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Simultaneous Causality and the Spatial Dynamics of Violent Crimes as a Factor in and Response to Police Patrolling

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Abstract: Simultaneous causality occurs when two variables mutually influence each other, creating empirical contexts where cause and effect are not clearly unidirectional. Crime and policing often appear in urban studies presenting the following characteristic: sometimes, increased police patrols can reduce criminal activities, and other times, higher crime rates can prompt law enforcement administrations to increase patrols in affected areas. This study aims to explore the relationships between patrol dynamics and crime locations using spatial regression to support public policies. We identify spatial patterns and the potential impact of crime on policing and vice versa. Data on crimes and patrol locations were collected from the database provided by the Planning and Management Secretariat and the Social Defense Secretariat of Pernambuco, Brazil. The study employed Ordinary Least Squares (OLS) to create a spatial simultaneous regression model for integrated security zones within the Brazilian geography. This approach provides a holistic visualization, enhancing our understanding and predictive capabilities regarding the intricate relationship between police presence and crime. The results report a significant relationship, with crime locations explaining police patrols (varying in geographic domain and type of crime). No statistically significant results from most geographic locations point to the inverse relation. The quantitative analysis segregated by typology presents a potential for effective public decision support by identifying the categories that most influence the patrol security time.

Keywords: crime; spatial analysis; statistical simultaneous causality; geographic information systems; ordinary least squares; police vehicles; Pernambuco



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1. Introduction

Crime can affect both the sense of security in a region and its economic stability. It is often regarded as a social disease, creating a sense of embarrassment and discomfort. However, its effects on social, economic, political, cultural, and family characteristics differ from society to society [1,2]. The growing development of nations has been accompanied by a consequent increase in urban violence and crime, affecting various population segments.

As a result of this joint development, crime has become an increasingly recurring topic in the literature on urban studies [3].

In this context, the action of the police force emerges as a component of the criminal justice system, with its central role being policing, aimed at ensuring compliance with laws and contributing to social order within a system that is composed of multiple population characteristics and institutional arrangements influencing and being influenced by crime [4–8]. Police work achieves significant results in combating crime and violence when policing is focused on critical points. A common assumption is that crime is not uniformly distributed in space but is instead geographically concentrated in critical areas. Therefore, concentrating police forces at strategic points is a way to better utilize police resources to reduce crime rates [9].

Empirical studies on understanding crime control have significantly increased since the 2000s, driven by the volume of available data and advances in software and techniques such as GIS (Geographic Information Systems) [10–12]. Nepomuceno and Costa [13] and Poleto et al. [14] suggest that data visualization allows users to analyze patterns and explain phenomena for better decision-making. Ref. [15] argue that the GIS approach aids both the visual perspective and the structural relationships between relevant spatial and temporal information. It combines geographical location with other data types, making the generated information valuable for planning, promoting productivity gains, and better decision-making quality [16]. The primary motivation for using GIS techniques in situations involving crime is to address strategies and guidelines of public policies to combat and prevent these actions. Mapping allows for the identification of hotspots and the assessment of crime trends and patterns spatially and temporally.

A series of empirical evidence discusses the application of GIS methods with these analytical characteristics. For instance, the works of Balogun et al. [17], which utilized data from questionnaires for police officers and the general public in Nigeria, reveal that GIS is valid for proactive decision-making and suitable for crime prevention. Ref. [18] used data from Baltimore, Maryland, covering a variety of crime records (shootings, homicides, and assaults by threat). The authors identified areas prone to certain types of crime and provided justifications that aid in identifying these hotspots and the effectiveness of police action for minor crimes. This empirical evidence suggests initial relevant considerations regarding applying GIS to crime analysis. First, GIS allows for a multidimensional analysis of crime indicators, consequently promoting a broader perception of criminal activities. Second, it encompasses various data collection methods, such as questionnaires, microdata, aggregated or disaggregated data, and temporal characteristics for one or multiple periods. Finally, combining crime patterns with trends enables more effective actions by covering the characteristics of criminal phenomena in combination with police force actions.

In the context of Brazil, a country marked by high crime rates, income inequality, and poverty, GIS can aid in combating crime. Most studies on empirical evidence of crimes using GIS approaches employ aggregated data, which limits the understanding of specific scenarios. To fill this gap about specific scenarios, the main objective of this research is to analyze the spatial dynamics between the locations of police vehicles (patrol locations) and crime occurrences using GIS combined with linear regression models. The study was conducted in Pernambuco (Brazil) using disaggregated data to measure the effectiveness of the Pacto pela Vida program, an initiative led by the local government to reduce the rates of intentional violent crimes (Crimes Letais Violentos Intencionais, CVLI) at municipal and state levels. The government management model implemented involves monitoring the program's actions, which resulted in the territorial division of Pernambuco into 26 Integrated Security Areas (Áreas Integradas de Segurança, AIS) [19].

Second, this study investigates the potential mutual relationship between police activities related to operational routes, pathways, and crime locations, investigating potential simultaneous causalities that might occur in similar contexts. Simultaneous causality occurs when two variables influence each other reciprocally, making distinguishing between the cause and the effect challenging. We categorize the data into three main categories for

econometric inference, enabling a nuanced analysis and facilitating the examination of various patterns and trends. We assess the impact of police patrol routes on crime locations and vice versa, accounting for spatial dependencies and correlations. This approach allows us to derive robust and reliable inferences about the relationship between police patrol dynamics and the spatial distribution of homicides within specific urban environments.

We analyze the spatial dynamics between police vehicle locations (patrol locations) and crime occurrences using Geographic Information Systems (GIS) combined with linear regression models on three main perspectives: evaluating the effectiveness of the *Pacto pela Vida* program to contribute to potential adjustments by the government, offering a disaggregated data approach that allows for comparison with other studies using aggregated data, and evaluating the spatial dynamics of crimes concerning patrol points. Our investigation is distinct from other regional studies focusing on the spatial concentration of specific types of homicides and their relationship with the urban environment. By addressing simultaneous causality and employing spatial regression analysis, we offer valuable insights for public policies regarding public security in urban spaces, potentially guiding strategic decisions in law enforcement and crime prevention [20–27].

This study's distinctive feature is constructing a spatial regression model based on Ordinary Least Squares (OLS) to better understand the complex dynamics between policing and crime in a target geographic space. The model design can be reused in other geographic locations besides the one analyzed in this research, aiming to provide public security agencies with a statistically based tool to support their decisions on police action. From a social perspective, the proposed model aims to guarantee public safety actions that are more adjusted to the context of the geographic space. Results can facilitate strategies for constructing a safer atmosphere, improving the quality of services and housing, and developing local commerce.

From a social perspective, since the proposed model aims to guarantee public safety actions that are more adjusted to the context of the geographic space analyzed, there is the effect of a feeling of improvement in the quality of services by the local population, facilitating the development of the space with impact on the improvement of housing quality and the development of local commerce. With these two contributions, the present study seeks to fill in the literature about dynamic spatial crime.

This article comprises five sections: this introduction, theoretical and empirical framework, data and methodology, results and discussion, and conclusion. In the following section, readers may find a brief literature discussion on this investigation's theoretical and empirical elements. The third section describes the database and methodological approach of the research, and the fourth section comprises the results and discussion, considering theoretical and empirical implications. Lastly, the conclusion summarizes the main prospects and limitations of the findings.

2. Theoretical and Empirical Framework

Policing and Crime

Crime prevention is motivated by several interventions that involve managing city planners, community leaders, and police officers, using past crime data as a source, and including police patrols as one of the solutions [28]. Also, it is cited in the literature that the issues of crime prevention and reducing the fear of crime are associated with police patrols as a way to improve the public security perception of the community [29,30]. With advanced computational tools available, the spatial maps produced by GIS have become a strong tool for understanding crime occurrences and supporting police patrols.

The literature recently brought methodological and applications to crime prevention and spatial analysis. Risk Terrain Modeling (RTM) is an innovative approach whose objective is to create hotspot maps using relevant data to forecast vulnerable places [31]. In Wang et al. [32], an optimization tool was built to improve the identification of crime hotspots, allowing the creation of spatial clusters based on variables related to the crimes. Nepomuceno and Costa [13] applied an optimized hot spot analysis to crime data in the

Brazilian city of Recife, working with disaggregated data and evaluating the number of incidents and the criminal patterns that originated through hot spots.

These three studies are similar because they include a hotspot analysis. A hotspot is defined as a place where the concentration of crime is relatively more significant than in other areas [30]. The approach is supported by criminal theories in the literature [33].

However, the growing interest in revealing critical areas, considering the importance of identifying crime geographical patterns, has motivated effective practical contributions to other themes to emerge. The research conducted by Hajela et al. [30] combines a hotspot with two-dimensional cluster analysis incorporating a machine learning algorithm, obtaining better performance than clustering techniques without hotspots.

Han et al. [33] proposed a new spatial-temporal kernel density estimation method considering the incidence of robberies with cyclic trends performed in Baton Rouge, Louisiana, achieving an adequate fit to forecast. Also, we verified a model based on simulation agents to create synthetic characteristics and evaluate the vulnerable targets, enabling us to find hotspot zones [34].

Although critical points associated with other variables draw attention in the present study, other academic contributions propose approaches to ensure public order and a sense of security. Both aspects are essential to provide quality of life in cities. A model in which citizens generate data and help support decisions in crime monitoring was proposed by [35].

In Brazil, Mota et al. [36] developed a GIS-multi-criteria decision model to identify and classify areas vulnerable to homicide, evaluating different spatial approaches. Rosa et al. [22] proposed a multi-methodology framework based on spatial multiple-criteria analysis to reveal the critical regions of robberies in street incidents. Edel [34] examines long-term trends in the Netherlands compared to the hooligan dynamics in Brazil, and Nepomuceno and Costa [13] discuss the challenges of aggregating large samples of criminal data in visual representations, highlighting the risk of compensation bias in spatial association measures.

Table 1 summarizes the recent papers using quantitative analysis to map crime occurrence, either to forecast new events using the generation of spatial surface to highlight areas with more chances for crime events or to evaluate the vulnerability condition using classification analysis. We observe that the methods available in the papers bring interesting contributions that involve public security themes. However, the purpose here is to include the police patrol routes together with crime occurrence analysis considering OLS to investigate the patterns of crime.

Table 1. Quantitative analysis to map the occurrence of crime.

Approach	Type of Violence	Spatial Analysis Used	Objective (Forecast or Vulnerable Places)	Variables	Country	Reference
To evaluate the vulnerable places, decision rules were induced based on multiple criteria, spatial analysis, and statistical methods.	Robbery	Classification	Vulnerable	Demographic Social interaction Bus stops	Brazil	[25]
Risk Terrain Modeling combining map layers (factors) and assigning weights. The results produced a map with risk values that permit the allocation of resources to reduce risk.	Shootings, drug market, gangs' activities	Hotspots	Forecast crime types' behavior	Built environment Crime past data	USA	[31]

Table 1. Cont.

Approach	Type of Violence	Spatial Analysis Used	Objective (Forecast or Vulnerable Places)	Variables	Country	Reference
Geospatial Discriminant Patterns (GDPatterns) and Hotspot Optimization Tool (HOT) are used to visualize clusters and better identify hotspot zones. Both approaches capture information that kernel density alone does not achieve.	Street robbery, commercial burglary, and larceny	Hotspots	Vulnerable places and hotspots	Population N° of house units Distance to colleges Foreclosed homes	USA	[32]
Stochastic analysis and a deep learning approach were integrated into a web tool to identify hotspots and forecast new criminal events.	Passerby robbery, commercial burglary, vehicle robbery	Hotspots	Hotspot and forecast	Socioeconomic factors	Brazil	[37]
Kernel density was adjusted to include temporal crime cycles in the predictive analysis and obtain effective results.	Robbery	Hotspots	Hotspot and forecast	No apply	USA	[33]
Crime simulation using synthetic agents based on Routine Activity Theory.	Robbery	Hotspots	Vulnerable zones and Hotspots	Police patrols Offender activities Population density	USA	[34]
Web applications are based on citizens' reports about crimes and events that occur in the places considered. The app includes geographic information and crime analysis.	Car theft, house theft, murder, bag snatching	Semantic analysis	Vulnerable places	Citizen reports about characteristics of the neighborhood where the criminal events happened	Iran	[35]

On the other hand, the context of spatial patterns may be explored by statistical spatial techniques, as in the study by Camargo et al. [38], which sought to model the risk of homicide in the city of São Paulo using a semi-variogram risk estimator. Evaluating 96 municipality districts through a geostatistical approach, the homicide risk was estimated using binomial co-kriging as a linear interpolator. The city's central region had a greater focus, with this hotspot being dissolved as the distance from the center, and, in the sequence, new risk areas located on the periphery appeared. The authors also pointed out that these results were consistent with previous studies and the city's urban structure.

Police patrol strategies differ based on the perceived severity and urgency of crimes. Violent crimes typically trigger immediate, focused responses due to their direct threat to public safety, while property crimes lead to more distributed patrol efforts aimed at broader surveillance and prevention. Some studies highlight this dynamic. For instance, Ratcliffe et al. [30] found that foot patrols in high-crime areas of Philadelphia significantly reduced violent crimes, and Dewinter et al. [39] examined methods for optimizing patrol routing. Ramakrishnan et al. [40] used the Random Forest and greedy algorithms to predict crime-prone areas and optimize patrol routes. These studies highlight the relationship between crime types and patrol strategies.

Santos et al. [41] aimed to study the relationship between the spatial distribution of homicides and demographic socioeconomic indicators. Thus, using the *K*-means algorithm and a smoothed kernel, the authors used two complementary approaches to characterize the city, one considering the socioeconomic areas and the other the homicide rate areas. One of the results indicated that regions where socioeconomic conditions are worse have higher

homicide rates. However, it was still possible to observe that the interactions between demographic conditions and urban and socioeconomic factors have different impacts in each region.

In terms of spatial-temporal patterns, Nery et al. [42] aimed to validate whether such patterns related to homicides in the city of São Paulo, Brazil, respect the geographic limits of the administrative divisions of the city. For this, they analyzed the existence of a spatial and local correlation structure using the box map technique and the Moran index. In their results, the authors identified seven types of regimes that do not follow the geographic limits of the districts. Thus, it was validated that the census sectors present patterns of territorial aggregation that do not correspond to the existing political-administrative division.

Pereira et al. [24] sought to study whether homicides in Recife follow the law of concentration of crimes and, if positive, whether these are stable over time, considering the scenario of falling homicide rates in recent years. The authors used the spatial point pattern test developed by Andresen [40] and the Spearman correlation to verify stability. Considering two spatial units (census sectors and street segments) to validate the results, they obtained strong support to affirm that in the city of Recife, there is a concentration of homicides, yet there was mixed support to validate the presence of stable spatial patterns over time.

Considering the research bias of Santos et al. [41], Pereira et al. [43] investigated the role of demographic, social, and economic variables associated with homicide. Using a spatial regression technique that controls heteroscedasticity, in addition to spatial autocorrelation and using 28 explanatory variables, the research sought to associate the theory of social disorganization with homicides in Recife. By identifying average income and income inequality as the most important variables for the distribution of homicides, the study validated that, in general, the theory of social disorganization can explain homicides in the city in question.

Employing multiple linear regression analysis, Reis et al. [44] studied the relationship between the occurrence of four types of offense in four different periods of the day and spatial-physical variables in two neighborhoods of Porto Alegre, Brazil. It was observed that, as in other works, variables related to spatial configuration, such as the movement of people on the street, significantly impact crime reduction. On the other hand, unlike other works, the study identified that variables that characterize the relationship between buildings and streets are associated with increasing crime.

Finally, in a similar scope of application, Walker et al. [45] used the Ordinary Least Squares Regression and two variants, spatial lag and spatial error, to assess the associations between homicide rates and six socioeconomic variables in the municipalities of Alagoas, Brazil. Aiming to explore the usefulness of local knowledge in conducting an epidemiological analysis and test spatial associations between socioeconomic deprivation and homicide, the study identified that inequality, education level, and criminal activity are strongly related to homicide. Thus, multiple factors of economic deprivation and social environment influence violence and homicide.

Other relevant empirical contributions have been made within the context of Latin America. Gelvez-Ferreira [46] assessed the perception of safety in Colombia using data from Bogotá. Through spatial descriptive analysis, they identified a higher average incidence of crimes in the north, specifically in Suba, Chapinero, Barrios Unidos, and Teusaquillo. Using local autocorrelation analysis, Chapinero was identified as a cluster associated with the perception of safety, meaning that a person's sense of security depends on the perception of safety among their closest neighbors.

Temporal and spatial patterns of crime are the focus of a study by de Melo et al. [47] in Campinas, Brazil. Using georeferenced crime data at the level of hours, days, and months, they applied tests of mean differences and count regression models. Although the evidence points to temporal and spatiotemporal patterns, the temporal scale varies depending on the dimension of crime.

From a different perspective, Cummings et al. [48] studied the spatial distribution of crime in Guyana. Their analysis started with hotspots to understand the mutation of crime based on reports of violent crimes over 20 years. The authors found evidence that the center of gravity of criminality has shifted over time beyond coastal areas and towards locations where Indigenous peoples reside.

Spatial autocorrelation was the method employed to measure the effect of environmental characteristics on criminality in Monterrey, Mexico. Using data from 2010, it was observed that neighborhoods with high crime rates positively impact criminality in neighboring areas [48]. In addition, the spatial concentration of homicides in Argentina, specifically in the city of Santa Fe, was the focus of Hoet's [49] study. Using data from 2001 to 2020, a pattern of concentration of crimes in a small portion of micro-units was observed, with some stability over time.

Cadena-Urzúa et al. [50] contributed to the understanding of criminality in the metropolitan region of Santiago, Chile. Using data from 2010 to 2018 at the commune level, they evaluated spatial and temporal effects using spatial panel data methodology with fixed effects. The analysis involves 12 different crime indicators, which are grouped into categories of crimes against people and property. As a result, the variables of infant mortality, birth rate, poverty, and green areas significantly affect crimes against people. Additionally, there is a displacement of crime to neighboring communes.

The effect of access to police services on crime was measured in Ramírez's [51] research at the regional level of districts in Paraguay. Using data on cattle theft, sexual crimes, homicides, thefts, robbery, and bodily harm, spatial descriptive statistics analyses and OLS regressions were conducted. The evidence suggests that greater accessibility to police precincts significantly reduces the level of homicides and generates incentives for a higher volume of crime reports. The studies reported can be divided into two categories related to the approach used to verify which places have more crime incidents. The first category has several quantitative methods to create hotspot zones or vulnerable units (Table 1).

On the other hand, in the second category, an extensive review shows a concern about the use of statistical spatial techniques to explore crime occurrences and social, economic, and environmental variables. It is important to assume that the purpose of searching the papers is not to dedicate attention to criminal offending or the association between risk factors and offending. Instead, it is to synthesize how past contributions highlight what is a dangerous place through distinct methods.

In comparative terms, studies that integrate the perspective of developed and developing countries may present distinct characteristics. For instance, Cummings et al. [48] state that in developing countries, the availability of official data can be restrictive, which is why it can be challenging to understand the spatial concentration of crime. De Melo et al. [47] suggest that the cultural perception of the country may be a relevant factor in determining how crime patterns form in the Brazilian context.

3. Data and Methodology

This section outlines the data curation and methodological approaches used to analyze the collected data. This comprehensive evaluation examines the relationship between police patrol dynamics and crime locations, aiming to understand how police activities related to routes and pathways can be explained by crime locations and crime locations by police patrolling, investigating potential simultaneous causalities. The database comprises detailed records of violent crimes, explicitly focusing on categories of homicide. These data were obtained through an institutional agreement for technical cooperation between the Federal University of Pernambuco and Pernambuco's public administrations, specifically Pernambuco's Secretariat for Planning and Management.

For econometric inference, we divide the data into three main categories. This categorization enables a nuanced analysis and facilitates the examination of patterns and trends within the dataset. By employing spatial regression, we aim to derive robust and reliable inferences about the relationship between police patrol dynamics and the spatial

distribution of homicides within specific urban environments. The following subsections discuss data and methodology.

3.1. Database

The database involves instances of violent crime and police patrolling in the state of Pernambuco, sourced from Pernambuco's Secretariat for Planning and Management (SEPLAG, Secretaria de Planejamento e Gestão). Crime indicators refer to the count of Intentional Lethal Violent Crimes (represented by the acronym CVLI—Crimes Violentos Letais Intencionais) categorized by integrated security areas (denoted by the abbreviation AIS—Áreas Integradas de Segurança), which represent territorial areas composed of one or more municipalities in Pernambuco or neighborhoods in Recife (capital city). Depending on its territorial size, an AIS is covered by one or more battalions, and one or several patrol vehicles may correspond to the same battalion. The information is summarized in Table 2. Due to some data restrictions, we consider only AIS 1 to 7 in this assessment.

Table 2. AIS description.

AIS and Municipalities	Region
1—Santo Amaro; 2—Espinheiro; 3—Boa Viagem; 4—Várzea; 5—Apipucos; 6—Jaboatão; 7—Olinda; 8—Paulista; 9—São Lourenço da Mata; 10—Cabo de Santo Agostinho.	Metropolitan Region of Recife
11—Nazaré da Mata; 12—Vitória de Santo Antão; 13—Palmares; 14—Caruaru; 15—Belo Jardim; 16—Limoeiro; 17—Santa Cruz do Capibaribe; 18—Garanhuns.	Zona da Mata and Agreste
19—Arcoverde; 20—Afogados da Ingazeira; 21—Serra Talhada; 22—Floresta; 23—Salgueiro; 24—Ouricuri; 25—Cabrobó; 26—Petrolina.	Sertão

The geolocation data for patrolling refers to the vehicles of each battalion. Information on latitude, longitude, and patrol time is considered. Precisely, the coordinates where police vehicles are located at each geographic point were collected per second. By considering the start and end times at a given coordinate, the subtraction of the time interval generated the period, in minutes, that vehicles remain at the respective location. For this reason, patrol data are aggregated in Python to construct the patrolling indicators for each AIS, as they cover more than one neighborhood. Both crime and patrolling indicators refer to the monthly period between January 2019 and May 2021.

3.2. Sample Composition

Three data samples are constructed to provide a broader understanding of the proposed relationship in the research. The first sample refers to the daily data for the entire crime and patrolling variables set. The second sample incorporates a segregation of data into quarterly periods. The chosen period includes the last two quarters of 2019 and the first two quarters of 2020. The choice for a quarterly-based analysis is made to validate whether more precise results can be obtained, given that evaluating data in smaller temporal spaces might highlight characteristics more specific to the semester, such as the occurrence of crimes during holidays.

The third sample covers the quarterly data, categorizing them by type of crime. The idea of the categories is to provide a more specific level of understanding of the criminal relationship with the police, as the degree (from less severe to more severe) of the criminal occurrence can represent different scenarios. Table 3 describes each category.

The first category is related to diverse motivations or unclear intent. Crimes in this category encompass a wide array of motivations that are not tied to drug trafficking or organized crime. These homicides often come from situational factors or personal conflicts. For example, a person may be killed in a robbery gone wrong, where the primary intent

was theft but escalated to murder. Reckoning or personal revenge also falls here, where the crime is driven by the desire to settle a personal score. Self-defense is another motivation, where an individual kills in response to a perceived threat to their life. Confrontations with police or public security agents can lead to homicides during high-stress encounters, as well as stray bullets during conflicts causing unintended deaths. There are also instances of financial interest, where a person is killed for monetary gain, and witness elimination (or *Queima de Arquivo* in Brazilian Portuguese), when the intent is to silence someone who could testify against the perpetrator. Crimes under “to be defined”, “uninformed”, or “others” include those with unclear motives or that are still under investigation. This category highlights the complexity and variety of reasons behind homicides, demonstrating that not all murders are connected to the structured and often predictable motives of organized crime or drug-related activities.

Table 3. Crime categories.

Category	Type of Violent Crime
Category 1	To be defined, reckoning, stray bullets, disagreement in a criminal group—except drugs, confrontation with the police, confrontation with public security agent, confrontation with criminal(s), deceit, death squad, financial interest, robbery, self-defense, uninformed, others, witness elimination, citizen’s reaction to a crime, theft, and personal revenge.
Category 2	Intrafamily fights against a man, intrafamily fights against a woman, family fights, intimate-affective conflicts against a man, intimate-affective conflicts against a woman, misunderstanding (neighbors), quarrels (other circumstances), traffic or transit quarrels, arguments between neighbors, drunkenness, femicide, and brawl.
Category 3	Disagreement in a criminal group—illicit drugs, gang dispute, disputes over territory or market—illicit drugs, narcotics/drugs, and debt retaliation—illicit drugs.

The second category relates to interpersonal and domestic conflicts. This category includes crimes rooted in personal relationships and domestic settings. Homicides here often arise from intrafamily fights, where disputes among family members escalate to lethal violence. Femicide, the killing of a woman because of her gender, is a stark example of violence within intimate relationships, and the category also includes arguments between neighbors or misunderstandings resulting in homicides. Alcohol-induced quarrels, such as those involving drunkenness or brawls, frequently lead to violent confrontations. This category emphasizes how close personal connections and everyday interactions can, under certain circumstances, lead to extreme violence. It underscores the need for interventions and conflict resolution strategies within homes and communities to prevent such tragedies.

Lastly, the third category is about drug-related and gang violence. This category explicitly involves homicides driven by drug-related activities and gang conflicts. Disagreements within criminal groups, often over illicit drug operations, can result in violent resolutions, including murder. Gang disputes frequently revolve around territorial control or market dominance for drug sales, leading to lethal confrontations. The narcotics trade is a primary motivator for many homicides as criminal organizations protect their interests and settle scores. These crimes are typically premeditated and executed with a level of brutality designed to send a message or maintain control. This category highlights the systemic and organized nature of violence within the drug trade and gang dynamics, illustrating how these illegal activities inherently breed lethal conflict and contribute significantly to homicide rates.

For the three samples, there is a combination of patrol data by AIS, measured by latitude and longitude, and crime data. The idea of this stage is to construct a spatial segregation of the AIS data for visualization on a map built using ArcGIS software (version 10.8). For the analysis of aggregate data, we have included occurrences of property crimes (CVP) and violent crimes for comparison purposes.

3.3. Methodology

The methodological strategy consists of two stages of analysis. The first stage is dedicated to a spatial analysis containing maps combining crime and patrol data. This analysis results from an Ordinary Least Squares (OLS) regression model for each AIS. The functional form is given by Equation (1):

$$y_i = x_i^T \beta + \varepsilon_i \quad (1)$$

$$x_i^T = y_i \lambda + u_i \quad (2)$$

where y_i represents the time spent patrolling in AIS i , x_i^T is the count of the crime indicator in AIS i in period T , and ε_i refers to the idiosyncratic error per geographic unit (AIS). Similarly, estimates are also conducted for the inverse relationship in the second expression, that is, the crime variable being explained by police patrolling. The regression model, which seeks to study the relationship between crime and patrolling, is conducted for the years in question. Considering the three crime categories, the two proposed relationships are evaluated for each of the four quarters.

The spatial simultaneous regression models offer a comprehensive method to better understand and predict the two-way relationships between police presence and crime. This technique produces an output feature class that uses a hot/cold rendering scheme to highlight model residuals. The OLS model is misspecified if the residuals exhibit statistically significant spatial autocorrelation (measured by the Moran index). To address this, Hot Spot Analysis is performed on the residuals, visualizing the spatial clustering of over- and underpredictions. The spatial modeling assesses whether the explanatory variables are consistent with the dependent variable across geographic and data spaces. Consistency in geographic space means that the spatial processes represented by the explanatory variables are uniform throughout the study area. Consistency in data space means that the relationship between predicted values and explanatory variables does not vary with changes in the magnitudes of those variables.

The spatial autocorrelation step involves calculating global and local Moran indices. Nery et al. [42] state that Moran's index is a measure that evaluates the spatial association of a dataset, which can be global or local. The global index assesses the spatial interdependence between polygons in the study area, expressing it as a single value [52]. On the other hand, the local Moran index studies the relationship between the polygon under investigation and its neighborhood, producing clusters that allow the analysis of data homogeneity or heterogeneity [52]. The analysis scale used is characterized by seven dimensions, defined in terms of spatial autocorrelation with the support of the Moran index.

4. Results and Discussions

4.1. Aggregated Data

Table 4 reports the statistically significant regression estimates for the first model (crime as a determinant of policing) performed on aggregated data. AIS 6 consists of two battalions, so two regressions were generated independently for each one.

The results are statistically significant for all AIS in at least one type of crime, except for AIS 2. The occurrence of CVP in AIS 1 impacts an additional 24 min of patrol time. A similar interpretation applies to CVLI, where the occurrence of a violent crime causes an increase of 5786 min in patrol time. The incidence of CVLI has a more significant impact on all AIS compared to CVP (greater influence for decision-making when allocating police vehicles and the patrol regions as a response). Table 4 indicates that the CVLI (Crimes of Lethal Intent) coefficient for AIS 1 is significantly higher than that for AIS 6. This discrepancy can plausibly be attributed to the smaller geographic area of AIS 1 compared to AIS 6. Consequently, AIS 1 receives more intensive patrolling due to its smaller territorial space. Table 5 and Figure 1 report the results considering the aggregate data analysis.

Table 4. Model results by AIS.

AIS 1.		AIS 2		AIS 3		AIS 4	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
CVP Crime	24	CVP Crime	-	CVP Crime	65	CVP Crime	69
CVLI Crime	5786	CVLI Crime	-	CVLI Crime	-	CVLI Crime	-
AIS 5		AIS 6 (126)		AIS 6 (330)		AIS 7	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
CVP Crime	-	CVP Crime	30	CVP Crime	22	CVP Crime	23
CVLI Crime	1622	CVLI Crime	611	CVLI Crime	474	CVLI Crime	-

Table 5. Summary of results.

Estimates	First Model	Second Model
Intercept	122.31	0.21623
Coefficient	103.63	0.00001
Significance (intercept)	<0.0001 *	<0.0001 *
Significance (coefficient)	<0.001 *	<0.001 *
Koenker (BP)	0.9440	0.01862 *
Overestimated features	214	1051
Underestimated features	4	1
Effectiveness	0.9149	0.5895

* *p*-value rejecting the null hypothesis at 95% confidence.

The analysis includes two models exploring the relationship between policing and violent crime. In the first model, described by Equation (1) and depicted in Figure 1 Panel (a), the dependent variable is policing (measured by patrol time), which is considered a latent variable influenced by violent crime, an observed variable aggregated from the categories in Table 3. The second model, detailed in Equation (2) and shown in Figure 1 Panel (b), reverses this relationship by making violent crimes the dependent latent variable, influenced by policing as an explanatory variable. Both models have statistically significant intercepts and coefficients at the 95% confidence level, as evidenced by *t*-test results.

In the first model, the coefficient of 103.63 indicates that an increase of one homicide leads to an additional 103.63 min of police patrol time in a region. This substantial increase in patrol time underscores the responsive nature of police activity to violent crime incidents. Conversely, the second model demonstrates that a rise in one minute in police patrol time has no significant effect on reducing violent crime, highlighting a lack of support for the notion that increased policing immediately deters crime. This suggests that crime dynamics are more complex and less responsive to short-term changes in patrol time.

The Koenker (BP) statistic helps assess the presence of heteroscedasticity, which occurs when the variability of the residuals is not constant across all levels of the independent variables. For the first model, the Koenker (BP) statistic is 0.9440, failing to reject the null hypothesis of homoscedasticity. This indicates that the variability of the residuals is consistent across different levels of violent crime on the different census tracts (features), suggesting that the crime-to-police model is well-specified. In contrast, the second model's Koenker (BP) statistic is 0.01862, which rejects the null hypothesis at the 95% confidence level. This indicates the presence of heteroscedasticity, suggesting that the police-to-crime model's residuals vary significantly with levels of policing and thus the model may be misspecified.

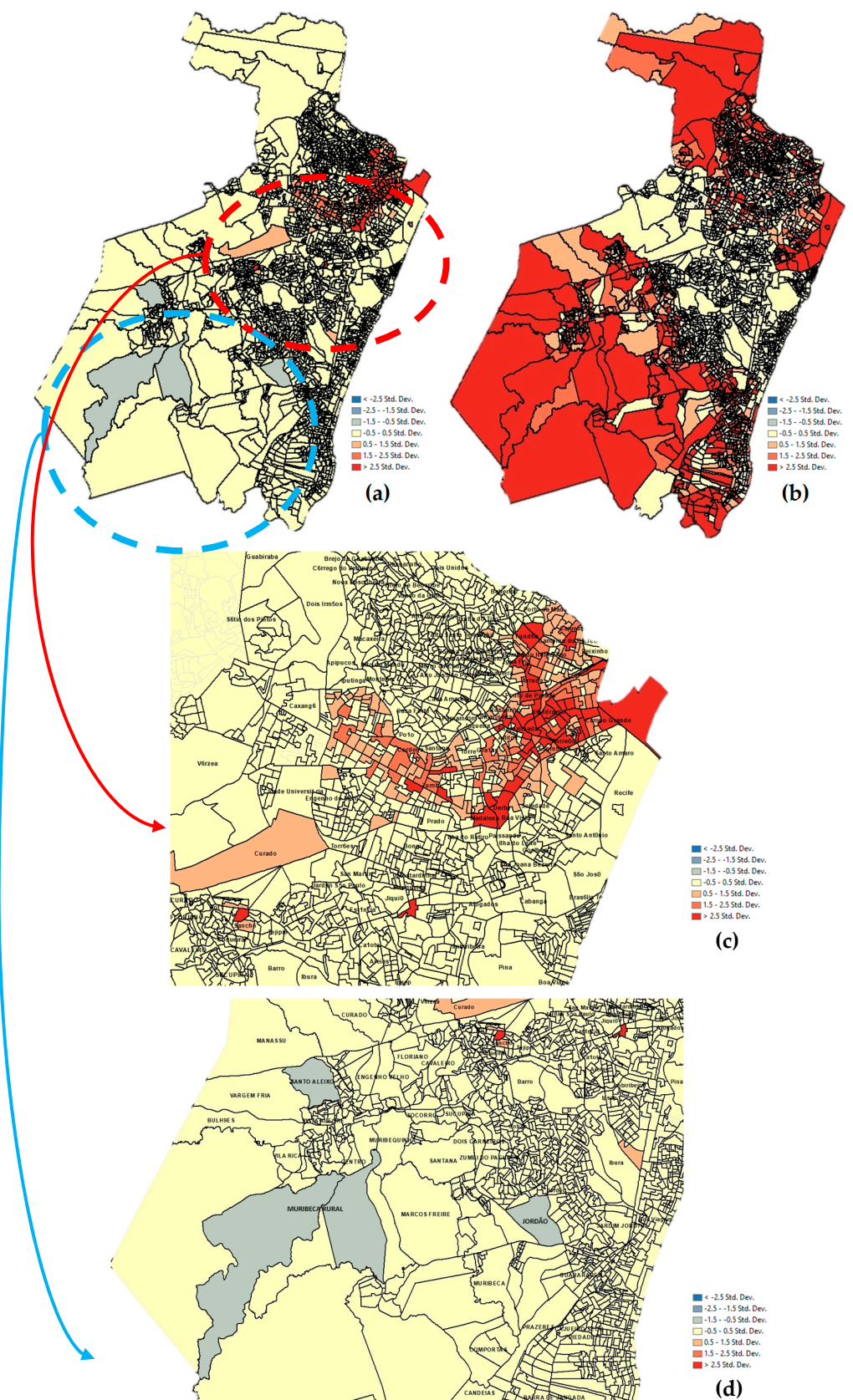


Figure 1. Aggregate spatial regressions. Panel (a): first model (policing as a latent variable and violent crimes as observation). Panel (b): second model (crime as a latent variable and policing as observation). Panel (c): overestimated features from the first model (a). Panel (d): underestimated features from the first model (a).

In addition, the number of overestimated features in the second model (1051) is significantly higher than in the first model (214). This indicates that considering the effect of policing on crime leads to overestimation in almost half the urban areas under consideration. These overestimations are particularly prevalent in beaches, tourist areas, and commercial neighborhoods of Recife, areas characterized by higher built environments and significant pedestrian traffic. This complexity in these areas likely reflects the intricate dynamics of crime and policing, where traditional measures of police effectiveness may not account for all contributing factors. The second model's underestimation occurs predominantly in the neighborhood of Campo Grande, a residential zone. This localized underestimation suggests that the first model's predictions might be less accurate in specific residential areas, potentially due to unique local factors not captured in the model. The few underestimated features in the first model belong to rural areas of Muribeca in Jaboatão dos Guararapes, which have low population density and significant outliers when considered separately.

The effectiveness of the models is measured by the proportion of geographic features that fall within a reasonable prediction range. Specifically, effectiveness is determined by the features whose estimates vary within the range of -0.5 to 0.5 standard deviation from the model's predictions. This range indicates a close fit to the actual data, reflecting the model's accuracy in predicting the dependent variable based on the independent variables.

In the first model, which predicts police patrol time as a function of violent crime, 2345 out of 2563 geographic features fall within the -0.5 to 0.5 standard deviation range. This represents 91.5% of all census tracts in the geographic space, indicating a high level of effectiveness. The high percentage suggests that the model is highly accurate in predicting patrol time based on the occurrence of homicides. The model's ability to closely match actual patrol times across most geographic areas demonstrates its robustness and reliability in understanding the relationship between violent crime and police response.

The second model, which predicts violent crime as a function of police patrol time, shows a lower effectiveness. Only 1511 of 2563 features, or 59% of census tracts, fall within the -0.5 to 0.5 standard deviation range. This lower percentage indicates that the model is less accurate and less reliable in predicting crime rates based on patrol time. The many features outside the reasonable prediction range suggest that this model does not adequately capture how police patrol time influences crime rates.

The stark difference in effectiveness between the two models highlights their respective strengths and weaknesses. The first model's 91.5% effectiveness suggests a strong and predictable relationship where increased violent crime leads to increased police patrol time. This model's high accuracy across most geographic features confirms that police response is closely tied to crime incidents, supporting the reactive nature of policing strategies. In contrast, the second model's 59% effectiveness indicates significant limitations in using patrol time to predict crime rates. The lower accuracy suggests that crime rates are influenced by many factors beyond just police presence. This finding aligns with the broader understanding that crime is a complex social phenomenon not easily mitigated by increased policing alone.

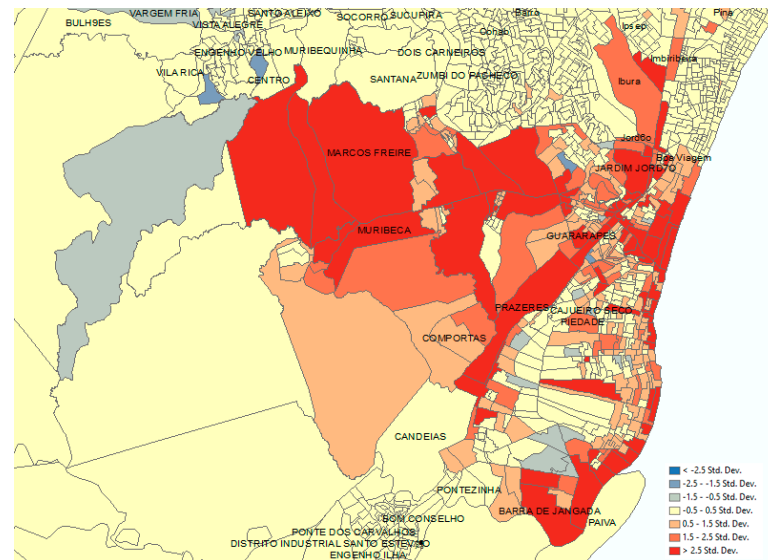
4.2. Quarterly Data

The results obtained from the quarterly regression for AIS 6 (330), referring to Jaboatão, are reported in Table 6. When considering patrolling as the independent variable, the relationship is positive. Still, the coefficients are small for all quarters, leading to the interpretation that patrolling is not contributing to the crime dynamics in this region, which is consistent. The p -values of these variables are statistically significantly smaller than 0.01, thus allowing the null hypothesis to be rejected for $\alpha = 0.01$.

Figure 2 displays the visual results from the regression analysis conducted for the fourth quarter of 2019, where crime is the explanatory variable for patrolling. As shown in Figure 2, neighborhoods like Marcos Freire, Muribeca, Barra de Jangada, Prazeres, and others showed the most significant regression results, where crime can better explain patrolling.

Table 6. Coefficient results of the quarterly regression for AIS 6 (330).

Type of Regression	3° Q 2019	4° Q 2019	1° Q 2020	2° Q 2020
Crime explaining patrolling	570.68	1027.84	951.70	1008.45
Patrolling explaining crime	0.00001	0.00001	0.000011	0.000006

**Figure 2.** Regression result in AIS 6 in the fourth quarter of 2019 (330).

4.3. Data Segregated by Type of Crime

Table 7 reports the results by segregating data by type of crime. Crimes were separated into categories due to their variety, with Category 1 showing the most significant results compared to the others. It is also worth noting that, for the third quarter of 2019, the data for Category 2 were insufficient to perform the regression.

Table 7. Coefficient results of quarterly regression by type of crime for AIS 6 (330).

Crime explaining patrolling				
	3° Q 2019	4° Q 2019	1° Q 2020	2° Q 2020
Category 1	670.489272	1280.559165	2287.141385	1815.948869
Category 2	-	238.555169	185.759307	618.882126
Category 3	491.644236	876.639317	691.419614	814.366004
Patrolling explaining crime				
	3° Q 2019	4° Q 2019	1° Q 2020	2° Q 2020
Category 1	0.000008	0.000009	0.000006	0.000003
Category 2	-	<0.00001	<0.00001	<0.00001
Category 3	0.000001	0.000001	0.000005	0.000002

Upon analyzing the resulting p -value in each category, it is evident that the regressions for Categories 1 and 3 are statistically significant, with p -values less than 0.001 in all instances, allowing for the rejection of the null hypothesis at $\alpha = 0.01$. Conversely, in Category 2, the p -value indicates a lack of statistical significance in the third quarter of 2019. Patrolling does not respond to increases in the types of crimes included in Category 2 as precisely as compared to increases in the other categories. This is consistent with Category 2 crimes, which are primarily domestic and thus is more challenging for police units to monitor and address.

Regarding the previous analysis, the results indicate minimal influence when considering patrolling as the explanatory variable. When crime is the independent variable,

Category 1 crimes have the most substantial impact on increasing patrol time across all quarters, reflecting a higher incidence of these crimes. Crimes in Category 1 and those in Category 3 (the second most significant category each quarter) exert the most considerable influence on patrolling.

Understanding the significant impact that Category 1 and Category 3 crimes have on patrol time highlights the need for police departments to rethink how they approach these incidents. Crimes in Category 1, which often arise from personal conflicts or unpredictable situations, demand a more focused and community-centered response. The significant increase in patrol time caused by crimes in Category 1, which can add up to 2287 min of patrol time for just one additional incident in the first quarter of 2020, shows the heavy toll these crimes take on police resources. Before the pandemic in 2019, one additional crime in this category could lead to an average of 975 min of patrol time. During the pandemic, this number spiked to an average of 2051 min.

When it comes to Category 3 crimes, which involve drug-related and gang violence, the challenges are different but equally significant. Each additional crime in this category resulted in an average increase of 684 min of patrol time in 2019 and 753 min in 2020. These crimes require a more strategic and targeted approach, such as increasing patrols in gang hotspots, gathering intelligence to disrupt criminal activities, and working with community organizations to provide alternatives to gang involvement.

These crimes are often tied to deeper issues like territory disputes and control over the drug trade, requiring more than just a strong police presence. Effective strategies might include gathering intelligence to disrupt criminal networks, collaborating with other agencies to address the problem from multiple angles, and engaging with at-risk youth to steer them away from gang life.

The impact of Category 1 and Category 3 crimes on patrol time highlights the importance of data-driven policing strategies. Crimes in Category 1 consistently lead to the most significant increases in patrol time each quarter, indicating a higher frequency and impact of these incidents. These observations point to the need for public policies prioritizing crime prevention in these categories rather than merely responding to them. Figure 3 illustrates the regression results for Category 1 crimes in the first quarter of 2020, highlighting their explanatory power regarding patrolling.

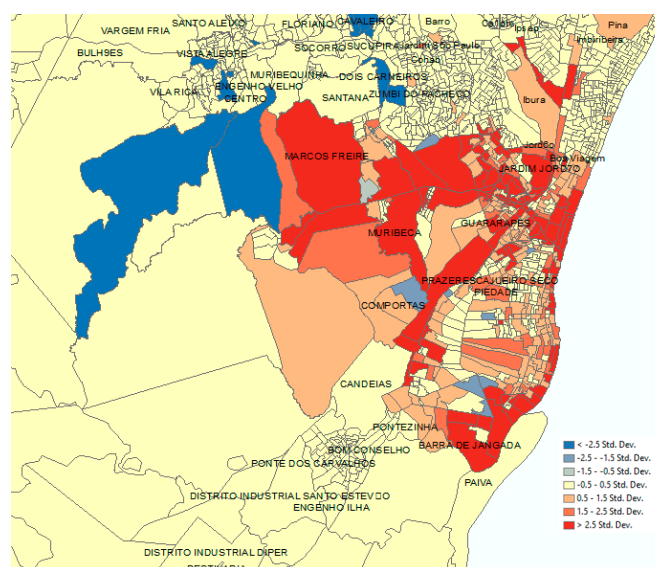


Figure 3. Regression result of category 1 in the first quarter of 2020 for AIS 6 (330).

Neighborhoods such as Marcos Freire, Muribeca, Guararapes, and Barra de Jangada, among others, showed more prominent results. At this point, it can be analyzed that the regression indicated the same neighborhoods as those with the most relevant results in both

the quarterly analysis and the segregation by type of crime, thus indicating the attention that such neighborhoods should receive in increasing patrol time.

4.4. Quarterly Analysis of Hotspots

Figure 4 shows the analysis of hotspots for quarterly data. It represents regions of high crime incidence surrounded by similarly high-incidence areas. Cold spots are regions of low incidence surrounded by other low-incidence regions. The remaining areas exhibit random patterns without spatial correlation.

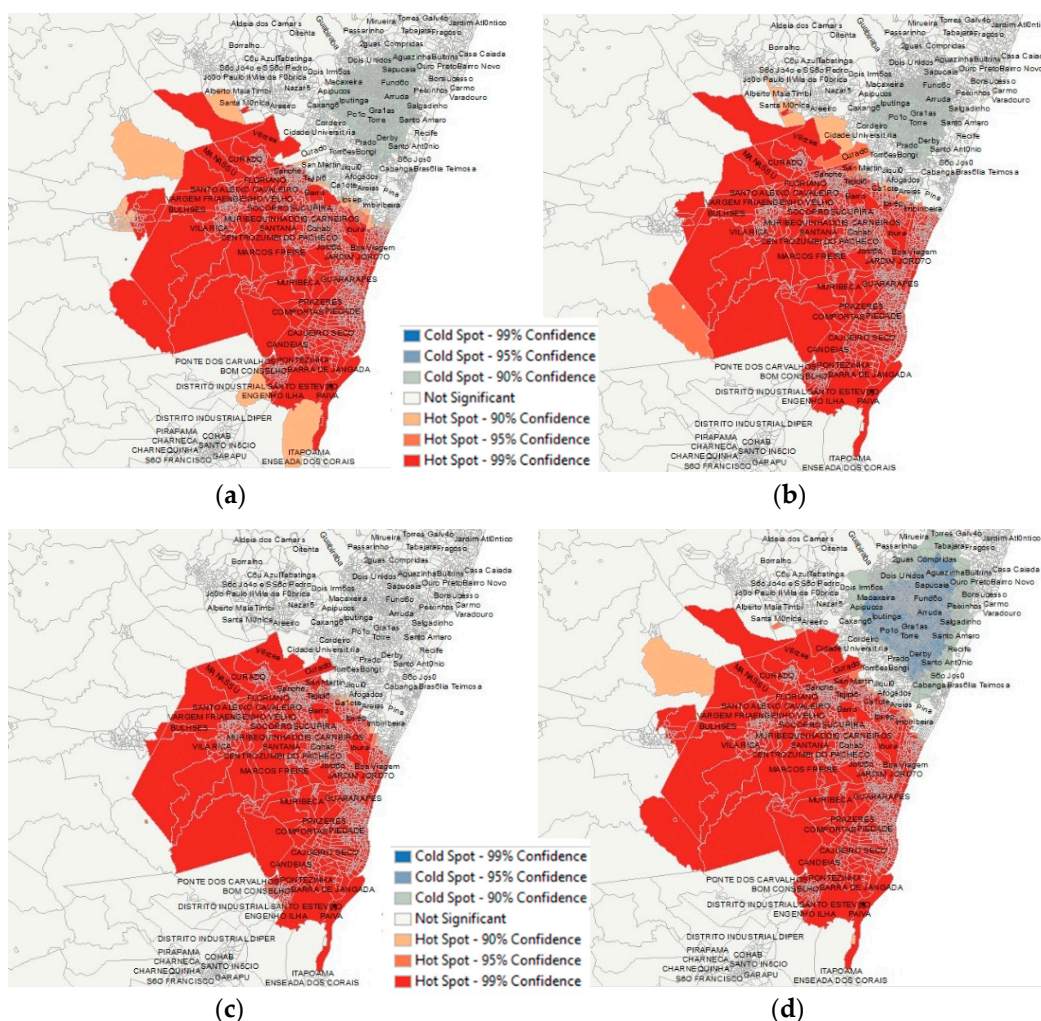


Figure 4. Hotspot analysis with quarterly data. Note: (a): third quarter of 2019, (b): fourth quarter of 2019, (c): first quarter of 2020, (d): second quarter of 2020.

The analysis indicates that the criminal pattern has remained consistent, with the southern region emerging as the most critical area. This region is characterized by clusters of high-incidence areas adjacent to others with similarly high crime rates, creating a concentrated zone of criminal activity. Cold spots, indicating areas with lower crime rates, demonstrated a higher confidence index throughout the quarters, reinforcing their stability and reliability in the analysis.

Jaboatão dos Guararapes (AIS) exhibits distinct differences over the territory, including rural areas with low population density and movement, contributing to fewer incidents, and tourist zones with beaches and higher income per capita. However, the suburban and urban parts of Jaboatão display moderate to high crime rates but lack contiguous high-incidence clusters. Nevertheless, those differences do not affect the distribution of criminal

incidence over the short term. The disparity highlights the need for tailored policing strategies that account for each area's unique geographic and demographic characteristics.

4.5. Research Implications

The methodology has theoretical and practical implications. The theoretical implications stem from how the developed research study contributes to our knowledge of crime spatial analysis. Meanwhile, the practical implications impact public security management from a social perspective.

4.5.1. Theoretical Perspective

As presented in Table 1, previous works deal with the same topic of spatial analysis of crimes, employing different methodological approaches. Therefore, seeking to highlight what the research reported in this article adds to current knowledge, some comments will be made, reiterating these previous works.

Rosa et al. [25] mainly used a GIS Multicriteria framework based on a Dominance-based Rough Set Approach (DRSA) to classify geographic areas according to their level of vulnerability, also considering socio-demographic and social interaction features for the analysis. The study differed from the research reported here, especially due to its methodological design, which mainly used a multicriteria model to perform area classifications.

The RTM approach by Caplan and Kennedy [31] defines a process for generating hot spot maps according to risks for predicting criminal activity spots. This graphical approach is very close to that used in the study reported here since it also uses the analysis of hot and cold zones for crime prediction. However, regarding the methodology used to generate the maps, this study used a regression analysis based on OLS, unlike the studies presented by Caplan and Kennedy that used logistic regression.

Wang et al. [32] focused on crime hotspots detection using HOT, which is based on two main concepts: (i) a hotspot as a source of disorder in its adjacent blocks, and (ii) using the GDPatterns with the footprints on the related variables that are more frequent in hotspot areas than in typical areas. The approach of Wang et al. is not based on a regression model to predict, for instance, cold and hot zones of crime but on the differences between classes labeling a targeted crime in a geospatial database to support crime classification. Thus, unlike Caplan and Kennedy, the research reported in this article does not aim to provide a prediction but to classify crime areas.

Garcia-Zanabrial et al. [37] dealt with the problem of the sparse nature of crime activity and how it spread in large areas, using crime time series to develop their analysis of crime patterns. The approach involves a stochastic tool to support visualizing “probable versus intensive” crime hotspots, followed by a deep learning mechanism using the time series in a 2D (Cartesian) space. Within the process is a step for similarity detection and grouping similar hotspots, which acts as a clustering model. The problem here also differs from the application developed in the research reported in this article, as the objective is to generate an intelligible interpretation of crime patterns in a geographic space, subsequently seeking an association of these patterns with socioeconomic factors.

Han et al. [33] approach also focuses on crime hotspot prediction using the cyclically adjusted spatial-temporal kernel density estimation (cSTKDE) method, using a time series with the temporal evolution of robbery from a USA locality. The cSTKDE implementation considers a crime period detection using a periodogram referred to as a least-squares spectral analysis, which, according to the authors, fits with a least-square model of sinusoidal functions, also being a regression model. Zhu et al. [34] proposed and applied an agent-based model for urban crime simulation based on an architecture with three layers: the first containing a spatial database, the second applying simulation logic, and the third presenting the results in animated maps. Unlike previous-commented studies, the task here is to simulate robberies in a USA locality, creating scenarios to support policymaking or provide public information.

Based on information about crime occurrences coming from the local population of Tehran (Iran), Jelokhani-Niaraki et al. [32] developed a geographic system based on volunteering to assist law enforcement agencies in monitoring criminal occurrences, enabling, for example, the identification of areas where they occur. This is also a different approach from those in previous studies and the one reported in this article.

All previously cited studies have different methodological approaches, although some application problems may be the same. The present study adds the use of patrolling information based on the location of police vehicles to understand the places with the highest probability of property crimes occurring. While the studies mentioned above sought to be more general, covering a broader typology of crimes, our study focused on a specific group of crimes due to the data obtained from the responsible agencies. Using OLS, a widely used and simple regression model, we successfully predicted crime hotspots in analyzed locations within Pernambuco (Brazil). This validates its usefulness alongside more advanced analytical tools. However, as a reflection of these results and the literature presented, the need to test other models and approaches that may apply to the problem in question stands out, seeking alternatives for understanding the space-time distribution of crime.

Finally, it is reinforced that the applied analysis corroborated that, within the space-time context, policing is explained by the incidence of crimes, observing hot spots as those that most require police containment actions. This is in line with what the other research mentioned previously also points out, supporting the idea that that local police actions are carried out depending on the observed crime rates, functioning as a response to them.

4.5.2. Practical and Social Perspectives

Regarding the implications from a practical perspective, it is necessary to highlight that the methodological solution presented constitutes the basis of a decision support tool based on GIS and statistical analyses to make predictions [27]. It is a methodological assembly that constitutes a component of spatial decision support systems, guaranteeing responsible authorities' and policymakers' informational inputs for decision-making and construction of actions to combat urban violence [34].

From the perspective of the positioning of policing and dedicated vehicles, the study's findings indicate exact locations that require more intense policing action precisely because they have a greater chance of crimes against property occurring. For example, generating dashboards with hotspot information by type of crime can help indicate the need for more direct police action to contain it. Depending on the granularity of the information, that is, if it is possible to detail times of the highest incidence of that type of crime according to the location under analysis, it is possible to carry out combative actions with better planning.

From a social perspective, the most direct repercussion is the citizen's sense of security. Even though this type of analysis is not traditionally presented to the population, the effects of the decision-making will be felt, with the perception of a reduction in a specific type of crime that occurs with greater incidence and is being combatted by security agencies. The locality generally benefits from the power that the tools used in the research have, qualifying as a safe community, free from crime, and improving people's well-being and quality of life.

An "expected" social reflection is the mitigation or even elimination of violence in the community that impedes local development in terms of housing quality, improvement of urban living spaces, and business development. Reducing crimes has helped reduce socio-economic inequalities and the effect of marginalization [53].

5. Conclusions

This study corroborates an increase in speed and quality in decision-making based on an empirical investigation of potential causality bias in the relationship between crime and policing, considering the notoriety that the study of crimes in urban spaces has recently

received and the current scenario in Brazil, where social inequalities are increasingly pronounced and directly influence the increase in crime occurrence.

We offer an analysis of the spatial dynamics of crimes through the location of patrol vehicles, identifying neighborhoods where the relationship between these variables is relevant and the category of crimes that most influence patrol time. Results emphasize the strong relationship of crime influencing police activity but not vice versa. The first model's adequacy supports the notion that police patrol time increases in response to crime incidents, reinforcing the reactive nature of policing strategies. The second model's failure to show a significant impact of increased patrol time on reducing crime highlights the inertia of crime and the complexity of its response to policing efforts.

Considering AIS 6 (330), neighborhoods such as Marcos Freire, Muribeca, and Barra de Jangada, among others, should receive greater attention regarding patrol. Crime such as settling scores, stray bullets, clashes with the police, robbery, self-defense, theft, and others should have their causes further investigated so that strategies can be devised and public policies created to reduce them. Furthermore, it was also possible to observe through the hotspot analysis how criminal patterns presented themselves throughout the quarters, thus inducing a greater need for police action in hotspot areas. These results corroborate the Pact for Life.

In the segregated georeferenced assessment (AIS 6), Category 1 and 3 crimes exert considerable pressure on police resources, emphasizing their influence on patrolling demands. Policies to mitigate such effects can include increased investment in community outreach programs that foster stronger relationships between residents and law enforcement, implementing conflict resolution initiatives in schools and neighborhoods, and using predictive analytics to identify potential hotspots for these crimes before they escalate. Additionally, early intervention strategies, such as providing support services to individuals at risk of engaging in or becoming victims of these types of crimes, can support reducing such incidents.

The lack of updated data can be mentioned as one of the study's main limitations. It was impossible to conduct a more recent study of the relationship between the variables in question. Additionally, there is a lack of explanatory variables that could better justify the spatial incidence of crime. In this sense, a future opportunity is mentioned to establish the temporal evolution of crime occurrences and check if there is a variation in where crimes occur. This would involve analyzing crime data over different periods to identify patterns and trends. By doing so, insights could be obtained into how crime hotspots shift over time and patrol strategies must be adjusted accordingly.

Therefore, as a suggestion for future studies, the addition of variables such as income, environmental factors, as well as those related to demographic, ethnic, and social characteristics, would better support spatial analysis and allow studying beyond the relationship between vehicle location and crimes as well as the environments of criminal occurrence. It is also suggested that new research based on predictive policing be developed, seeking to evaluate its impact on crime conditions in the target location of the study using artificial intelligence models. The application of artificial intelligence models in predictive policing holds significant potential for crime prevention, enabling more efficient allocation of police resources. However, the application must be designed strictly to ethical and legal principles involving human beings, such as data protection.

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