Acre did not exhibit significant effects in either specification. The three states with the highest coefficients are known for their concentration of illegal mining activities, which appears to be a recurring pattern in the analysis. At least during the analyzed period, the intersection between crime and mining was the main driver of higher concentrations of illegal airstrips.

Regarding whether the hexagon belongs to indigenous territory, the model indicates that the probability of more airstrips occurring (again, given that it is not a structural zero) decreases when this is the case. This may seem surprising, given the news reports about conflicts and impacts on indigenous tribes (YANOMAMI; YE'KWANA, 2021; G1, 2021). However, it is evident - looking at the map in Figure 11 - that in most regions (except Roraima), criminals do indeed stay close to indigenous lands but generally concentrate around the outskirts.

This makes sense considering the structure of these territories: If the government respects the demarcation, there is no physical infrastructure for land transportation. Thus, positioning themselves near indigenous areas provides a lower degree of exposure while ensuring greater discretion due to the lack of urban centers nearby. As mentioned in the Introduction, there is a higher cost of federal surveillance around protected indigenous land that criminals are making use of (GOV, 2024).

Regarding the distances in the count component (exclusive to the first specification), some results were as expected ex ante, while others were not. The distance to highways was negative, but not significant. It was expected that, given the target is viable, criminals would prefer to establish themselves closer to highways, but it seems that it is not as heavily factored after non-viable observations are not taken into account. That was the case for both federal and state highways. It can be argued that the required infrastructure might be better described by the number of households and that would justify the indifference to highways.

However, distances to waterways and airports were positive and significant for both specifications, indicating that criminals increase their utility by distancing themselves from these points. In the case of airports, one possible hypothesis is that it is not only dangerous to fly near airports, but it may also increase the risk of detection. There might also be an optimal distance, or perhaps this is simply not a factor considered by the criminals. The distance from the waterways is a bit more challenging to interpret - what would be the value of this variable for the agent's utility?

Although the first specification is more intuitive in terms of the relationship with distances, the second specification may provide a more profound analysis, but the l_p-norm did not show significance for the count component. Perhaps the distance to highways carries more weight, but even so, the criminal agent still tries to minimize the distance to a multiple of these points of interest when assessing where an airstrip can be established.

This would imply that, in isolation, the distance from airports and waterways is not as prioritized compared to the distance to highways. However, when evaluated together, they provide a more comprehensive understanding of the offenders' decision-making process.

In summary, the models seem to be able to describe, with statistical significance, both described phenomena: (1) what observations are not accounted for as suitable by criminals and (2) what factors contribute to higher concentrations of airstrips. In general, the model shows that criminals avoid capital cities and higher-density regions while maintaining access to reasonable infrastructure, fitting the rational perspective of minimizing risk exposure while also minimizing [transport and infrastructure] costs.

Table 9 – Zero Handling Models

	S1 ZI	S2 ZI	S1 Hurdle	S2 Hurdle
Count model: (Intercept)	-4.009^{***}	-3.975^{***}	-4.208^{***}	-4.437^{**}
	(0.185)	(0.196)	(1.234)	(1.355)
Count model: t_households	3.256^{***}	2.748^{***}	2.008	1.839
	(0.784)	(0.821)	(1.954)	(1.938)
Count model: t_population	-1.637^{***}	-1.473^{***}	-1.714^{*}	-1.537
	(0.294)	(0.295)	(0.872)	(0.860)
Count model: d_highway_fed	0.920		3.246^{*}	
	(0.692)		(1.450)	
Count model: d_highway_est	-0.209		1.913	
	(0.457)		(1.107)	
Count model: d_city	-1.037		-1.577	
	(0.898)		(2.047)	
Count model: lp_norm_distance		1.036		2.075
		(0.587)		(1.116)
Count model: d_waterroute	1.026^{***}	0.860^{**}	-0.111	0.211
	(0.294)	(0.290)	(0.764)	(0.713)
Count model: d_airport	3.965^{***}	3.777^{***}	3.717^{***}	3.831^{***}
	(0.359)	(0.358)	(0.872)	(0.883)
Count model: indigenous	-0.270^{**}	-0.267^{**}	-0.945^{***}	-0.920^{***}
	(0.083)	(0.083)	(0.192)	(0.191)
Count model: Acre	0.022	-0.036	0.508	0.628
	(0.355)	(0.356)	(1.211)	(1.209)
Count model: Amapá	-0.011	-0.034	-0.599	-0.661
	(0.330)	(0.328)	(1.201)	(1.205)
Count model: Maranhão	0.248	0.280	-1.230	-1.170
	(0.234)	(0.232)	(1.135)	(1.136)
Count model: Mato Grosso	0.805^{***}	0.873^{***}	0.341	0.391
	(0.187)	(0.183)	(0.520)	(0.519)
Count model: Pará	1.583^{***}	1.504^{***}	0.922^{*}	0.974^{*}
	(0.162)	(0.162)	(0.464)	(0.463)
Count model: Rondônia	0.554^{*}	0.574^{*}	0.292	0.280
	(0.244)	(0.241)	(0.817)	(0.814)
Count model: Roraima	2.721^{***}	2.768^{***}	3.269^{***}	3.337^{***}
	(0.197)	(0.196)	(0.533)	(0.534)
Count model: Tocantins	1.030^{***}	1.086^{***}	0.632	0.741
	(0.201)	(0.198)	(0.587)	(0.584)
Count model: Log(theta)	-0.742^{***}	-0.594^{***}	-1.862	-1.973
	(0.110)	(0.135)	(1.254)	(1.377)
Zero model: (Intercept)	1.968^{***}	1.682^{***}	-3.535^{***}	-3.538^{***}
	(0.438)	(0.386)	(0.101)	(0.103)
Zero model: t_households	-94.514^{**}	-53.317^{**}	6.002^{***}	5.075^{***}
	(31.645)	(18.692)	(0.648)	(0.662)
Zero model: t_population	10.580^{*}	6.047^{*}	-1.236^{***}	-1.058^{***}
	(4.231)	(2.921)	(0.268)	(0.270)
Zero model: d_highway_fed	-1.556	-2.156	3.288^{**}	4.826^{***}
	(5.377)	(4.177)	(1.269)	(1.268)
Zero model: d_highway_fed^2	42.351^{*}	32.246^{*}	-28.154^{***}	-22.404^{***}
	(17.056)	(13.878)	(4.542)	(4.484)
Zero model: d_capital	-3.484^{***}	-4.004^{***}	2.109^{***}	2.907^{***}
	(0.893)	(0.829)	(0.182)	(0.207)
Zero model: lp_norm_distance		3.399^{*}		-2.918^{***}
		(1.326)		(0.376)
AIC	8551.515	8549.247	9142.703	9072.336
Log Likelihood	-4251.757	-4251.624	-4547.352	-4513.168
Num. obs.	15154	15154	15154	15154

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Source: author elaboration.

Table 10 – Marginal Effects

Variables	ZI S1	ZI S2
t_households	0.001594	0.00108
t_population	-0.0003053	-0.0002564
lp_norm_distance		0.2133
d_highway_est	-0.02081	
d_city	-0.1035	
d_waterroute	0.1024	
d_airport	0.3955	
indigenous	-0.02692	-0.0221
d_highway_fed	-0.02185	-0.09678
d_capital	0.04677	0.1054
Acre	0.000733	-0.004351
Amapá	-0.0003568	0.01153
Maranhão	0.009135	0.02102
Mato Grosso	0.04018	0.08057
Pará	0.1256	0.1393
Rondônia	0.02404	0.02899
Roraima	0.4611	0.3417
Tocantins	0.05851	0.06376

Source: Author elaboration (2025).

5 FINAL CONSIDERATIONS

Transnational illicit trafficking is estimated to generate between 1.6 and 2.2 trillion dollars annually (NSF, 2023), reflecting the increasing sophistication and reach of criminal networks. In this context, this study advocates for a new approach to criminal understanding by analyzing the location of the criminal infrastructure. By synthesizing various criminological theories, as discussed in the literature review, this approach enriches the academic discourse on crime, emphasizing the importance of multifaceted and integrated strategies for crime prevention.

In this context, Brazil unfortunately stands out in international crime due to its geographical position, neighboring major drug-producing countries, having areas of low governmental presence, vulnerable populations, and access to various means of transportation. This strategic location not only facilitates the flow of illicit goods, but also amplifies the challenges faced by law enforcement. Therefore, it is crucial for academia to contribute to understanding the dynamics of these factors so that public authorities can adapt to the evolving nature of crime. There are potential gains in public spending efficiency if a better understanding of transnational crime is invested.

To enable analysis and understand how crime evolved to the point of creating illegal airstrips, a review was conducted not only to understand what classical criminology from the international literature has to offer but also to introduce a new perspective into this line of research. This approach bridges traditional criminological insights with other well-founded analytical frameworks. It is evident that as criminal organizations become more sophisticated, they increasingly operate as profit-maximizing institutions, which should be understood as an opportunity for predictability. Recognizing this economic rationality allows for the anticipation of criminal behavior and strategic interventions. To achieve this, it is necessary to adapt different areas of economics to what already exists in criminological theory.

In our first model (ZI S1), we concluded that there is evidence consistent with the theory of a suitable target and absence of guardians. The quadratic term for distance shows that criminals do not seek locations that are too close or too far away. In this sense, there is an optimal safe distance where guardians are absent, yet suitable targets are nearby, whether these targets are gold, access to drug routes, or other criminal activities.

Our second model (ZI S2) highlights the influence of the facility location literature, leading to the conclusion that criminals minimize the distance to demand points when deciding whether a location is viable. In other words, they strategically position themselves close to the necessary points for the outflow of their product. Using the variables *d_highway_fed*, *d_highway_est* and *d_city*, we found evidence that criminal organizations tend to minimize these distances. This also aligns with the residential location literature, as criminals seek to minimize the time cost required to access the various nodes of their criminal network.

Both models provide different inputs and attempt to apply approaches grounded in different theoretical frameworks, yet offer complementary insights. Criminals minimize distances to key points, but there is also an interest in "not minimizing too much" to avoid becoming more vulnerable. Therefore, a next step could be to combine these two insights to gain a deeper understanding of this phenomenon. Again, criminals show rational aspects to their methods and this is very important: recognizing these patterns shows opportunity for predictability in criminal behavior, and this is where the benefit of investing in intelligence resides, especially when criminals behave using know patterns from traditional economics.

Evidently, the results highlight two key aspects for the reader's evaluation: the areas criminals avoid when constructing illegal facilities and the factors that increase the expected number of airstrips in the observed region. Both perspectives are valuable; understanding where airstrips are unlikely to be built allows government authorities to allocate resources more efficiently for criminal surveillance in the Amazon. In addition, identifying the factors that influence criminal choices enables policy makers to target areas with higher risk with more effective public policies.

Thus, this dissertation contribution to the literature has different components. In terms of criminal location, the perspective of analyzing crime equipment and not the offense itself is something new to this type of research, but it resembles the efforts of illegal dumping studies (TASAKI *et al.*, 2007; JOO; KWON, 2015; DU *et al.*, 2023). Moreover, the rational agent perspective was already common in crime literature, but treating crime organization as an institution comparable to firms in the logistics sense is a more undeveloped approach. Therefore, this work contributes to further microeconomic grounding of crime, now from a firm theory viewpoint.

Furthermore, the data set used represents a new approach for criminal studies in the Amazon region in the context of the current challenges of public security in the country. The discretization process utilized provides a valuable tool for processing data for such an enormous biome with vast characteristics. By definition, demographic information is more scarce for lower density regions and the discretization allied with the weighted mean method for calculating expected demographic characteristics also represents a new step for criminal studies in isolated areas.

As a contribution to public authorities, the variables identified in this modeling can aid in the patrolling of the Amazon. It becomes possible to determine crime hotspots, making the fight against the transportation of illegal products more effective. Moreover, a similar approach could potentially be replicated in other known trafficking routes throughout the country. This type of application can generate economic gains by spending efficiency, a necessary budget gain to combat criminal factions in such a challenging region. Our findings also reinforce the need to protect the perimeters of indigenous land, as they are one of the most victimized communities of TOC in this country. For public policy recommendations:

- Implement patrol practices in areas considered optimal by criminal organizations.
- Build a sufficiently rich database to conduct even deeper analyses on the determinants of the location of criminal infrastructure.
- Create surveillance plans for critical resources, such as gold mining areas and for zones under deforestation pressure.
- Develop partnerships with university research centers to create new opportunities for crime prevention and control.
- Create a legal mechanism for acting on indigenous land while respecting the sovereignty of their communities.

For this research limitations, there are innumerable variables that could be considered for addition: altitude, forest density, proximity to military bases, distance to cocaine producers, police force, and many others. Another point is that there are more recent data available, but it was out of scope to include due to the heterogeneity of the series, especially given the pandemic.

For future research, there are still many more factors to be taken into account, there are also many innovations that seem promising to include such as satellite imaging with Artificial Intelligence support. The complete census data IBGE were not available in this research conception, so there may be some new variables available.

Furthermore, as cited in the Methodology section, no spatial weight was used as a parameter even though Moran's I showed significancy. Evidently, some spatial correlation is taken into account by the use of distance measures, but factors such as having nearby hexagons with higher density or precedence of airstrip existence have not been taken into account. Therefore, further econometric analysis for proper inclusion of such variables would benefit the model, especially if different approaches to weighting were tested, as it also demands further exploration.

Another important scope is the sample size; the high concentration of zeros, one of our greatest challenges, could have been diminished if we further limited the sample space, as there could be additional exclusion criteria. Future research could zoom in on specific crime operations, such as "Garimpo" in Pará, to develop stronger tools for policy making. One opportunity fitting this area of research is the use of Artificial Intelligence for prediction, given this dissertation and the available literature on crime in the Legal Amazon, there definitely are opportunities for more accurate predictions of crime given the use of AI, as it is its stronger application. To structure some suggestions, take the following:

- Enrich demographic data with the new information from the 2022 Census published between December 2024 and January 2025.
- Add spacial autocorrelation through spacial weight in different variables.
- Test other variables such as distance from military barracks and distance to other relevant points.
- Conduct tests focusing on proposing an optimal surveillance distance for federal highways.
- Replica of the analysis for airstrips in the Southeast along the "Rota Caipira".
- Further restrict the sample space by attempting to exclude nonviable locations based on aviation knowledge. It is also possible to develop a similar study focusing on a specific state, such as Pará, with an emphasis on illegal mining activities.
- Using machine learning models to improve predictive power and test them to empower the state to forecast the location of new airstrips.
- Investigate the effect of specific criminal organizations in territorial conflicts on the distribution of airstrips.

In summary, this study establishes an innovative foundation for understanding criminal facility location in the Legal Amazon and a new approach to understanding the location of criminal facilities. The protection of natural resources and indigenous tribes in this region requires coordinated efforts from Brazilian authorities and international cooperation from neighboring countries. Such collaboration is essential to dismantle transnational criminal networks that exploit geographical and jurisdictional gaps. Given the global importance of the Amazon biome, ultimately defending its integrity is not only a national responsibility but also a matter of global interest.

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APPENDIX A – MODEL CHOICE, HURDLE AND POISSON COMPARISON.

Compare the Negative Binomial (NB), Zero Inflated Negative Binomial (ZINB) and Hurdle Negative Binomial (HNB) models (table 11). Only the variable distance to nearest highway and its square were included for simplification. There are 3 different interpretations for the count component of each model - for NB only containing the count model. Take $z\_d\_highway^2$, its coefficient is positive for NB and negative for both zero handling models. For NB, each normal deviation - as standardized variables were used - increases the number of airstrips by 0.19; for ZINB -0.277 given that the observation is not a structural zero and HNB -0.234 given that the observation contains airstrips. Both zero handling model show the expected rational criminal behavior of a "optimal" distance to roads, while the NB model shows inconclusive behavior indicating that criminals prefer to be as closes as possible or as distant as possible from roads. This NB behavior might occur because the NB model is mostly predicting zeros, making the information for positive dependent variables diluted.

Table 11 – Appendix Simple Model Comparison

	Coefficient	NB	ZINB	HNB
Count Component	(Intercept)	-2.749 (0.057)***	-1.160 (0.180)***	-11.067 (55.748)
	z_d_highway	1.046 (0.065)***	0.122 (0.130)	0.337 (0.152)*
	z_d_highway²	0.194 (0.041)***	-0.277 (0.077)***	-0.234 (0.106)*
	Log(theta)		-0.701 (0.196)***	-11.115 (55.749)
Zero Component	(Intercept)		1.361 (0.229)***	-3.080 (0.061)***
	z_d_highway		1.923 (0.175)***	-1.222 (0.069)***
	z_d_highway²		-0.844 (0.146)***	0.276 (0.039)***
Log-likelihood		-4645	-4602	-4585

Source: author elaboration.

For the Zero Component, both models show significant values, but with different signs. The opposite signs are explained by the fact that the hurdle() function in pscl (JACKMAN *et al.*, 2024) is modeling the probability of a non-zero count instead of the probability of a (structural) zero count as is the case for zeroinfl().

APPENDIX B – BASELINE MODELS.

Table 12 – Baseline Models

	Logit	Poisson	NB
(Intercept)	-4.596^{***}	-4.305^{***}	-4.286^{***}
	(0.132)	(0.104)	(0.131)
t_households	4.516^{***}	4.379^{***}	5.102^{***}
	(0.675)	(0.520)	(0.704)
t_population	-0.453	-0.608^{**}	-0.722^{*}
	(0.272)	(0.222)	(0.281)
d_highway_fed	1.614	4.366^{***}	4.268^{**}
	(1.401)	(1.144)	(1.441)
d_highway_fed^2	-18.194^{***}	-26.066^{***}	-28.080^{***}
	(5.117)	(4.196)	(5.319)
d_highway_est	-1.732^{***}	-0.386	-0.366
	(0.458)	(0.361)	(0.445)
d_waterroute	0.435	0.573^{*}	0.829^{**}
	(0.273)	(0.227)	(0.288)
d_airport	3.778^{***}	4.027^{***}	3.935^{***}
	(0.351)	(0.284)	(0.366)
d_cport	1.157^{***}	1.159^{***}	1.248^{***}
	(0.184)	(0.149)	(0.187)
d_city	-0.452	-0.934	-0.744
	(0.783)	(0.612)	(0.773)
d_capital	2.102^{***}	1.221^{***}	0.932^{***}
	(0.274)	(0.231)	(0.281)
indigenous	-0.138	-0.275^{***}	-0.224^{**}
	(0.078)	(0.065)	(0.080)
AIC	7221.028	9805.389	9048.499
BIC	7312.540	9896.901	9147.637
Log Likelihood	-3598.514	-4890.694	-4511.249
Deviance	7197.028	7358.361	4116.991
Num. obs.	15154	15154	15154

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Source: Author elaboration.