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CARLOS FABRICIO ASSUNÇÃO DA SILVA

ANÁLISE ESPACIAL DOS HOMICÍDIOS DA ÚLTIMA DÉCADA NA REGIÃO NORDESTE DO BRASIL

Recife
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Dissertação apresentada ao Programa de Pós-Graduação em Ciências Geodésicas e Tecnologias da Geoinformação da Universidade Federal de Pernambuco, como requisito parcial para a obtenção do título de Mestre em Ciências Geodésicas e Tecnologias da Geoinformação.

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Aprovado em: 12 / 02 / 2021.

BANCA EXAMINADORA

____

Profa. Dra. Simone Sayuri Sato (Coorientadora)

Universidade Federal de Pernambuco

____

Prof. Dr. Alex Mota dos Santos (Examinador Externo)

Universidade Federal de Goiás

____

Profa. Dra. Maria das Neves Gregório (Examinadora Interna)

Secretaria de Educação e Esportes do Estado de Pernambuco

____

Prof. Dr. Silas Nogueira de Melo (Examinador Externo)

Universidade Estadual do Maranhão

RESUMO

A dissertação é formada por dois capítulos na forma de artigos, os dois realizam uma análise espacial dos homicídios, o primeiro para a região Nordeste do Brasil e o segundo para Pernambuco, com uma aquisição de dados semelhantes, com anos diferentes. O primeiro artigo utiliza dados do ano de 2010, já o segundo artigo utiliza dados de 2016 a 2019. Os capítulos, um e dois, têm como metodologia a estatística espacial, como o índice de Moran, a regressão linear múltipla e a regressão geograficamente ponderada. No capítulo 1, o artigo apresenta a análise espacial para a região Nordeste, sustentada pela teoria da desorganização social, através de dados de heterogeneidade étnica, socioeconômicos e de infraestrutura urbana. Para ambos os capítulos, a metodologia foi implementada num Sistema de Informação Geográfica e aplicados os métodos de análise Índice de Moran Global e LISA map, Ordinary Least Squares (OLS) e a Regressão Geograficamente Ponderada (GWR) para taxas de homicídios, como referido. Os resultados revelam que o índice de Moran Global foi de 0,404 de autocorrelação positiva e com nível estatisticamente significativo acima de 95%, mostrando que o fenômeno do homicídio não é aleatório no espaço. Além disso, para ambos os modelos OLS e GWR, os coeficientes estimados para as variáveis índice de Blau, Porcentagem de Negros, Porcentagem de índios, taxa de desemprego, percentual de domicílios alugados e chefes de família com cônjuge, foram positivos, ou seja, existe uma associação positiva com a taxa de homicídios. Constatou-se que os resultados indicam que a heterogeneidade étnica está positivamente relacionada a ao aumento da taxa de homicídio na região Nordeste do Brasil. Para o segundo capítulo também foram utilizados dados de heterogeneidade étnica, socioeconômicos, de infraestrutura urbana. Os resultados, mostraram a distribuição dos clusters, onde revelou autocorrelação espacial para as taxas de homicídio, confirmando a dependência espacial. Esses dados também mostraram a polarização da taxa de homicídios entre litoral e interior do estado de Pernambuco.

Palavras-chave: Análise espacial de homicídio. Sistema de informação geográfica. Autocorrelação espacial. Regressão geograficamente ponderada.

ABSTRACT

The dissertation consists of two chapters in the form of articles, both of which carry out a spatial analysis of homicides, the first for the Northeast region of Brazil and the second for Pernambuco, with similar data acquisition, with different years. The first article uses data from the year 2010, while the second article uses data from 2016 to 2019. Chapters one and two have spatial statistics as their methodology, such as the Moran index, multiple linear regression and geographically weighted regression. In chapter 1, the article presents the spatial analysis for the Northeast region, supported by the theory of social disorganization, through data of ethnic heterogeneity, socioeconomic and urban infrastructure. For both chapters, the methodology was implemented in a Geographic Information System and the methods of analysis of Moran Global Index and LISA map, Ordinary Least Squares (OLS) and the Geographical Weighted Regression (GWR) for homicide rates were applied, as mentioned. The results reveal that the Moran Global index was 0.404 of positive autocorrelation and with a statistically significant level above 95%, showing that the phenomenon of homicide is not random in space. In addition, for both OLS and GWR models, the estimated coefficients for the variables Blau index, Percentage of Negroes, Percentage of Indians, unemployment rate, percentage of rented households and heads of family with spouse, were positive, that is, there is a positive association with the homicide rate. It was found that the results indicate that ethnic heterogeneity is positively related to the increase in the homicide rate in the Northeast region of Brazil. For the second chapter, data from ethnic, socioeconomic and urban infrastructure heterogeneity were also used. The results showed the distribution of clusters, where it revealed spatial autocorrelation for homicide rates, confirming spatial dependence. These data also showed the polarization of the homicide rate between the coast and the interior of the state of Pernambuco.

Keywords: Spatial analysis of homicide. Geographic information system. Spatial autocorrelation. Geographically weighted regression.

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LISTA DE ABREVIATURAS E SIGLAS

AIC	Akaike Information Criteria
CIMI	Conselho Indigenista Missionário
DSD-PE	Department of Social Defense of Pernambuco
ESDA	Exploratory Spatial Data Analysis
GDP	Gross Domestic Product
GIS	Geographic Information System
GWR	Geographically Weighted Regression
HDI	Human Development Index
HH	High-High
IBGE	Instituto Brasileiro de Geografia e Estatística
IPEA	Instituto de Pesquisa Econômica Aplicada
ILVC	Intentional Lethal Violent Crimes
ISA	Integrated Security Areas
LISA	Local Indicators of Spatial Association
LL	Low-low
MVI	Mortes Violentas Intencionais
MRR	Metropolitan Region of Recife
OLS	Ordinary Least Squares
OMS	Organização Mudial da Saúde
ONU	Organização Das Nações Unidas
PFL	Pact For Life
PNUD	Programa Das Nações Unidas Para O Desenvolvimento
SAR	Spatial Autoregressive Models
SDS-PE	Secretaria De Defesa Social De Pernambuco
SIG	Sistema De Informação Geográfica
SDT	Social Disorganization Theory
SUS	Unified Health System
UN	United Nations
UNODC	Organização Das Nações Unidas Sobre Drogas E Crimes
VIF	Variance Inflation Factor
WHO	World Health Organization

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1 INTRODUÇÃO

O homicídio doloso, latrocínio, violência interpessoal de causa intencional e com desfecho letal, é um fenômeno global, que tem apresentado tendência crescente em países em desenvolvimento, sobretudo no Brasil, no qual já desponta como principal causa de morte por fatores externos, constituindo um grande problema de saúde pública, principalmente em capitais, onde estão localizados as regiões metropolitanas, que possui grande parte da população brasileira (BASTOS *et al*., 2009; INGRAM *et al*, 2016; BORGES *et al*., 2015, CERQUEIRA *et al*., 2017).

O número de homicídios no Brasil é alarmante considerando que no país não há conflitos de religião, etnia, raça ou de território (SILVA *et al*.,2020). Em todos os estados brasileiros, a quantidade de homicídios excede o limite estabelecido pela OMS - Organização Mundial da Saúde, considerado epidêmico acima de 10 homicídios por 100.000 habitantes (Programa das Nações Unidas para o Desenvolvimento, 2013).

De maneira geral, a Região Nordeste possui as maiores taxas de homicídio do Brasil SINESP (2015). Embora as taxas de alguns estados e municípios pareçam menores, notamos que a situação dessa região é a mais grave quando comparada ao restante do Brasil. A taxa média de homicídios na Região Nordeste é de 33,76 por 100 mil habitantes. Para se ter uma noção comparativa no âmbito internacional sobre essa taxa, países com históricos de guerra civil, como o Congo (30,8), e com altas taxas de 56 homicídio associadas ao narcotráfico, como a Colômbia (33,4), possuem taxas menores que a do Nordeste brasileiro SINESP (2015).

Já em Pernambuco, segundo a Secretaria de Defesa Social (SDS-PE, 2017), as taxas de homicídios posicionaram o estado com um dos mais violentos do Brasil. Em 2011, a taxa de homicídio era 37,3 por 100 mil habitantes e em 2017 passou a ter uma taxa de 57,3 ocorrências por 100 mil habitantes, ou seja, quase o dobro da média nacional.

Com o aumento dos episódios criminosos no país e, em particular nas grandes cidades, torna-se inegável a importância dos estudos sobre violência (ENDLICH, 2014). Essa temática passou a ter um grande espaço no âmbito das discussões acadêmicas, na imprensa em geral e no dia-a-dia do cidadão, despertando a atenção e a preocupação dos mais variados segmentos da sociedade civil. Desta forma, torna-se necessário analisar a distribuição espacial dos homicídios por meio da literatura e de técnicas espaciais, para interpretar as discussões desse fenômeno.

Por isso, o emprego da análise estatística espacial e do uso da visualização cartográfica aplicada à produção de mapas, vêm contribuindo para a avaliação de concentrações de casos de homicídios, identificando os possíveis fatores relacionados. Portanto, o emprego dessas tecnologias da geoinformação agilizam em análises espaciais e temporais dos índices de criminalidade, tornando possível, operacionalizar ações investigativas com bases em conhecimentos geográficos que facilitam a prevenção e as ações de combate à violência, consequentemente, reduzindo a criminalidade.

Para a dissertação, foi priorizado a forma de artigos. Esse tipo de formatação foi aprovado recentemente pelo Programa de Pós-Graduação em Ciências Geodésicas e Tecnologias da Geoinformação. O *template* foi disponibilizado pela biblioteca central da Universidade Federal de Pernambuco- UFPE. A estruturação da dissertação se dá inicialmente pela Introdução, logo após o primeiro artigo, em seguida o segundo artigo e por fim as conclusões e recomendações.

No capítulo 1, encontra-se o artigo que foi submetido ao periódico *Applied Geography*, com o seguinte título: "*The effect of racial minorities and ethnic heterogeneity in the estimation of homicide rates in Northeast Brazil*". Este artigo será submetido posteriormente. Cujo objetivo do estudo é avaliar o efeito das minorias raciais e da heterogeneidade étnica na estimativa de taxas de homicídios na região Nordeste do Brasil, tendo a teoria da desorganização social (TDS) como embasamento teórico.

O Capítulo 2 encontra-se o artigo que foi aceito e publicado pelo periódico *ISPRS International Journal of Geo-Information*, com o seguinte título: "*Spatial modeling for homicide rates estimation in Pernambuco State-Brazil*". Esse artigo foi desenvolvido com intuito de fornecer informações das análises espaciais dos homicídios do estado de Pernambuco, que vêm sofrendo com um aumento do número de homicídios. Dessa forma, a seleção do estado de Pernambuco teve como objetivo retribuir com a população do estado de Pernambuco, através dos conhecimentos adquiridos pelo programa de Pós-Graduação em Ciências Geodésicas e Tecnologias da Geoinformação.

2 THE EFFECT OF RACIAL MINORITIES AND ETHNIC HETEROGENEITY IN THE ESTIMATION OF HOMICIDE RATES IN NORTHEAST BRAZIL

O EFEITO DAS MINORIAS RACIAIS E DA HETEROGENEIDADE ÉTNICA NA ESTIMATIVA DE TAXAS DE HOMICÍDIOS NA REGIÃO NORDESTE DO BRASIL

ABSTRACT
The aim of this study is to evaluate the effect of racial minorities and ethnic heterogeneity in the estimation of homicide rates in the Northeast region of Brazil, with the Social Disorganization Theory (SDT) as a theoretical basis. This research was based on two hypotheses: (H1) ethnic heterogeneity- black and indigenous population have a positive relationship regarding the homicide rate; (H2) metropolitan regions are areas where the relationship between the presence of ethnic heterogeneity and racial minorities is associated in a greater extent with homicides. Using spatial analysis and modeling techniquessuch as Moran 'I, LISA map, and Geographically Weighted Regression, the results indicated the plausibility of both hypotheses. Our discussions also made implications for policies on public homicide prevention and recommendations for future research.

Keywords: Racial minorities; Ethnic heterogeneity; Homicide; Social Disorganization; Geographically Weighted Regression

RESUMO

O objetivo do estudo é avaliar o efeito das minorias raciais e da heterogeneidade étnica na estimativa de taxas de homicídios na região Nordeste do Brasil, tendo a teoria da desorganização social (SDT) como embasamento teórico. A pesquisa está ancorada em duas hipóteses: (H1) a heterogeneidade étnica, população negra e indígena possuem uma relação positiva com a taxa de homicídios; (H2) as regiões metropolitanas são áreas em que a relação entre presença da heterogeneidade étnica e minorias raciais estão associadas em uma magnitude maior com os homicídios. Utilizando técnicas de análise e modelagem espacial (Moran'I, LISA map, e a Regressão Geograficamente Ponderada), os resultados indicam a plausibilidade das hipóteses. Nossas discussões também possuem implicações para políticas públicas de prevenção de homicídios e recomendações para pesquisas futuras.

Palavras-chave: Minorias raciais; Heterogeneidade Étnica; Homicídio; Desorganização Social; Regressão Geograficamente Ponderada

1 INTRODUCTION

Violent deaths occur worldwide and efforts are being made to identify strategies in order to reduce them. Therefore, the international community assumes that it is necessary to prevent ethnic-social and economic conflicts, to fight the causes of tensions, and also, seek to build and strengthen institutions and obligations, in order to respect human rights (UNSG, 2017). Homicides can be explained in a variety of ways, such as ethnic/racial conflicts, police violence, racism, and so on. In this sense, according to Fjelde et al. (2019), there is an evidence that suggest that ethnicity is a prominent dimension when taking into account patterns of civil abuse (or omission) by the state and non-state actors.

Another aspect to be considered, from the perspective of White et al. (2020), is the intentional deaths caused by the police and security guards, which led to the occurrence of social movements and international protests. Such movements claim that, while the loss of white lives is seen as a tragedy, the loss of black and Hispanic lives are treated as normal, acceptable, and even inevitable (White et al. 2020). For Dave et al. (2020), spurred on by the death of George Floyd, who was in police custody, the Black Lives Matter protests in 2020 brought a new wave of attention to the issue of racial inequality in criminal justice. In Brazil, this process had an impact on the death of João Alberto Silveira Freitas, by two vigilantes from a highly kown hypermarket and it also generated public demonstrations on several cities in the country.

In this sense, the objective of this study is to evaluate the effect of racial minorities and ethnic heterogeneity in the estimation of homicide rates in the Northeast region of Brazil, with the Social Disorganization Theory (SDT) as a theoretical basis. Brazil is a focal country in the discussion about lethal violence, as it concentrated around 14% of homicides in the world (IPEA, 2017). In absolute numbers, about 1.2 million people lost their lives as a result of intentional homicide in Brazil, between the years of 1991 and 2017.

In the following sections, it was have carried out a brief review on the literature about SDT, focusing not only on ethnic heterogeneity but also racial minorities. Then, it was presented two hypotheses that served as the basis for a wide range of regression models, as well as presenting a study area. Finally, the results, discussions and its implications on public policies and recommendations for future research were shown.

2. LITERATURE REVIEW

The following is a literature review on the Social Disorganization Theory that used the first article.

2.1 Social DisorganizationTheory (SDT)

The Social Disorganization Theory (SDT) was developed by the Chicago School, and it attempted to explain the variation in youth delinquency associated with limited informal social control in American cities at the neighborhood level (Shaw and McKay, 1942). With the popularization of the use of this approach, studies have grown in other countries (Pereira et al. 2015; Melo et al. 2017; Lee and Lee, 2019; He and Messner, 2020) and in other scales (Ingram et al. 2017; Peres and Nivette, 2017; Ojedokun et al. 2019; Umar et al. 2020). Generaly, SDT emphasizes that more disorganized communities are less able to share common values and to mobilize and control delinquent behavior, which leads to an increase in crime (Sampson and Groves, 1989). The literature indicates that places with high social disorganization, operated by socioeconomic disadvantages, residential instability, and ethnic heterogeneity, generally have high rates of violent crimes (Hipp, 2007; Wang and Arnold, 2008; Schreck et al, 2009; Ye and Wu, 2011; Chamberlain and Hipp, 2015; Quick et al. 2018).

According to Sampson and Groves (1989), low economic status, ethnic heterogeneity, residential mobility, family disturbance, and urbanization leads to social disorganization in the community. In their foundational study, they also incorporated three other indicators: local friendship networks, community participation, and young people supervision. They found a positive relationship between urbanization, low economic status, ethnic heterogeneity, family dysfunction, and residential stability in Great Britain. They also found that communities characterized by poor friendship networks, unsupervised groups of teenagers, and low community participation, had higher crime rates. Upon completing the test, they observed a strong support for the Social Disorganization Theory. A second test on SDT used the research of Sampson and Groves as a basis, incorporating the subsequent interactions of the British Crime Survey (Lowenkamp et al, 2003). The research confirmed Sampson and Groves' results, showing even more relevance to this approach.

Since then, numerous researches have emphasized these elements to define social disorganization and to explain crime. For example, initially for Shaw and McKay (1942), the two main explanations for criminal activity, in the framework of social disorganization, were ethnic heterogeneity and population rotation. Ethnic heterogeneity or cultural diversity reveals the degree of interaction of ethnic groups in a locality. Population rotation reveals that few residents are willing to invest time in discussing common issues, as they plan to leave the place as soon as possible.

2.2 Ethnic heterogeneity, racial minorities and crime in the context of SDT

In most of the researches about the application of the social disorganization theory (SDT), ethnic heterogeneity refers to the existence of minorities such as blacks and native immigrants versus native whites in the chosen units of analysis (Andresen, 2006; Cahill and Mulligan, 2013; Ross et al. 2000, Sampson et al. 1997). According to Shaw and McKay (1942), places where people with the most socio-economically disadvantaged live, are also characterized by the presence of newly arrived immigrants from different places, which can presents a great ethnic and racial heterogeneity. Initially, these studies on the relationship between ethnic heterogeneity and crime were based on the size of the black population and its relationship to violence rates in the United States of America (Stacey, 2019). For example, Blau and Blau (1982) mentioned in their study that a percentage of black population in a given city had a positive relationship with the rates of violent crimes, including homicides. Braithwaite (1979) did not find a correlation between ethnic heterogeneity and homicide rates in developed countries. However, Andresen (2006) found a strong and significant negative relationship with a crime in Vancouver, Canada. The author's explanations are based on Canadian specificities, such as, the country's culture of the relatively good reception of immigrants and the inhigh flow of wealthy immigrants, as well as the existence of immigrant neighborhoods with a low domain of the English language that favors for the social cohesion. The study also raised the hypothesis of the possibility of underreporting crimes in the neighborhoods with a greater presence of minority ethnic groups.

In addition to the studies in developed countries, international literature also makes few, but important contributions to the understanding of ethnic heterogeneity issues associated with crime in countries of the global south. Studies had also reported a positive or negative relationship between ethnic diversity and crime rates, including homicides. For example, Melo et al. (2017) found different results between ethnic heterogeneity and the type of crime for the city of Campinas, Brazil. In one hand, car and residential theft showed a negative coefficient in relation with ethnic heterogeneity, but rape, in the other hand, had a positive coefficient. Marzbali et al. (2019) found that the influence of ethnic heterogeneity on crime varies in neighborhoods in the city of Penang, Malaysia. In general, the results revealed negative effects of ethnic heterogeneity and violent crime, both caused directly or indirectly.

Adekoya and Razak (2020), in theirs study on SDT in Nigeria, observed a positive effect of criminal activities with ethnic heterogeneity, especially on the poor population, concluding that it is an endemic phenomenon. According to the authors cited, ethnic diversity and poverty are important factors to explain crime in Nigeria. The growth in revenue and in public security expenses has a significant effect in reducing crime, suggesting to the formulators of policies that this generation of public policies is aimed at generating income and good health programs for the poorest people, generating a contrary effect to crime.

According to Opoko and Oluwatayo (2014), the effects of ethnic heterogeneity on crime are growing in cities in the global south where there is no urban planning, as citizens face several urban infrastructure problems, for example severe housing shortages, a situation that lead directly toto the growth of favelas, causing a social and also physical distance between ethnic groups.

Breetzke (2010), when testing SDT in a post-apartheid city in South Africa, identified that the black population was not significant in explaining the rates of violent crime. Besidescanceling out much of the stigma that blacks are more prone to commit a crime, the author suggests measuring ethnic heterogeneity not based on skin color, but on belonging to tribal groups and native language.

Researchers also assessed the relationship between indian population and homicide rates using the social disorganization theory. The importance of those analysis is due to the fact that a great part of this research on crime and homicides have generally been aimed at the white and black populations, with few studies addressing this subject on Indians. Bachman et al. (1991) used multivariate statistical models, where were able to examine the influence of social disorganization and economic deprivation on homicide rates among American Indians at the county level. Their results showed that measures of social disorganization and economic problems were positive and significantly related to the homicides of Indians in the United States of America. Lanier and Huff-Corzine (2006) verified whether the variation in homicide rates of American Indians at the county level could be explained by SDT in a period from 1986 to 1992. Specifically, the authors investigated the impact of economic deprivation, along with ethnic heterogeneity, family mobility, and disorganization in homicide levels among Native American populations. The research results indicated to a positive and significant relationship between ethnic heterogeneity and homicides of American Indians. It was also shown that the ethnic composition of a community can affect the social stability of that community, preventing communication between individuals or increasing the levels of hostility and fear, which can lead to higher rates of lethal violence.

3 THE PRESENT STUDY

A limitation of the studies that apply the social disorganization theory (SDT) framework to model crime is the use of a single variable to verify the effect of ethnicity. Thus, the present research intends to fill this gap, by investigating in the same study the effect of indigenous populations, black population, and ethnic heterogeneity in the estimation of the homicide rate in Brazil. In this sense, it was used two hypotheses based on SDT and the Brazilian context:

H1: Ethnic heterogeneity, black and Indian population have a positive relationship in regards to the homicide rate. In addition to following the initial formulation of the theory (Sampson and Groves, 1989; Shaw and McKay, 1942), the hypothesis is based on the history of Brazilian racial conflict.

Brazilian literature has demonstrated over the decades the presence and persistence of racial inequalities and the subordinate situation of blacks and Indians in the country (Fernandes, 1978; Guimarães, 2002). Although SDT has been used in many studies in Brazil, some did not use the ethnic minority/heterogeneity variable (Silva 2014), others did not analyze homicide, but they did use other types of crime (Melo et al., 2017). In this sense, it is necessary to take the underreporting situation into account for other types of crimes other than homicides. Thus, the H1 test takes this bias into account when working with homicides and ethnicity.

H2: Metropolitan regions are areas where the relationship between the presence of ethnic heterogeneity and racial minorities is associated to a greater extent with homicides.

In addition to urbanization being a factor that indicates social disorganization (Sampson and Groves, 1989), it is in the large city that socioeconomic inequality is more evident in the countries of the global south (Davis, 2006; Opoko and Oluwatayo, 2014). In this sense, racial disparities are more discrepant in the layers with a higher monthly income in Brazil (Bailey et al. 2013), producing cities with a high degree of racial and urban segregation, for example high-end condominiums with white residents (Caldeira, 2000).

3.1 Study Area

Brazil is one of the most violent countries in the world, and it has concentrated about 14% of homicides on the planet in 2017. In absolute numbers, about 1.2 million people had lost their lives as a result of intentional homicide in Brazil between the years of 1991 and 2017 (IPEA, 2017). The study area is the Northeast Region of Brazil, which is formed by nine states, subdivided into 1794 municipalities (Figure 1). The estimated population, for the year 2019, was 57.071.654 million inhabitants, which represented 27.16% of the country's total population.

In general, the “historical evolution is marked by the economic and social backwardness and by the regional economic disparities that had repercussions on deep regional social inequalities” (Lima and Barreto, 2015, p. 277). This scenario places the Northeast Region in an unfavorable position within Brazil, in which the poorest and most violent cities in the country stands out. In 2017, all nine northeastern states reached the top of the rank, according to the Atlas of Violence - a survey of homicides reported by the Unified Health System (UHS). The Atlas of Violence summarizes this scenario and "In recent years, while there has been a residual decrease (in the homicide rate) in the Southeast and Midwest regions, there has been some stability of the index in the South region and marked growth in the North and Northeast. "

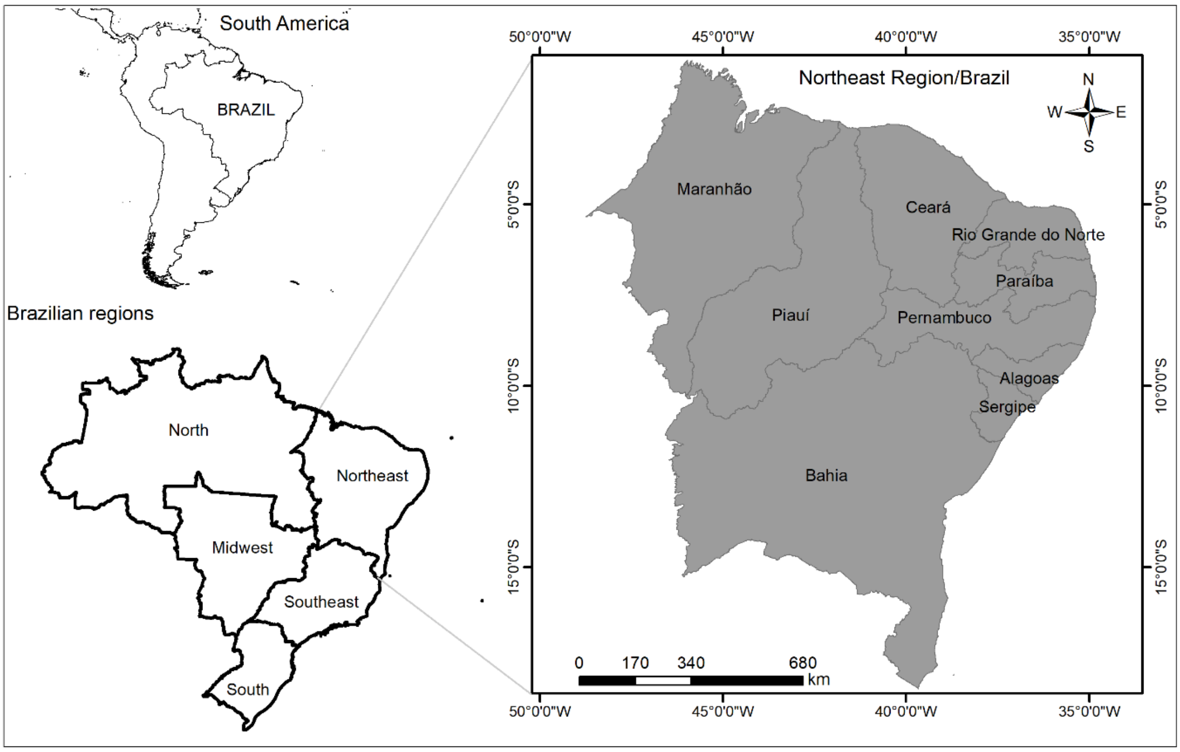

Figure 1: Study Area.

From an ethnic and racial point of view, Brazil was one of the last countries in the world to abolish slavery in 1888. One of the territorial inheritances of that period is the existence of Quilombos throughout almost the entire country, especially the Northeast region. In the past, quilombos were places of refuge for African slaves and Afro-descendants, today called Quilombolas (Bowen, 2010). In the other hand, the Brazilian indigenous population, has decreased by more than 80%, a process that is described as genocide in a nation that had more than one million indigenous people and that today has about 300,000 (Cunha, 2013). The 1988 Brazilian Constitution recognizes the right of the Indians to follow their traditional ways of life and the permanent and exclusive possession of their "Indigenous Lands". In practice, the indigenous population is currently guardians of Brazilian forests and also, they live in constant threat (Van Solinge, 2010).

Most of the traditional quilombola and Indian people are ethnic-racial minorities that struggle to stay on land and with the survival of customs in the rural or forest areas. Black and indigenous populations also struggle for their social reproduction in the Brazilian cities marked by inequality. Regarding to the ethnic heterogeneity, of the cities in the Northeast Region of Brazil, it is possible to verify their spatial distribution pattern in Figure 2. The index was calculated using data from the percentage of the number of self-declared black, white and indigenous people in relation to the total number of inhabitants from each municipality (IBGE, 2010). It was observed high values in the coastal and central-south portion.

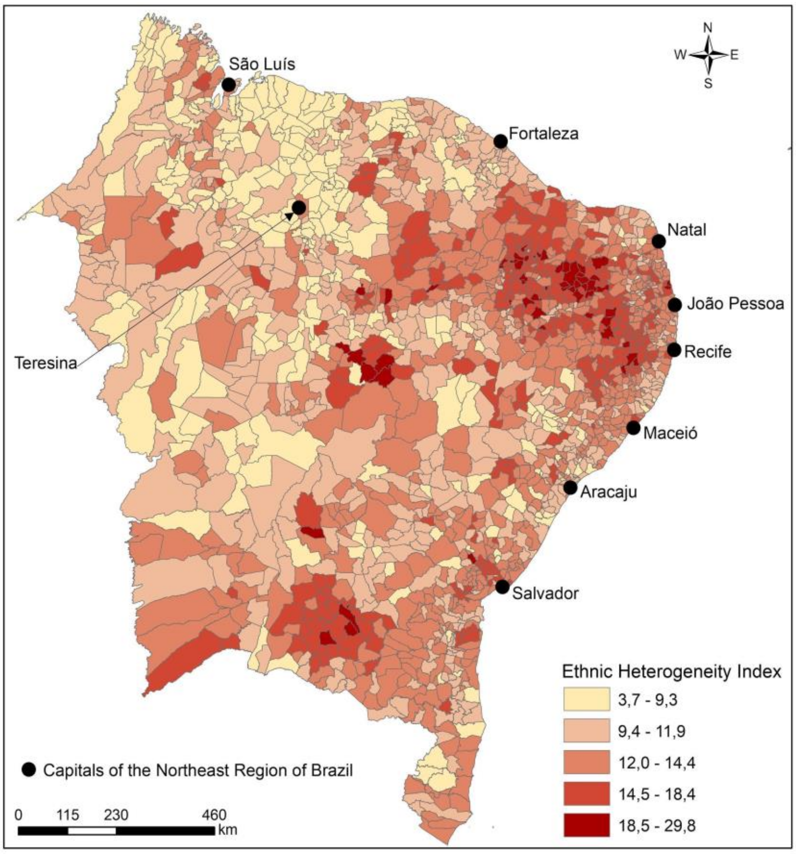

Figure 2: Ethnic Heterogeneity Index.

4 MATERIALS AND METHODS

4.1 Data Source

The homicide data for 2010 were acquired from the DataSUS portal, which is the IT department of the Brazilian Unified Health System. The other research data were obtained from the demographic census of the Brazilian Institute of Geography and Statistics (IBGE) from the year of 2010. For example, the population of 2010 that served to calculate homicide rates per 100,000 inhabitants. Therefore, socioeconomic data were highlighted as proxies for the measurement of social disorganization: unemployment rates (low economic status), percentage of rented households (residential mobility), heads of family living with a partner (without family disturbance) and percentage of black, white and indigenous (ethnic heterogeneity or racial minorities). It is important to mention that it was not found the variable “heads of household who live without a spouse” to measure family disturbance. Thus, it was used the variable of heads of family living with the spouse expecting a negative association with crime from the perspective of SDT. Theanalysistook place at the municipal level (N = 1974). In this sense, statistical analyzes were performed using the statistical software R and QGIS, both available from open source.

4.2 Analytical strategy

From the tabulated data, it was applied the Moran Global Index and LISA map, Ordinary Least Squares (OLS), and Geographically Weighted Regression (GWR) analysis methods for homicide rates, described in the next topics and summarized in Figure 3.

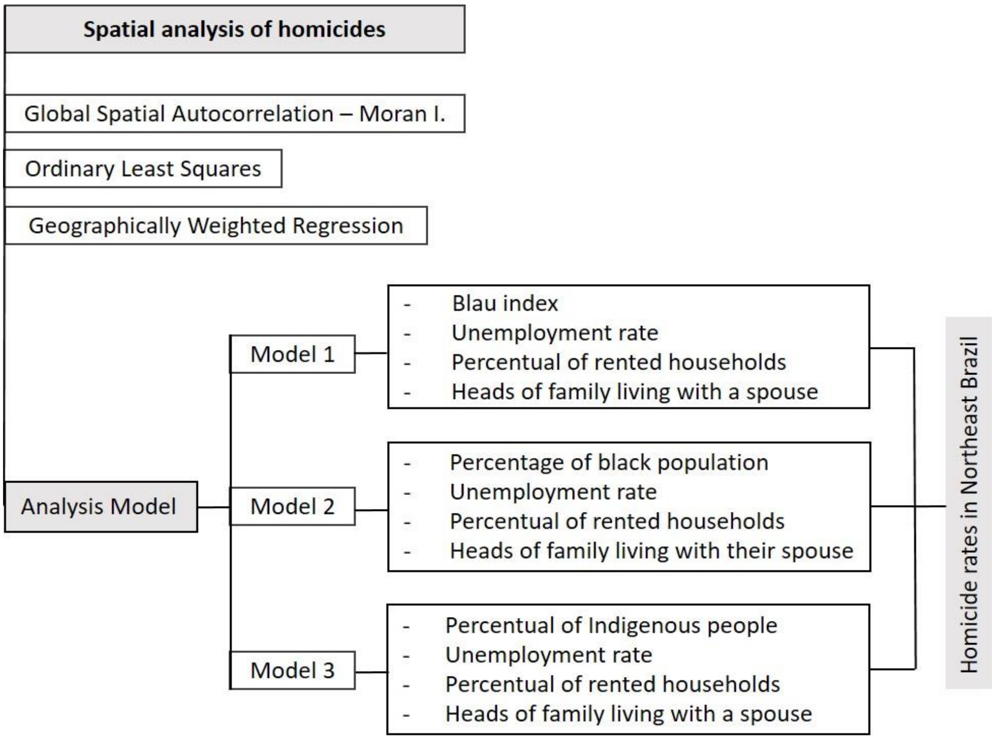

Figure 3: Synthesis of the methodological procedure.

4.2.1 Moran Global Index and LISA map

Moran's global index (I) was applied to check for the presence of spatial autocorrelation, in order to its negative value provides itself to a test whose null hypothesis is of spatial independence. In this case, its value would be zero. On the opposite, positive values indicate a direct correlation. Despite the wide application of the Moran global index, it is often desirable to examine patterns on a more detailed scale, to see if the stationarity hypothesis process is verified locally. In this sense, the local index of spatial autocorrelation analysis was applied, such as the Local Indicators of Spatial Association (LISA). This technique is very useful, as it generates a map indicating the regions that have a local correlation significantly different from the rest of the data (Anselin, 1998). In this way, the results of global and local statistics are complementary.

4.2.2 Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR)

Initially, the Ordinary Least Squares (OLS) regression model was applied. OLS regression can be used to identify statistically significant associations between the response variables and co-variables. In order to find the best model, an analysis was repeatedly conducted to make the choice of the model with the best Akaike Information Criteria (AIC) and R^2. In addition to that, a parsimonious model free from multicollinearity problems was sought. Thus, it was estimated the homicide rates from the perspective of three different models in order to check the study's hypotheses.

Geographically Weighted Regression (GWR) has already been proposed in the literature by Brunsdon et al. (1996) for the relationships between variables in the regression model that can vary in space. GWR is an adaptation of the local regression model in spatial econometrics. The purpose of local regression is to estimate the value at a given point based on your neighborhood. According to Fotheringham et al. (2003), the GWR model can be written as:

$$y_i = \beta_0 (u_i , v_i) + x_{i1}\beta_1 (u_i , v_i) + \ldots + x_{ip}\beta_p (u_i , v_i) + \varepsilon_i \qquad (1)$$

in which, y_i is the value of the response variable of the *i*-th point in space, $x_{i1}, \ldots, x_{ip}$ are the co-variables of the *i*-th point, u_i and v_i are the geographic coordinates, $\beta_k (u_i , v_i)$ represents the value of the k-th covariate effect for certain graphical coordinates and finally ε_i it's a value attributed for any random error. Thus, the GWR model recognizes that spatial variations in relationships can exist and it provides a way in which they can be measured.

In GWR, an observation is weighted accordingly to its proximity to location *i*, so that the weighting of an observation is no longer constant, but it varies with *i*. The observation data close to *i* will have greater weight in relation to data from more distant observations. Therefore, it can be estimated that the regression parameters is as follows:

$$\hat{\beta}(u_i, v_i) = (X^\top W(u_i , v_i)X)^{-1} X^\top W(u_i , v_i)Y \qquad (2)$$

in which X denotes the matrix of covariates, $\hat{\beta}$ represents an estimate of β and $W(u_i , v_i)$is an $n \times n$ matrix whose elements outside the diagonal are zero and whose diagonal elements exhibit the geographical weighting of each of the n data observed for the regression point i. In the approximation process, an iterative maximization algorithm is required to estimate the model parameters at location *i*.

The motivation of the GWR proposal is the idea that it is not reasonable to assume that a set of constant regression coefficients can adequately capture relationships between independent variables and response variables, which are spatially correlated. In this article, as it was verified the strong positive spatial autocorrelation (Univariate) for the dependent variable, it was also chosen to use the GWR to identify possible local spatial associations and to confirm the spatial effect of the multivariate model. The behavior of the GWR model was evaluated based on the AIC, R^2, and Moran's I indicators of the model residues.

5 RESULTS

The result of the Moran Global index indicated the presence of positive spatial autocorrelation in homicide rates in Northeast region of Brazil in 2010 (0.404, $p < 0.05$). There were 179 cities with High-High clusters, which represents high homicide rates close to areas with the same characteristics. However, it was possible to identified cities with low homicide rates close to similar areas (Low-Low clusters). Thus, Figure 4 shows the distribution of spatial autocorrelation in the study area.

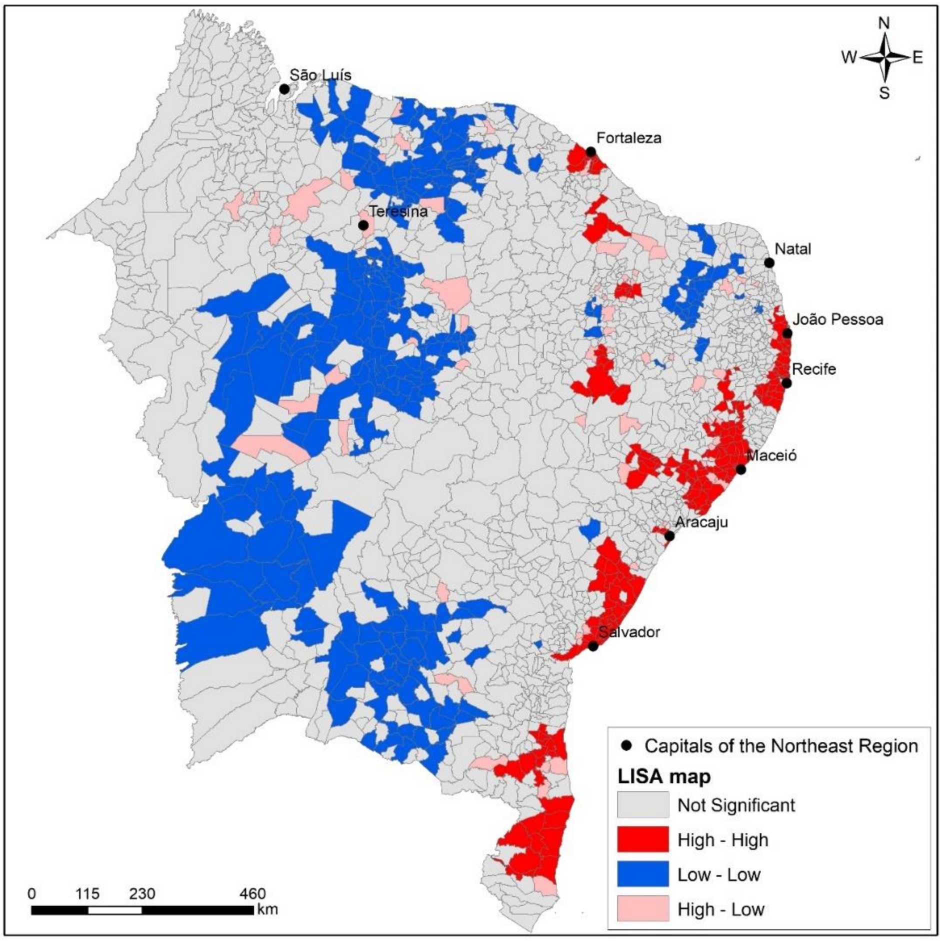

Figure 4: LISA map of homicide rates.

It was observed that the High-High clusters were more concentrated in the main metropolitan regions that are closer to the coast. These metropolitan regions are the areas where the largest populations are concentrated, as well as where the highest homicide rates are found. In contrast, the Low-Low clusters are concentrated in the interior/west of the region, where the municipalities have small populations.

The result of the OLS Regression is available in Table 1, as well as the VIF index used to identify the existence of multicollinearity. Thus, it was found that the models, the estimated coefficients for the variables unemployment rate, percentage of rented households, and heads of the family with a spouse were positive, that is, there was a positive association with the homicide rate. Therefore, the higher the unemployment rate, the percentage of rented households and heads of families with a spouse, the higher the homicide rate.

Table 1: Results of the OLS model for homicide rates

Models	***Variables***	***Estim. Coef.***	***Stan. Error***	***T-Value***	***p-Value***	**V IF**
M1	Intercept	-7.527	2.996	-2513	0.012	-
	Blau Index	13.518	5.968	2265	0.024	1.090
	Unemployment Rate	0.324	0.,089	3625	0	1.033
	Percentage of rented households	1.123	0.069	16316	< 0.001	1.196
	Heads of Family living with a spouse	0.002	0.001	4563	< 0.001	1.079
	R^2	0.200				
	AIC	14837.280				
M2	Intercept	-1.908	1.019	-1873	0.061	-
	Percentage of black population	0.121	0.060	2024	0.043	1.046
	Unemployment Rate	0.290	0.091	3198	0.001	1.068
	Percentage of rented households	1.181	0.067	17656	< 0.001	1.129
	Heads of Family living with a spouse	0.002	0.001	4461	< 0.001	1.085
	R^2	0.200				
	AIC	14838.320				
M3	Intercept	-1.191	0.935	-1274	0.203	-
	Percentage Indigenous Population	0.215	0.110	1958	0.05	1.000
	Unemployment Rate	0.323	0.089	3617	< 0.001	1.033
	Percentage of rented households	1.166	0.066	17568	< 0.001	1.112
	Heads of Family living with a spouse	0.002	0.001	4646	< 0.001	1.078
	R^2	0.200				
	AIC	14838.580				

The Blau index variables, percentage of black population and Indians, for models 1, 2 and 3, respectively, obtained positive coefficients. Regarding the supposition of multicollinearity, all variables had a VIF value <1.5, indicating that there was no multicollinearity in the linear regression models. The adjusted R^2 indicates that the models were able to explain about 20% of the total variance of homicide rates, for all the models. However, the residues of the OLS models had shown a significant positive spatial autocorrelation (Model 1: Global Moran's I = 0.40, p-value <0.01, the same is valid for models 2 and 3), thus, the OLS regression assumption that the residues are independent is not satisfied. To solve this limitation, GWR models are more suitable.

In Table 2, the GWR coefficients, for models 4, 5 and 6, are presented in terms of statistical measurements, such as: minimum, first quartile, median, third quartile and maximum. The adjusted R^2 of the GWR was 0.36 (both models), that is, the GWR model was able to explain 36% of the variations in homicide rates in the Northeast region of Brazil. In addition to that, it was possible to verify that, the value of R^2 of the GWR model is higher when comparing it to the OLS regression model. Therefore, there is a significant gain in the model when using an approach that takes into account the relationship between neighboring cities.

Table 2: Estimated coefficients of GWR regression

Models	Variables	Min.	1st Q.	Median	3rd Q	Max.	Global
M4	Intercept	-33.577	-11.515	-3.534	1.713	25.084	-7.527
	Blau Index	-37.476	0.977	10.125	22.551	50.833	13.518
	Unemployment Rate	-0.210	0.040	0.158	0.252	0.541	0.324
	Percentage of rented households	0.319	0.605	0.829	1.233	2.466	1.123
	Heads of Family living with a spouse	0.000	0.001	0.002	0.004	0.008	0.002
	R^2	0.360					
	AIC	14494.330					
M5	Intercept	-11.919	-2.436	1.423	4.656	11.449	-1.908
	Percentage of black population	-0.948	-0.217	0.038	0.228	2.606	0.121
	Unemployment Rate	-0.351	0.002	0.134	0.221	0.644	0.290
	Percentage of rented households	0.362	0.642	0.840	1.235	2.505	1.181
	Heads of Family living with a spouse	0.000	0.002	0.002	0.004	0.008	0.002
	R^2	0.360					
	AIC	14478.970					
M6	Intercept	-9.037	-0.030	1.759	4.048	8.660	-1.191
	Percentage Indigenous Population	-0.359	0.029	0.285	0.509	2.161	0.216
	Unemployment Rate	-0.205	0.034	0.149	0.237	0.535	0.323
	Percentage of rented households	0.366	0.649	0.852	1.274	2.368	1.166
	Heads of Family living with a spouse	0.001	0.002	0.003	0.04	0.007	0.003
	R^2	0.350					
	AIC	14501.110					

Through the local R^2, it was possible to identify the areas of best fit to the model. Thus, it is possible to have a spatial visualization of the model's performance in order to explain homicide rates in different areas. Figure 5A, Figure 5B and Figure 5C shows the distributions of the local R^2 accordingly to homicide rates in different cities in the Northeast region considered for models 4, 5 and 6. The distributions are not homogeneous between the municipalities for both models, that is, model performance may vary by region. In general, GWR performs well in great part of the Northeast region with R^2 values above 0.4. Mainly in the South and coastal region.

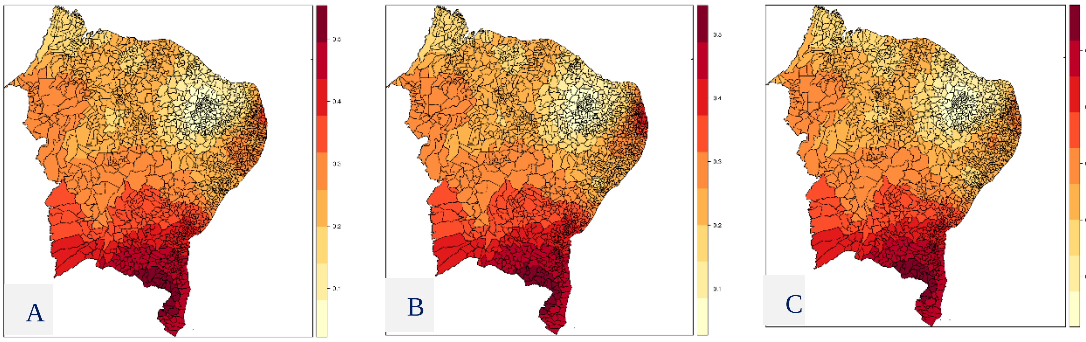

Figure 5: Distribution of local R^2 for the GWR model (Blau Index) A (Percentage of Black population) B (Percentage Indigenous Population) C.

In general, spatial patterns of the local GWR coefficients are similar to the results of the OLS regression, however, in some regions, the direction of the relationship between the response variable and the explanatory variables may change. Thus, as seen in the OLS model, the Blau index variables, percentage of black and Indigenous Population are positively related to the homicide rate in most cities in the Northeast region, but the GWR allows us to verify that these phenomena are actually heterogeneous in space. In the coefficients for the Blau Index variable (Figure 6), the positive associations were in the South and Northeast of the entire study region (corresponding to the states of Sergipe, Alagoas, Pernambuco and part of Paraíba, Ceará and Piauí).

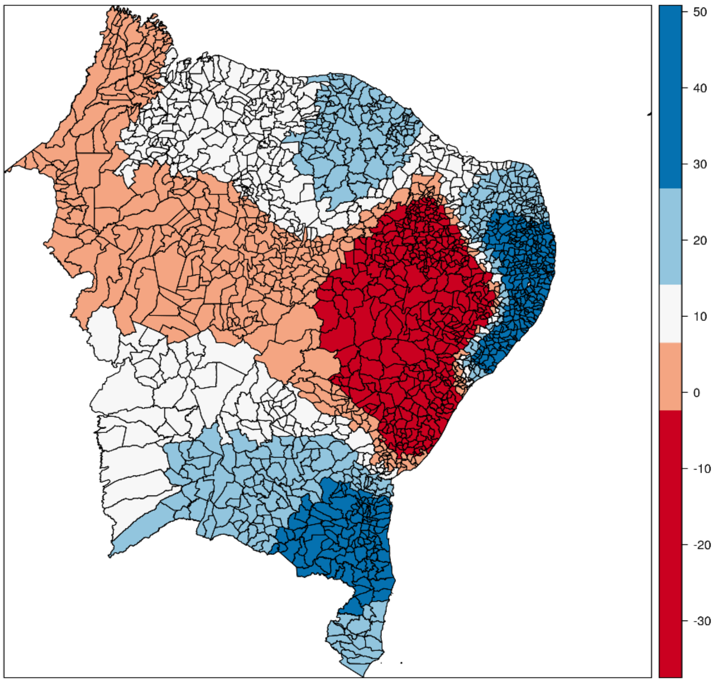

Figure 6: Blau index coefficient.

In the coefficients for the Percentage of black population variable (Figure 7), it was observed a large cluster at the top of the east coast of the map. In constrast, the percentage variable for Indigenous Population (Figure 8) shows the opposite of the other two variables since the high and positive coefficient values are found in the interior of the Northeast region of Brazil.

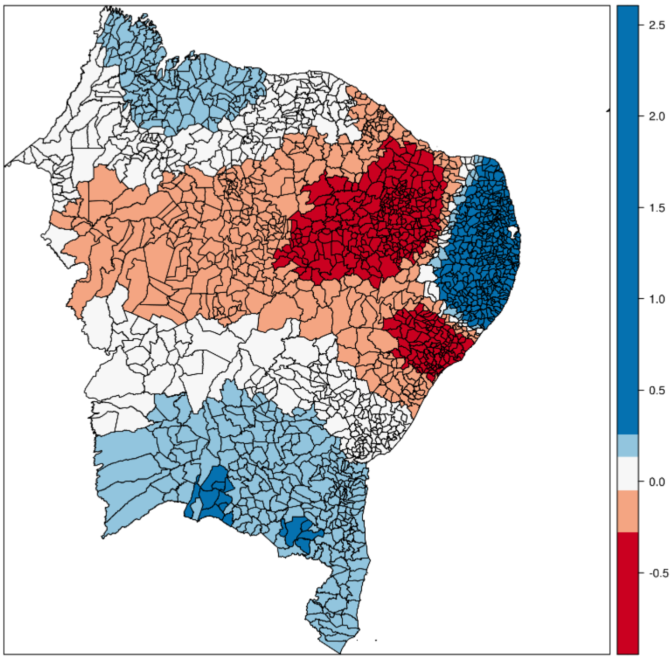

Figure 7: Coefficient of percentage of black population

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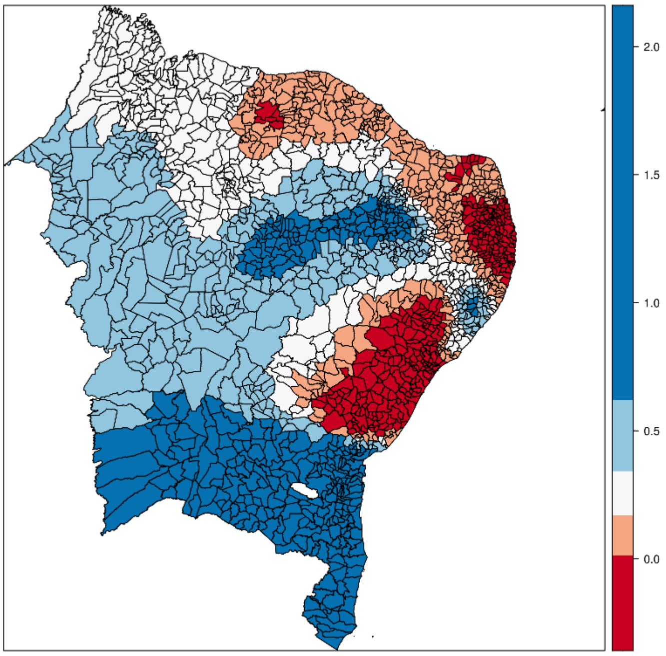

Figure 8: Coefficient of the percentage Indigenous Population.

The p-value for the GWR model indicates the significance of the coefficients that vary locally for the co-variables. It provides the spatial distribution of the p-values for the intercept and each co-variable in the study area for the Blau Index variable (Figure 9A), percentage of black and Indigenous Population (Figure 9B and Figure 9C), adopting a significance level of $\alpha = 0.10$. Therefore, it was observed that the region is significant when the value of $p < 0.1$, which are represented in the lightest grayscale, while the non-significant regions (p> 0.10) are represented in the darkest gray color.

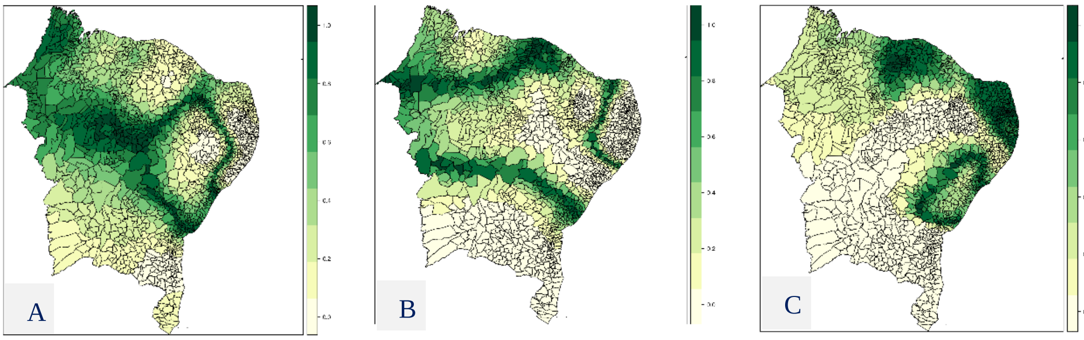

Figure 9: P-values of (Blau Index) A (Percentage of Black population) B (Percentage Indigenous Population) C.

6 DISCUSSIONS

The aim of this study was to evaluate the effect of racial minorities and ethnic heterogeneity in the estimation of homicide rates in the Northeast region of Brazil. Based on the Social Disorganization Theory (SDT), the study's control variables were the unemployment rate, the percentage of rented households, and heads of family living with a spouse. As expected (Shaw and McKay, 1942), the estimated results were positive, between homicide rates and proxies with low socioeconomic status (unemployment rate) and residential mobility (percentage of rented households). The result for the variable “heads of households living with a spouse” was unexpected, as family instability would be a measure captured by heads of households without a spouse (Sampson and Groves, 1989). According to Porter and Purser (2010), marriage rates can create a low level of social disorganization based on the relationship dynamic and interrelationships between and within families in a community. This result suggests that the institution of marriage in the Northeast region of Brazil does not generate enough impact to cause a negative correlation for the occurrence of homicides. Therefore, we believe that the variable “heads of households living with a spouse” alone is not enough to measure family instability in Brazil. It is necessary to recognize the type of union between couples, since accordingly to data from IBGE (2010), more than a third of the unions in Brazil are consensual, without civil or religious marriage. Thus, the IBGE study (2010) also shows that the union without formalization is more frequent in lower social classes, that is, socially and economically vulnerable.

The first hypothesis we tested was (H1) *that the black population, the indigenous population and ethnic heterogeneity, have a positive relationship* regarding *to the homicide rate.* The results of the models indicated that H1 is plausible, since all the coefficients (black /

indigenous population and ethnic heterogeneity) were positive and significant in estimating the homicide rate in the municipalities in the Northeast region of Brazil.

The black population is commonly used as a measurement of the presence of a racial minority or ethnic heterogeneity (Breetzke, 2010; Messner & Golden, 1992). According to Cerqueira and Bueno (2020), one of the main expressions of racial inequalities in Brazil is the strong concentration of lethal violence rates within the black population. In 2018 alone, black population accounted for 75.7% of homicide victims and for every non-black individual killed, 2.7 black people were killed. This scenario of deepening racial inequalities in Brazil is more evident when the authors find that between the years of 2008 and 2018, homicide rates had increased by 11.5% for blacks, while for non-blacks. A decrease of 12.9% was observed (Cerqueira and Bueno, 2020).

The indigenous population had also shown a positive association with homicide rates. The obtained results corroborate to the research by Lanier and Huff-Corzine (2006), where they found that social disorganization significantly affects homicides of Indians in the United States of America. In Brazil, violence against indigenous population is mostly associated with land tenure conflicts. It involves the conflicts resulting from the demarcation and repossession of lands, which reveals a continuous struggle for demarcation. In this sense, in Brazil, data on violence are organized by the Indigenist Missionary Council (CIMI). According to CIMI, unlike the Amazon Region, where the largest indigenous lands in Brazil predominate, most of the population in the South, Southeast, Midwest and Northeast regions, mostly live in small areas of degraded land, where there is no minimum housing conditions and without any sanitation. There are intense conflicts in the states of Ceará, Maranhão, Alagoas and Pernambuco. Homicides of the indigenous population in poor resource areas in the Northeast region had materialized through land grabbing processes, in which even subdivisions within indigenous lands stands out (Van Solinge, 2010).

One of the most interesting findings of this research is that although ethnic heterogeneity also had a positive coefficient in the estimative of homicides in the study area, its magnitude is much higher than the percentage of black and Indigenous Population. In this sense, the results provide support for the hypothesis of Blau (1977), which was also verified by Stacey (2019), who in his studies verified that there is an association of ethnic heterogeneity and segregation with violence between racial groups. Our second hypothesis (*H2 - metropolitan regions are areas in which the relationship between the presence of ethnic heterogeneity and racial minorities is associated to a greater magnitude with homicides*) converges to this idea. This occurs due to the metropolitan regions being configured as socioeconomic centralities and also areas with concentration of services, areas of commerce, and some forms of industrial activities. It can still be said that in metropolitan regions, social problems are fully materialized, as a result of the cosmopolitan condition and the asymmetric development of these areas (Davis, 2006; Opoko and Oluwatayo, 2014).

According to Graif and Sampson (2009), the concentration of people who migrate from one place to another, for example, (from interior to the capital) has complex implications for homicide rates. High concentrations of migrants may be the result of segregation and discrimination in the housing market. Places with low infrastructure with high ethnic heterogeneity can restrain migrants from low socioeconomic status in conditions that can amplify frustration, tensions and, ultimately, increase crime rates. This situation can be identified in the capitals of the Northeast region, where there is also a concentration of homicide rates, as shown in Figure 3.

Finally, it was used geographically weighted regression (GWR), which proved to be a very promising tool to explain the relationship between explanatory variables and homicide rates, in addition to finding an increase in the coefficients of ethnic heterogeneity and racial minorities in areas close to metropolitan regions (H2). Therefore, the use of GWR becomes important, as it spatially presents the locals that OLS regression is not able to identify, since the behavior of homicides is not random in space (Andresen et al. 2020). Thus, it was possible to identify how the spatial patterns of homicide rates vary in space according to the coefficients of the variables and statistical significance.

6.1 Limitations and recommendations

Some considerations need to be made in the context of this study. First, the analyzes depended on the census data that only happens every 10 years. In this sense, Brazil faces difficulties to carry out the census work, referring to the year 2020. This census should already be ready, or in the finalization phase, but its activities were compromised by political decisions and the pandemic of the new coronavirus (SARS- CoV-2). Therefore, new studies need to be carried out in Brazil considering a more extensive time series. Another recommendation from this research would be to work with longitudinal data to verify the causality of the variables of ethnic heterogeneity and racial minorities in homicide rates.

Secondly, the analysis were focused only on the Northeast region of Brazil and at the level of municipalities. Future research should verify the effect of racial minorities and ethnic heterogeneity in the estimation of homicide rates in other regions, not only in Brazil but also in the world. Smaller units of analysis, such as neighborhoods, where the Social Disorganization Theory (SDT) was originally formulated (Shaw and McKay, 1942) should also be considered.

Thirdly, Bailey et al. (2013) had revealed that social inequality is shaped by the way race is measured and operationalized in quantitative research. This implies in the reflection on how race is socially defined and whether self-classification differs from the race attributed by the interviewer or which dimension supports the definition of race (ancestry versus appearance). In Brazil, this definition is self-declared, therefore, it implies issues of identity, that are difficult to delimit without a qualitative study.

Finally, the results have implications that could help in public policies of homicide prevention in Brazil. It is evident that there is a latent racial inequality in the country, where there once had genocide of indigenous populations and genocide of the black population. Our results show that in large urban centers, where ethnic heterogeneity is greater, there is a higher concentration of homicide rates. Educational measures of racial tolerance need to be taken urgently, as well as the strengthening of the culture and identity of Brazilian racial minorities.

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3 SPATIAL MODELING FOR HOMICIDE RATES ESTIMATION IN PERNAMBUCO STATE-BRAZIL

MODELOS ESPACIAIS PARA ESTIMATIVAS DE HOMICÍDIO NO ESTADO DE PERNAMBUCO - BRASIL

ABSTRACT

Homicide rates have been increasing worldwide, especially in Latin America, where it is considered one of the most lethal of the continents. Despite that, the occurrence of homicides are not homogeneous in time and space on the continent or in the Brazilian cities. Therefore, the main objective of this study is to present a spatial analysis of homicides in the state of Pernambuco, Brazil, between the years of 2016 and 2019, by the use of an exploratory analysis of spatial homicide data with five variables that could explain its occurrence. In addition to that, it was applied the Global and Local Moran's Index, Ordinary Least Squares (OLS) regression, and Geographically Weighted Regression (GWR), all implemented in the Geographic Information System (GIS) software. Thus, the distribution of clusters revealed a spatial autocorrelation for homicide rates, confirming a spatial dependence. This data also showed the polarization of the rate between the coast and the interior of the state of Pernambuco.

Keywords: spatial analysis; homicide; mapping; homicide rates; GWR; GIS

RESUMO

As taxas de homicídio vêm aumentando em todo o mundo, principalmente na América Latina, onde é considerada uma das mais letais dos continentes. Apesar disso, a ocorrência de homicídios não é homogênea no tempo e no espaço no continente ou nas cidades brasileiras. Portanto, o objetivo principal deste estudo é apresentar uma análise espacial dos homicídios no estado de Pernambuco, Brasil, entre os anos de 2016 e 2019, por meio da utilização de uma análise exploratória de dados espaciais de homicídios com cinco variáveis que poderiam explicar sua ocorrência. Além disso, foi aplicado o Índice de Moran Global e Local, regressão de Mínimos Quadrados Ordinários (OLS) e Regressão Geograficamente Ponderada (GWR), todos implementados no software Sistema de Informação Geográfica (GIS). Assim, a distribuição dos clusters revelou uma autocorrelação espacial para as taxas de homicídio, confirmando uma dependência espacial. Esses dados também mostraram a polarização da taxa entre o litoral e o interior de Pernambuco

Palavras-chave: análise espacial; homicídio; mapeamento; taxas de homicídio; GWR; GIS

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Spatial Modeling for Homicide Rates Estimation in Pernambuco State-Brazil

Carlos Silva [1], Silas Melo [2,*], Alex Santos [3], Pedro Almeida Junior [4], Simone Sato [1], Katarina Santiago [5] and Lucilene Sá [1]

1 Department in Cartographic and Surveying Engineering, Federal University of Pernambuco, Avenida Acadêmico Hélio Ramos, s/n, Recife 50740-530, Brazil; carlos.assuncao@ufpe.br (C.S.); simone.sato@ufpe.br (S.S.); lacms@ufpe.br (L.S.)
2 Department of History and Geography, State University of Maranhão, Cidade Universitária Paulo VI, São Luís 65055-000, Brazil
3 Department of Transportation Engineering, Goiás Federal University, Rua Mucuri, s/n, Setor Conde dos Arcos, Aparecida de Goiânia 74968-755, Brazil; alexmota@ufg.br
4 Department of Statistics, Federal University of Pernambuco, Avenida Acadêmico Hélio Ramos, s/n, Recife 50740-530, Brazil; pmdaj1@de.ufpe.br
5 Department of Planning and Management, Rua da Aurora, 1377, Recife 50040-909, Brazil; katarina.santiago@seplag.pe.gov.br
* Correspondence: silasmelo@professor.uema.br; Tel.: +55-19-99185-6106

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Abstract: Homicide rates have been increasing worldwide, especially in Latin America, where it is considered one of the most lethal of the continents. Despite that, the occurrence of homicides are not homogeneous in time and space on the continent or in the Brazilian cities. Therefore, the main objective of this study is to present a spatial analysis of homicides in the state of Pernambuco, Brazil, between the years of 2016 and 2019, by the use of an exploratory analysis of spatial homicide data with five variables that could explain its occurrence. In addition to that, it was applied the Global and Local Moran's Index, Ordinary Least Squares (OLS) regression, and Geographically Weighted Regression (GWR), all implemented in the Geographic Information System (GIS) software. Thus, the distribution of clusters revealed a spatial autocorrelation for homicide rates, confirming a spatial dependence. This data also showed the polarization of the rate between the coast and the interior of the state of Pernambuco.

Keywords: spatial analysis; homicide; mapping; homicide rates; GWR; GIS

1. Introduction

In the 2019 Annual Report on drugs and crimes of the United Nations—UN, it was revealed that homicide rates have been increasing year after year in many countries, especially in Latin America, which can be considered the most lethal region on the planet [1]. However, according to the same document, resources for tackling and preventing this issue are scarce and poorly managed. Therefore, planning measures for crime control ends up being hindered due to several issues, such as financial, human, or management problems.

Consequently, this phenomenon is seen in major and medium-sized cities in the world [2], especially in developing countries. The analysis of Teivans-Treinovskis et al. [3] concluded that there was a definitive connection between a country's level of socioeconomic development and the proportion of specific types of crime that permeate it. The authors clarify that, in a more developed country, crimes against property predominate, different than the developing countries, in which violent crimes are more noticeable.

Brazil is responsible for 14% of the total homicides in the world [4]. In absolute numbers, about 1.2 million people lost their lives as a result of intentional homicide in Brazil between the years of 1991 and 2017. The number of homicides in Brazil, which in the year of 2017 was considered to be 30 murders per 100 thousand inhabitants, is alarming as conflicts about religion, ethnicity, race, or territory in the country are not significant issues in the country. In all the Brazilian states, the numbers of homicides exceed the number of 10 deaths per 100 thousand inhabitants. This number is alarming and it is considered epidemic by the World Health Organization—WHO [5]. Moreover, the data presented by Melo et al. [6] revealed that criminal issues are heterogeneous among Brazilian states. In 2017, from the 50 most violent cities in the world, 17 are located in the Brazilian territory and, of those, 11 are in the northeastern area, which are located in the surroundings of the Pernambuco state.

In this sense, according to the Department of Social Defense [7], in 2017, the state of Pernambuco, located in the Northeast Region of Brazil, was considered to be one of the most violent states in the country, with a rate of 57.3 occurrences per 100 thousand inhabitants; that is, almost twice as the national average, despite the development and implementation of the "Pact for Life" program in the last 12 years, a successful public security policy that reduced homicide rates by 39% in the period from 2006 to 2013 [8].

In light of this scenario and with the increase of criminal incidents in the country, particularly in major cities, the significance of studies on violence has become undeniable [9].

In this regard, the use of spatial analysis in crime studies contributes to a better understanding of the phenomenon and the development of action plans to prevent crime. Crime mapping using the Geographic Information System (GIS) and software with implementations of spatial analysis and methods of exploratory analysis of spatial data is recurrent in the contemporary world [10–15], and has been making new breakthroughs in recent years as a tool to broaden the understanding of crime patterns. In addition to the mapping approach, spatial statistics are widely employed for the identification of crime concentration and dispersion, as well as its correlation with socioeconomic, demographic, and urban infrastructure indicators. For example, Gupta et al. [11] analyzed crime patterns in the Jhunjhunu district in India using a GIS platform integrated with socioeconomic variables. Quink and Law [16] employed spatial clustering techniques to detect areas of low and high risk for drug trafficking crimes in Canada. The results allowed the identification of statistically significant hotspots or cold spots on the studied area, providing important information about the correlation between crime with socioeconomic and spatial indicators of criminal activities and the spatial pattern of crime. In Brazil, Oliveira et al. [17] described spatial patterns of intentional homicides in João Pessoa/Paraíba, on the period from 2011 to 2016. Overall, crime mapping [18] allow for the visualization and analysis of movement or target selection patterns of criminals, in addition to provide for researchers and professionals the exploration of crime patterns, criminal's mobilities, and serial offences across time and space.

Just as in a time series, spatial data possesses attributes and restrictions that require specialized techniques. For instance, spatial analysis, locations, and distances are important in the development of spatial statistic models and in the interpretation of their results [19]. In this context, the development of software with statistical implementations, such as, spatial visualization for the analysis of crime incident premises interacting with GIS packages, can aid agencies in their efforts in crime mapping, which is usually done in the main police departments in the world [20], but also can be found in smaller jurisdictions.

With this mind, this research outlines the mapping and analysis of homicides in the state of Pernambuco, Brazil, between the years of 2016 and 2019. Additionally, it presents the variables that explain the occurrence of this phenomenon in space, which is relevant according to Teivans-Treinovskis et al. [¯ 3], who affirm that any crime, violent ones in particular, are not usually the result of a cause, but is a combination of external and internal factors.

This study is justified on the grounds of the absence of up-to-date spatial analyzes of homicides in the state of Pernambuco. The relevance of the theme can be observed throughout recurrent studies in Brazil [14,21] and in other countries [3,16].

Therefore, the objective of this research is to present the spatial analysis of homicides in the state of Pernambuco, Brazil, between the years from 2016 to 2019. Consequently, it can contribute to crime studies in this state and also assist in the planning and in the spatial analysis of homicides, as described by Wang et al. [22]. The use of spatial statistical analysis and cartographic visualization applied in the production of maps has become analysis tools not only for the identification of crime-concentrated locations, but also for the criminal damages associated with the propagation of these transgressions. Even so, it can enable the understanding of phenomena that contribute to criminality, makes it possible to operationalize investigative actions based on geographic knowledge that facilitate prevention and actions to tackle violence and, consequently, to reduce crime, as described by Oliveira et al. [17]. Our findings can be useful for the Brazilian police, national criminal justice, healthcare institutions, and regional planners.

We structured this article in six parts. The first and second sections respectively present the introduction and the literature review, which contains the theoretical foundations of mapping and spatial analysis of crime. Section 3 describes the materials and methods employed in this study. The fourth part exhibits the results followed by the discussion section. Finally, in the last section are the conclusions and recommendations for any other future research.

2. Mapping and Spatial Analysis of Crime

The appearance of spatial analysis of crime dates back to the beginning of the 19th century France, where Quetelet [23] observed that crime exhibits some different patterns; that is, an individual is not likely to be a victim of a crime in certain locations. According to Brantingham [24], the phenomenon of crime is generally distributed differently in space in a town or a geographic region, and the occurrence of criminal episodes are not randomly distributed in space, but they do tend to be concentrated in very specific locations [25–27].

Overall, crime mapping and spatial analysis using GIS can cover a wide range of techniques and has been used to explore a variety of topics. In fact, Dag˘lar and Argun [28] carried out a comprehensive literature review on the use of geographic information systems in mapping crime and criminal analysis. The authors clarify that the location of a crime and the use of the geographic space by criminals are important components of the criminal incident [28]. In its most basic form, crime mapping uses GIS to visualize and organize the spatial data for a more formal statistical analysis. Crime data, described in a spatial domain, can be overlaid with education, sex and occupational data in order to obtain a correlation between each type of crime committed and the social conditions of the place it happened [11]. Spatial analysis can be used both in an exploratory or confirmatory form, with the main objective being to identify how a particular community or ecological factors (such as population characteristics or the constructed environment) can influence the spatial patterns of crime [18].

According to Perdomo [29], spatial mapping and analysis consists of a set of techniques that clearly consider the geographical position of the values of a given variable. Flores [30] affirms that spatial analysis allow for the study the phenomena related to any type of crime in a more exact way, in which it could facilitate the identification of concentrations in space. Flores [30] also points out that these techniques are not performed in a theoretical vacuum, but through mathematically formulated models that quantify and predict the variation of phenomena related to crime. In general, analyses that seek the existence of patterns—cluster areas—in the spatial distribution of the elements under analysis stand out [31].

These analyses can be developed through several types of tools, ranging from Exploratory Spatial Data Analysis (ESDA) techniques [32–34], to other procedures that allow the identification of correlations between variables, such as the Ordinary Least Squares Regression (OLS) [35–37] or the

Spatial Autoregressive models (SAR) [38], as well as the geographically weighted regression (GWR), which enables the detection of the heterogeneity and spatial variation of variables [39–41].

The use of the ESDA technique in Brazil is already disseminated among researchers who use it for crime studies (Sass et al.) [42]. For instance, Almeida et al. [43]; Farias et al. [44]; Carrets et al. [45]; Plassa et al. [46] used ESDA to identify a spatial autocorrelation between crime and socioeconomic variables in different timeframes in Brazilian towns. In these studies, it was observed that crime rates are not randomly distributed in space; and that there is a strong positive spatial autocorrelation, meaning that several cities in Brazil that have high (or low) crime rates and are close to other cities that also have high (or low) crime rates.

In Pernambuco, the use of spatial analysis to study the phenomenon of crime has already been the subject of some studies. Lima et al. [21] used ESDA techniques to identify the spatial pattern of homicide rates among men with ages from 15 to 49 years old in Pernambuco in the period of 1980 to 1984 and 1995 to 1998, and concluded that socioeconomic conditions are precisely the driving forces behind the increase of homicides. In this same study, the authors also concluded that the phenomenon of crime is not randomly distributed in space. Souza Sá [14] found that there is positive spatial autocorrelation between homicide rates for the year 2016 in Pernambuco, and spatial clusters have also been identified in some regions in the state.

In addition to the Exploratory Spatial Data Analysis (ESDA) techniques, other tools are widely being employed for crime studies. Sass et al. [42] used spatial models of Spatial Autoregressive Model (SAR) and Geographically Weighted Regression (GWR). The results of the SAR model revealed that homicide rates in different cities of Paraná are influenced by the poverty rate, the degree of urbanization, as well as the characteristics of the adjacent towns. The results for the GWR, the model applied in this research, indicated that the local characteristics of the municipalities are very important in determining the factors that influence homicide rates.

3. Materials and Methods

3.1. Study Area

The area studied was the state of Pernambuco, which is located in Brazil's northeastern (Figure 1).

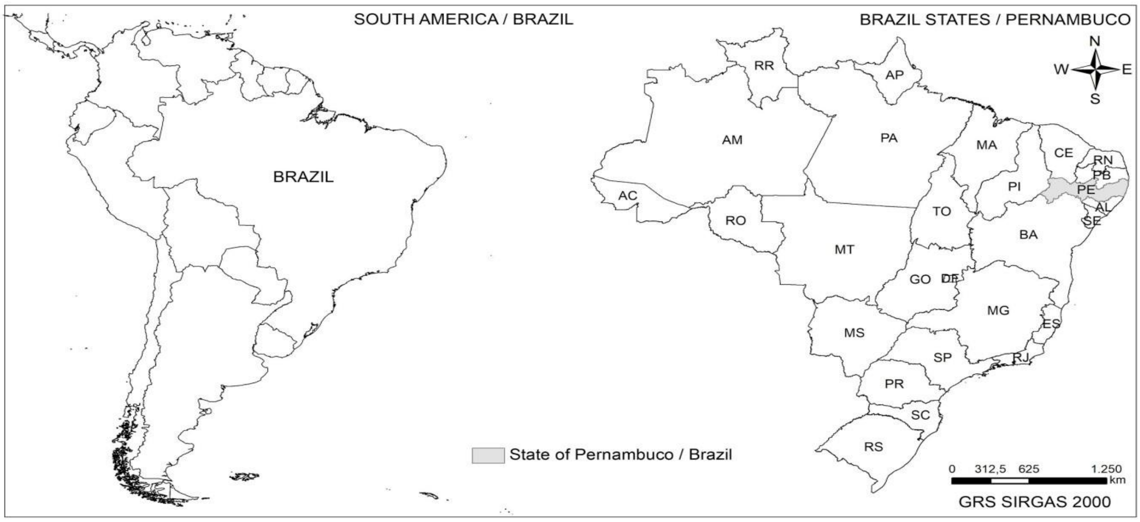

Figure 1. Location of the state of Pernambuco.

The state of Pernambuco is divided into 185 cities (Figure 2), which add to 9,557,071 inhabitants in the year of 2019, arranged in an area of 98,067.881 km². Additionally, the Instituto Brasileiro de Geografia e Estatística (IBGE), the official agency responsible for national census in Brazil, groups the cities into five mesoregions: Metropolitan Region of Recife, Mata Pernambucana, Agreste Pernambucano, Sertão Pernambucano, and São Francisco Pernambucano. The most populated city is the capital of Pernambuco, Recife, with an estimated population of 1,645,727 inhabitants in the year of 2019. Recife is located in the Metropolitan Region of Recife (MRR), which has an estimated population of 4,054,866 inhabitants (in the year of 2019). The MRR has an area of 218.435 km^2, with a Gross Domestic Product (GDP) of approximately 51,819,619 thousand reais at current prices in 2017. According to data from the 2010 Census [47] and the most recent estimations, the state of Pernambuco is considered to be the seventh most populous state in Brazil and it represents approximately 4.7% of the Brazilian population.

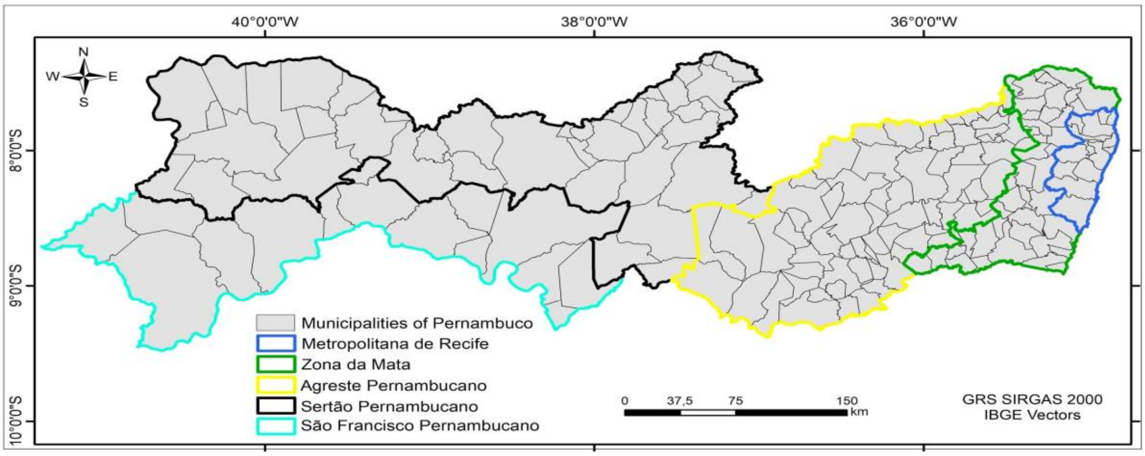

Figure 2. Location of Pernambuco's mesoregions.

On the ranking of the GDP, the state is in 10th position among the 27 units of the federation, with R$181,151 billion. It has a Human Development Index of 0.727, considered to be relatively high by the IBGE data [47].

The rest of the state's municipalities form 26 integrated security areas (ISA), which are smaller areas where police forces work in an integrated manner in order to reduce crime rates. The idea of dividing the state into smaller areas to concentrate the police effort and facilitate the monitoring of the indicators was developed in 2007, when Pernambuco implemented the Pact for Life (PFL) program.

The PFL comprises a public security policy based on the territorial logic from the state of New York, the CompStat which has as main objective the reduction of intentional lethal violent crimes (ILVC), subdivided in: serious aggression followed by death and theft followed by death. Monitoring is done using safety indicators, comparing areas, and allocating resources to those with the worst results [48].

3.2. Methodological Procedures

Methodological procedures were showed in the research according to the flowchart, illustrated in Figure 3. In this way, data acquisition (Section 3.3), data processing (Section 3.4), and homicide spatial distribution (Section 4) of Pernambuco State, Brazil are described below.

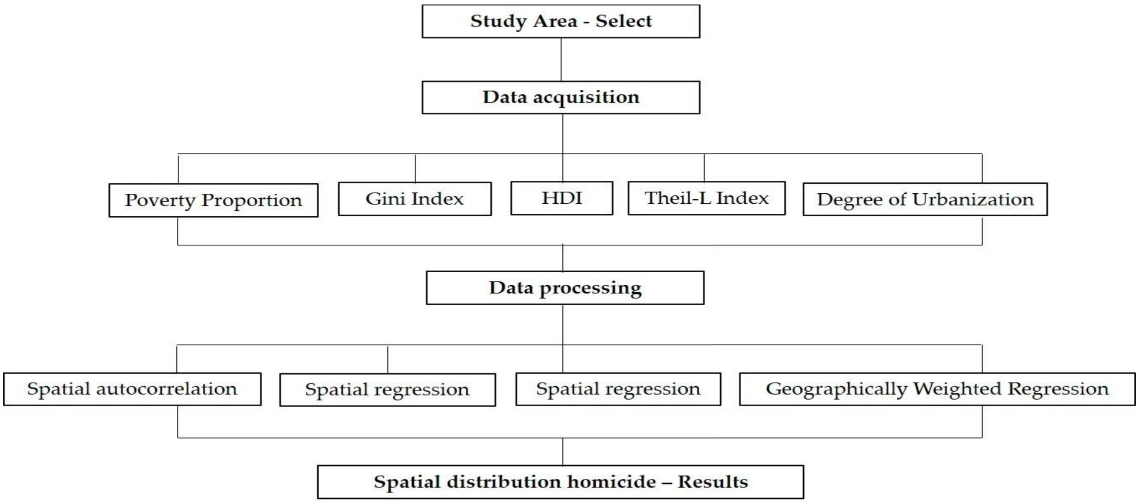

Figure 3. Synthesis of the methodological procedure.

3.3. Data Acquisition

The analysis was employed through the amount of homicide notifications (intentional homicide, injuries followed by death, and theft followed by death) for both sexes in the 184 cities of the state of Pernambuco from 2016 to 2019. These data were obtained from the Department of Social Defense of Pernambuco (DSD-PE).

Population data for each city were obtained from the Brazilian Institute of Geography and Statistics (IBGE) from the years of 2016 to 2019. Municipal socioeconomic, demographic and urban infrastructure (Table 1) data were based on the last demographic census (2010) and were formulated in two variables.

For the socioeconomic variables: Poverty Proportion (%), Gini Index (%), Human Development Index—HDI (%) and Theil-L Index (%). For the demographic variable: Degree of Urbanization (%).

All of them were obtained through IBGE (2010) data. The municipal limits were also acquired from IBGE, in the shapefile form.

Table 1. Explanatory variables, indicators and descriptions.

Variable	Indicators	Description
	Poverty Proportion	ercentage of the resident population with per capita monthly family income of up to half a minimum wage, in a given geographic space, in the year considered.
	Gini Index	neasurement for assessing the degree of unequal distribution of income.
Socioeconomic	HDI	Measurement composed of indicators of three dimensions of human development: longevity, education, and income.
	Theil-L Index	ietic indicator that measures unequal distribution of income.
Demographic	Degree of Urbanization	Percentage of the population residing in urban areas, in a given geographical space, in the year considered.

3.4. Methods

3.4.1. Spatial Autocorrelation

An exploratory analysis of spatial data was performed in order to determine the measures of spatial autocorrelation of homicide rates. Initially, to reduce the variation in homicide reporting rates by city and the possible random fluctuations resulting from the analysis of low populations, the empirical Bayesian estimator in the matrix of weights type Queen in the Geoda software, which considers all cities with common borders [49]. This estimator calculates a weighted reporting rate considering regional variations and, thus, enabling comparisons between different populations. In the state of Pernambuco, according to IBGE [50], 75 municipalities have less than 20 thousand inhabitants, which accounts for about 40% of the total 185 municipalities. Thus, most of these municipalities are small and the distribution of homicides is heterogeneous.

Using the Global Moran's Index, spatial autocorrelation was calculated based on the data on the homicide rate per 100 thousand inhabitants for each city in Pernambuco. According to Meng et al. [51] the Global Moran's Index is a form of measuring spatial autocorrelation, whose value ranges from −1 to +1, providing a general measure of spatial association. A positive spatial autocorrelation indicates that the neighboring areas present values similar to those of the studied area; a negative spatial autocorrelation points out that the neighboring areas have different values from those of the studied area. When those values are close to zero, these results indicate the absence of a significant spatial autocorrelation between the values of objects and their neighbors in the study area.

In addition, according to Anselin [31], local indicators of spatial association (LISA) are used to identify clusters, which can be viewed on the cluster map (Figure 5). Therefore, the results of global and local statistics are complementary. The Global Moran's Index answers the question whether the phenomenon of spatial autocorrelation occurs throughout the analyzed area, while the Moran Local statistics indicate in which part of the analyzed area this phenomenon occurs.

In this sense, spatial clusters were categorized accordingly to the patterns and characteristics of the adjacent cities. Spatial clusters from the type high-high (HH) form a set of municipalities with high rates that are surrounded by others with high averages of homicide rates. Low-low clusters (LL) form a set of cities with low rates surrounded by municipalities with low averages of homicide rates. All global and local spatial autocorrelation coefficients were considered significant when the p-value < 0.05.

3.4.2. Spatial Regression

Even though the Global and Local Moran's Index consists of very popular spatial statistical analysis techniques, these are univariate and do not consider multivariate effects. Thus, it was preferred to use regression models with and without control to identify spatial dependence within the model. Therefore, the Ordinary Least Squares (OLS) regression and the Geographical Weighted Regression (GWR) models were applied for the investigation of the relationship between homicide rates (dependent variable) in Pernambuco and the independent variables.

Ordinary Least Squares Regression (OLS)

For the analysis of Ordinary Least Squares (OLS) regression, all variables were included in a database later shown, as they are correlated with homicide rates. In order to find the best model, an analysis was repeatedly conducted to choose the model with the best R^2 value and Akaike Information Criteria (AIC). In addition to that, a parsimonious model free from multicollinearity problems was pursued. For the OLS, the variables of Human Development Index (HDI), Theil-L Index, Proportion of Poor Population, Gini Index, and Degree of Urbanization were included in the model. Soon after this, the residues of the OLS model were tested for spatial autocorrelation using the Moran's I to assess the extent of the result that could be explained by the spatial component after modeling the predictors. Spatial autocorrelation was perceived in its residues, so the OLS model is not the most adequate to represent the homicide rate. Thus, we opted to choose to use models that consider the spatial correlation, as already mentioned: the GWR [52], which is described below.

Geographically Weighted Regression (GWR)

Geographically weighted regression (GWR) has been proposed in the literature by Brunsdon et al. [52] for the relations between variables in the regression model could vary in space. GWR is an adaptation of the local regression model in spatial econometrics. The aim of local regression is to estimate a value at a given point based on your neighborhood. Fotheringham et al. [53] describes the GWR model according to Equation (1).

$$y_i = \beta_0(u_i, v_i) + \sum_n^{i=1} x_{i,k}\beta_k(u_i, v_i) \quad (1)$$

where i is the observation number, $i = \{1, \ldots, n\}$, k is the feature number in the set, $k = \{1, \ldots, P\}$, y_i is the value of the explained variable of the ith observation, x_i, k is the value of the kth feature of the ith observation u_i, vi are the geographical coordinates of the observation, and $\beta_k (u_i, v_i)$ is the value of the effect of the kth feature for given graphic coordinates. In the estimation process, an iterative maximization algorithm is required to estimate model parameters at location i. The maximum of each local log-likelihood function can be obtained by using the Newton-Raphson approach, defined by Franses and Paap [54] through Equation (2).

$$\theta_m = \theta_{m-1} - {}^{H-1}(\theta_m - 1)G(\theta_m - 1) \quad (2)$$

where $G(\theta)$ and $H(\theta)$ are the first-order and second-order derivatives of the local Log-likelihood function l (θ (u_i, v_i)) with respect to model parameters θ, which are also known as the gradient and Hessian matrix of a likelihood function, respectively.

The motivation of the GWR proposal is the idea that it is not reasonable to assume that a set of constant regression coefficients can adequately capture the relationships between independent variables and response variables, which are spatially correlated. In this article, as the strong positive spatial autocorrelation (univariate) was verified for the dependent variable, Geographically Weighted Regression (GWR) was chosen to identify possible local spatial associations and confirm the spatial effect of the multivariate model. That way, the coefficients for each explanatory variable that were significant in the global model were substantial to determine the impact of space on the result. Compared with the OLS model, which presents constant regression coefficients in relation to the geographic space (stationarity), the coefficients of the GWR models are estimated locally from an analysis of the spatial variability of the results generated for each area, which it allows checking for the presence of spatial non-stationarity. As a result, the GWR model generates a set of local linear regression models instead of a global model with estimates for each variable in space. The behavior of the GWR model was evaluated based on the Akaike information criterion (AIC), R^2, and Moran's I indicators of the residuals of both models.

3.5. Software Used

For the spatial autocorrelation, the Terra View software was used, available free of charge by the National Institute for Space Research (INPE), while for the OLS and the GWR models the R software was employed. QGIS Desktop Software 3.10.5 was used to create all the maps.

4. Results

4.1. Spatial Distribution of Homicide Rates in Pernambuco

Figure 4 represents the spatial distribution of the average rates of homicides from 2016 to 2019 in Pernambuco. In general, a high concentration of homicide rates in the Metropolitan Region of

Recife, Zona da Mata, and in the eastern portion of the Agreste Pernambucano mesoregion is found. For that matter, 37 cities in Pernambuco had a rate greater than 0.5 homicides.

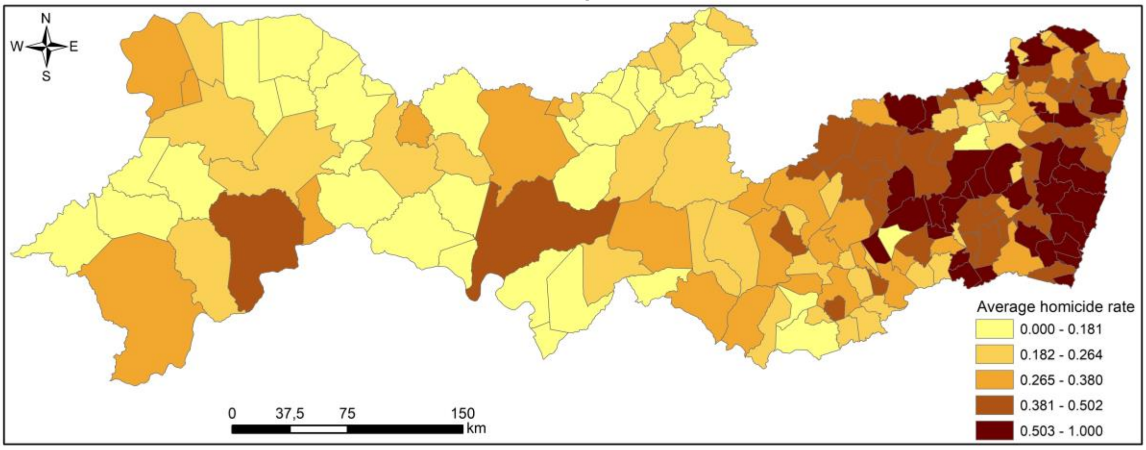

Figure 4. Homicide rates in the state of Pernambuco.

4.2. Moran Global I and LISA

For the Global Moran Index, which assesses the existence of a global spatial correlation, a results of I = 0.49 was obtained. The result of the pseudo-significance test indicates a significant spatial dependence on the average homicide rate with the *p*-value of $p = 0.001$. According to Almeida et al. [43] and Anselin [31], Moran's I is a measurement of global association, which may or may not conform to local standards. In that way, global measures can hide local patterns of association. Therefore, in a complementary way to the Global Moran I, it was used the local spatial autocorrelation statistics, LISA. The LISA statistics can provide a better understanding of the spatial distribution, on a more detailed scale of the patterns of homicide rates in the state of Pernambuco. In this process, the significant values of the Local Moran index obtained for each object (polygon) was evaluated, in relation to the hypothesis of the non-existent spatial autocorrelation (null hypothesis).

Thus, Figure 5 shows the distribution of clusters that reveal the spatial autocorrelation for homicide rates, confirming a spatial dependency. This data also sugestthe coastal-interior polarization of the state. In addition to that, it wasobserved that the High-High (HH) clusters are concentrated in the Metropolitan Region of Recife, Zona da Mata, and Agreste Pernambucano. The Low-Low (LL) clusters are concentrated in the Sertão Pernambucano and Sertão de São Francisco mesoregions; that is, these results corroborate the map from the previous session. In this sense, 33 citieswere grouped in a HH cluster.

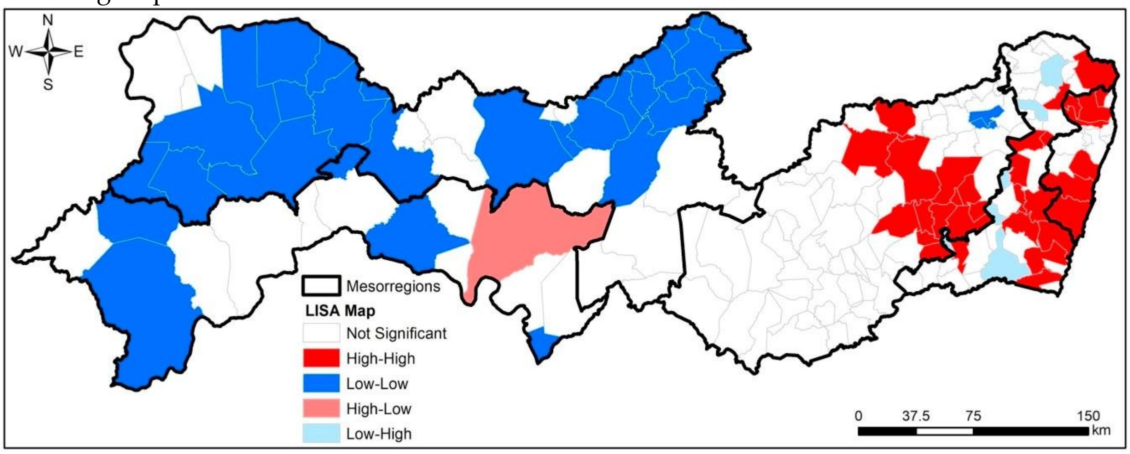

Figure 5. LISA map (Average homicide rate).

4.3. Ordinary Least Squares Regression

Initially, the Ordinary Least Squares (OLS) regression model was applied. OLS regression can be used to identify statistically significant associations between the variable response and the dependent variables. Here, the interest in identifying associations between homicide rates and socioeconomic variables in the cities of Pernambuco was the main objective. To select the independent variables for the proposed model, the stepwise method of variable selection was used, together with the Akaike information criterion (AIC) (the model with the lowest AIC was chosen). Table 2 outlines the variables selected for the model, such as, the regression coefficients, standard error, significance of the coefficients, and finally, the Variance Inflation Factor (VIF) index, which were calculated to identify the existence of multicollinearity. Consequently, the independent variables chosen for the model were: HDI, Theil-L Index, Degree of Urbanization, Poverty Proportion, and Gini Index. All variables were significant, with $p < 0.01$. The determination of these variables was, according to Teivans-Treinovskis et al. [3], important to determine the unlawful conduct of criminals who commit violent crimes, and it is necessary to point out socioeconomic factors that have a substantial impact on those crimes.

Table 2. Results of the OLS model for homicide rates.

Variables	Estimates	Std. Error	t-Valor	*p*-Value	VIF
Intercept	0.142	0.051	2.806	0.006	–
HDI	−0.428	0.095	−4.506	0.000	2.122
Theil-L Index	−0.333	0.069	−4.814	0.000	2.226
Degree of Urbanization	0.255	0.069	3.678	0.000	2.391
Poverty Proportion	0.433	0.090	4.788	0.000	3.077
Gini Index	0.338	0.099	3.404	0.001	2.587
R2	0.44				
AIC	−195.8				
Autocorrelation Test and heteroskedasticity tests	z statistic	*p*-value			
I de Moran (residuals)	0.161	0.001			
Breusch-Pagan test	9.578	0.08			

Additionally, it was identified that the estimated coefficients for the variables HDI and Theil Index were negative, meaning there is a negative association with the homicide rate. Therefore, the higher the city's HDI and Theil-L Index, the lower the homicide rate. In contrast, the variables degree of urbanization, proportion of poor population, and Gini index presented positive coefficients. Therefore, the higher the value of these variables, the higher the homicide rate. Regarding the the assumption of multicollinearity, all variables had a VIF value <7.5, indicating that there was no multicollinearity in the OLS regression model. The adjusted R^2 indicated that the models explained about 44% of the total variance in homicide rates. However, the residuals from the OLS model showed a significant positive spatial autocorrelation (Global Moran's I = 0.161, *p*-value = 0.001); thus, the assumption of the OLS regression that the residuals are independent was not reached. To solve this limitation, the GWR spatial model can be used to characterize the relationship between homicide rates and independent variables. Finally, the Breush-Pagan test, proposed by Koenker [55], were applied to check heteroskedasticity in the residuals (BP = 9.578, *p*-value = 0.08). The null hypothesis that residuals are homoscedastic

wasrejected, in other words., the heteroscedasticity was found to be statistically significant. ($p <$ 0.10). To solve this limitation, the GWR spatial model could be used to characterize the relationship between homicide rates and independent variables.

4.4. GWR for Homicide Rates

In Table 3, the GWR coefficients for the homicide rate were presented in terms of statistical measures, such as: minimum, first quartile, median, third quartile, and maximum. The adjusted R^2 of the GWR is 0.73, that is, the GWR model explains 73% of the variations in homicide rates in the cities of Pernambuco. Also, it was possible to verify that the value of R^2 in the GWR model is 62% higher compared to the OLS regression model. There was a significant gain in the model when using an approach that considers the relationship between the neighboring cities.

Table 3. Results of the GWR model for homicide rates.

Variables	Min.	1st Q.	Median	3rd Q.	Max.
Intercept	−0.156	0.070	0.132	0.258	0.359
HDI	−0.907	−0.488	−0.243	−0.049	0.245
Theil-L Index	−0.687	−0.243	−0.144	−0.045	0.225
Degree of Urbanization	−0.228	0.080	0.287	0.453	0.961
Poverty Proportion	−0.205	0.042	0.231	0.434	0.735
Gini Index	−0.361	−0.008	0.131	0.258	1.022
R2	0.73				
AIC	−290.36				

One of the great advantages of the GWR model, is that through the local R^2, it is possible to identify the areas to best fit the model. Thus, it is possible to have a spatial visualization of the model's performance to explain homicide rates in different areas.

Figure 6 illustrates the distribution of local R^2 according to homicide rates in different cities. The distribution is not homogeneous among the municipalities, that is, the performance of the model can vary in different mesoregions of the state of Pernambuco. In general, GWR performs well for part of the mesoregions with R^2 values above 0.6. However, the cities in the Zona da Mata

Sul, Sertão de Pernambuco, and Sertão de São Francisco mesoregions have a lower local R^2 values. These low R^2 values suggest that there could be additional independent variables that could have influence in homicide rates on these regions.

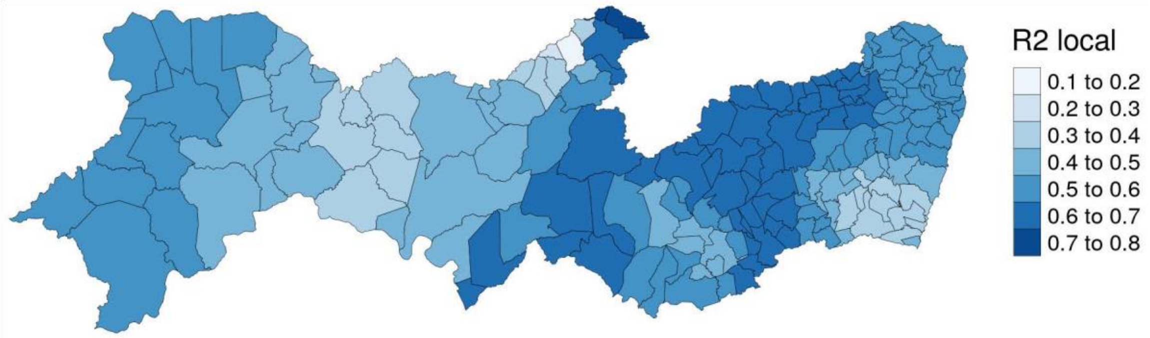

Figure 6. Distribution of local R^2 for the GWR model.

In the OLS regression model, the sign of the coefficient indicates the direction of the relationship between the variable response and the explanatory variables. In the case of GWR also, however, the strength and direction of the coefficients could vary accordingly to the region. In general, the spatial patterns of the local coefficients are similar to the results of the OLS regression; however, in some regions the direction of the relationship between the response variable and the explanatory variables may vary.

For example, the HDI variable (Figure 7) is negatively related to homicide rates in most of the municipalities in Pernambuco, for example, in the Mata Pernambucana, the Metropolitan and the

Agreste (north and east) regions. In addition to the cities in the Sertão Pernambucano mesoregion, Itapetim, São José do Egito, and Tuparetama, the strength of the relationship between the HDI and homicides is more evident in some municipalities, which are represented by the strongest red color.

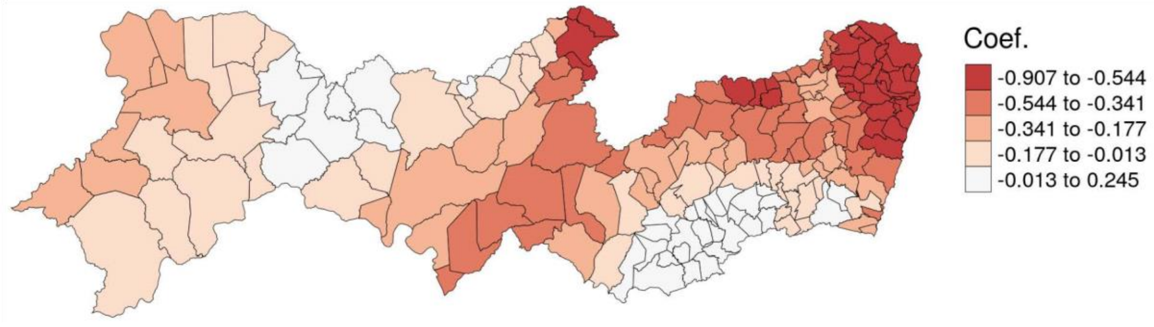

Figure 7. Distribution of the local coefficients of the GWR model (HDI).

Regarding the Theil-L Index variable (Figure 8), there was also a negative relationship in homicide rates, mainly evidenced in the mesoregions of Zona da Mata, North Metropolitan Region of Recife, and the municipality of Itapetim.

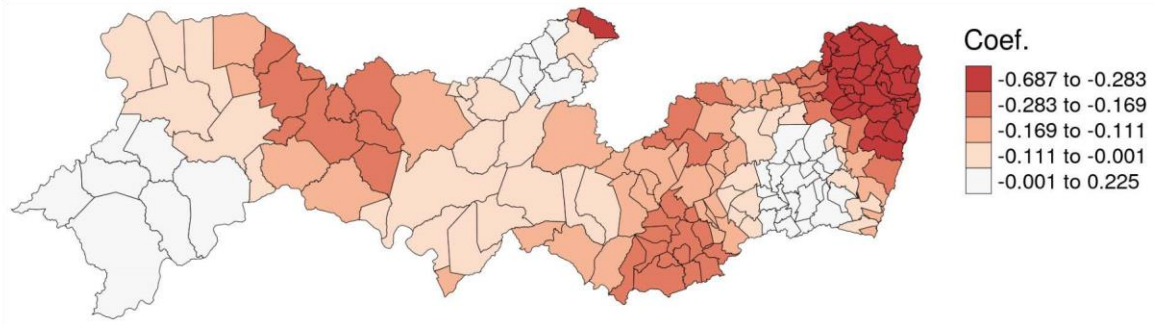

Figure 8. Distribution of the local coefficients of the GWR model (Theil-L Index).

The degree of urbanization (Figure 9) had a greater impact in the northeastern regions of the Agreste towards the Metropolitan Region of Recife.

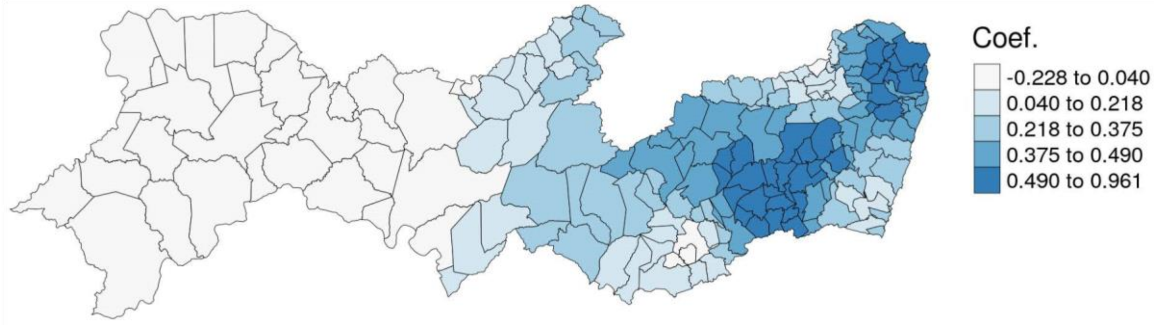

Figure 9. Distribution of the local coefficients of the GWR model (Degree of urbanization).

The GINI Index (Figure 10) had a greater impact in the Metropolitan Region of Recife and in the North Sertão de São Francisco. Finally, the poverty proportion (Figure 11) had a greater influence in the Sertão de São Francisco region, Zona da Mata/Litoral Sul, and Agreste.

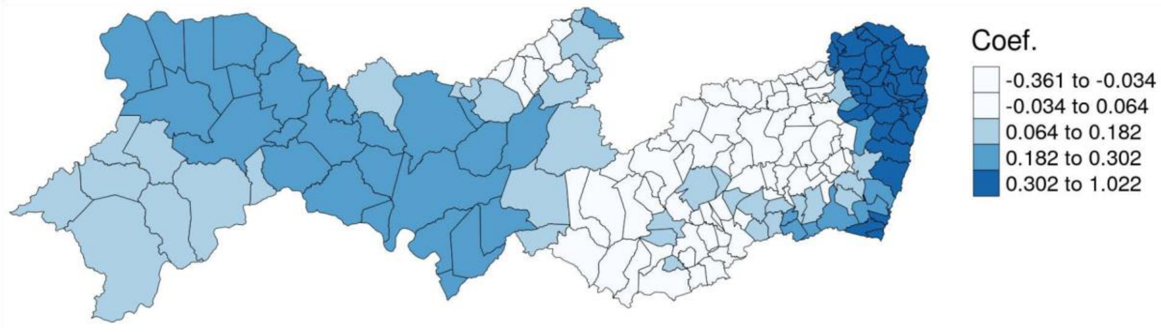

Figure 10. Distribution of the local coefficients of the GWR model (GINI Index).

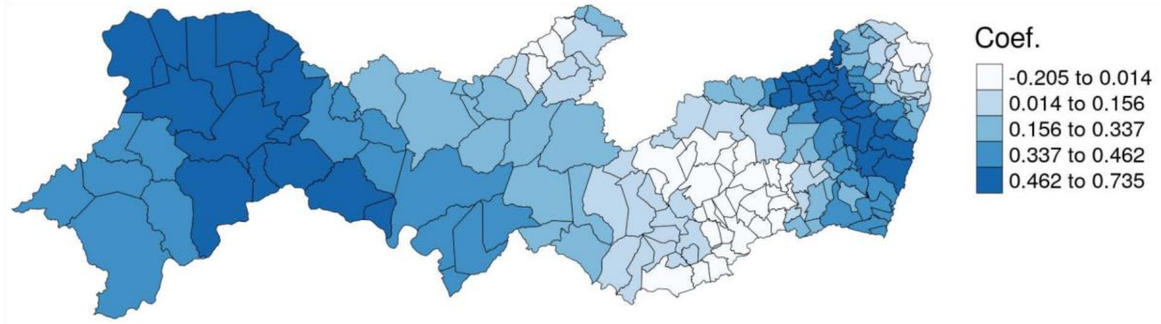

Figure 11. Distribution of the local coefficients of the GWR model (Poverty Proportion).

The use of GWR is of fundamental importance, as it presents local details that OLS regression is not able to visualize, as it assumes that the spatial distribution of homicide rates are random, which we previously observed that is not a valid assumption and, in addition to that, the results of the GWR model made a significant progress in the identification of clusters that can facilitate the identification of homicides according to each region.

5. Discussion

Spatial analysis of the average homicide rates in the state of Pernambuco have revealed clusters of cities with different areas in the period studied. Through the results, it was observed that the homicide phenomenon is not evenly distributed in space. This article complements existing research by empirically studying the spatial aspects of homicide patterns at the municipality level.

Thus, a comparison can be made with studies conducted in other Brazilian states, such as the works of [46,56–58] and it was observed that this research corroborates with those other studies. Therefore, it was observed that homicide clusters do occur in metropolitan regions. The authors found the presence of positive spatial autocorrelation in the data, meaning that regions with high homicide rates were surrounded by areas presenting the same pattern [46]. The exceptions are the high homicide rates mapped in the state of Pará. In this state, homicides are highly related to conflicts over land in rural areas [56].

It was observed that high population concentration is directly related to the occurrences of homicides in the state of Pernambuco. This conclusion was corroborated with the work from [14], who affirmed that homicides are associated with most populous cities [14]. Furthermore, according to [14], locations with greater economic prosperity, in addition to concentrated a high number of inhabitants, also have an ideal environment for violence growth. Other aspects that can explain the high homicide rates are for instance, a higher proportion of men aged between 18 and 24 years old in relation to the total population [59], the level of income, drug trafficking [60], school lag, among others. Despite this, there was no evidence in this research that illiteracy and low per capita income are directly related to high homicide rates. However, it was related to areas where the highest unemployment and urbanization rates occur.

Almeida [61] suggests the performance of statistical tests in order to confirm whether the variables are randomly distributed in space or auto correlated, through Global Moran's Index. Initially, the results of the spatial autocorrelation analysis using the Global Moran's Index revealed a possible spatial interaction between the homicide rates and socioeconomic, demographic and urban infrastructure variables throughout the analyzed period. Studies that were carried out by [22,62] indicated that the phenomenon of crime is not evenly distributed in space; rather, it is concentrated in municipalities, cities, or neighborhoods that share similar characteristics. Then, using the LISA map, groupings of spatial clusters of the High-High type were identified in the Metropolitan Region of Recife, Zona da Mata, and Agreste, indicating a high concentration of homicide rates in cities with large populations. Regarding to the Low-Low type, clusters were identified in the mesoregions of Sertão de São Francisco and Sertão Pernambucano, which are mesoregions that include a large part of the cities with populations of less than 20 thousand inhabitants. Studies performed by [14] identified clusters of High-High type in mesoregions such as the Metropolitan Region of Recife, Zona da Mata, and Agreste, also corroborating the results of the research presented here.

The relevancy of this article is highly noticeable since it considers the socioeconomic, demographic, and urban infrastructure characteristics from 2016 to 2019 at the municipality level. According to the choice of the regression model OLS diagnosis, it indicated that this transversal regression method cannot generate consistent results for the homicide phenomenon in Pernambuco. Lima et al. [21] also used the classic OLS regression model and found it was not suitable for analysis of the phenomenon, so the authors moved towards the use of spatial regression models, thus corroborating the choice of the GWR model for this article. Due to this, many studies of spatial analysis of crime in Brazil also have used the GWR regression model in order to explain the phenomenon of crime using variables such as: Gini Index [42,63], Degree of Urbanization [42,58], HDI [64], Theil-L index [65], and poverty Proportion.

According to de Barros et al. [64], the increase in the average Human Development Index (HDI) generally leads to a reduction in crime in a given region. In the cities of Pernambuco, this is no different, considering that this indicator is based on a series of factors (such as life expectancy, literacy, education, and living standards) that can directly impact the population's well-being. However, it can be considered that increases in the HDI should have a negative impact on the crime rates of a given location. More information about the Human Development Index can be seen at the United Nations Development Programme website (http://hdr.undp.org/en/content/human-development-index-hdi). This is possible, above all, because of the increase of the economy due to the legal sector earnings compared to the earnings of the illegal sector when education, life expectancy, and the standard of living of agents are improved.

Regarding the Gini Index variable, it is clear that a series of studies converge on similar results. Plassa et al. [46,58] among others, prove that crime grows when the income in a given region is more concentrated. A positive value for the Gini Index variable suggests that the higher the concentrated income on this cities, the higher the homicide rate gets. Becker and Kassouf [66] verified the influence of social inequality on crime for Brazilian states and the Federal District from the period of 2001 to 2009, and found that social inequality, represented by the Gini index, has a positive effect on crime, thus corroborating the present research.

With the Theil-L Index variable, it was observed that part of the MRR presented negative values.

These results are consistent with those found by Bezerra et al. [65]. According to the authors, the Theil-L Index variable shows results that are contrary to what was expected: as its negative sign states, when the number of homicides increases, the rates decrease, indicating less income inequality [65].

Crime is expected to increase with inequality, as reported by other authors.

As far as the variable Degree of Urbanization, it was possible to verify that there was a direct relationship between the high rate of urbanization and municipalities with a cluster of homicides, as already observed for the whole country by [59] and for the state of Paraná by [42]. In this sense, according to [46], variables such as urbanization and population density, when linked to large centers, were also considered statistically significant for the increase in homicide rates. According to [65], urbanization accentuates social inequality. Generally, the higher the rate of urbanization in Brazilian cities, the higher chance of basic problems of urban infrastructure are, complicating the access to educational establishments, among others. In addition, there are neighborhoods intended for housing for the upper and middle classes of the population coexisting with neighborhoods occupied by low-income residents, the so-called "favelas."

Finally, the GWR regression model proved to be quite promising to be able to explain the relationship between homicide rates and independent variables. Thus, the use of GWR is of vital importance, as it presents local details that the OLS regression is not able to visualize, as they assume that the spatial distribution of homicide rates is random. However, we saw in this article that this assumption is not valid; consequently, the results of the GWR model had a significant advance in the identification of clusters that can facilitate the identification of homicides accordingly to each region.

Some works in the literature have also found fine results to solve problems involving crime using the GWR model. Cahill and Mulligan [67] explored spatial patterns of violent crime in Portland, Oregon. The authors demonstrated the usefulness of GWR to explore local processes that promote higher crime levels. In the present study, we explored spatial patterns of homicide rates relating to socioeconomic factors in the municipalities of Pernambuco. A better performance was identified in relation to the OLS model. The adjusted R^2 of the GWR was 0.73, meaning that the GWR model explains 73% of the variations in homicide rates in the cities of Pernambuco (a 62% increase compared to the OLS regression model).

According to Wang et al. [22], criminal activities tend to be unevenly distributed in space, often concentrated in certain neighborhoods, and also influenced by socioeconomic factors and the opportunity for crime. This was observed in the occurrence of violent crimes in the adjacent cities to Toronto. In this article, the socioeconomic variables HDI, Theil-L Index, Degree of Urbanization, PovertyProportionandGiniIndexinfluencethevariationinhomiciderateSinPernambuco. Thevariable HDI and Theil-L index have a negative influence on homicide rates. Meanwhile, the Degree of Urbanization, Poverty Proportion, and Gini Index have a positive influence. Therefore, public policy proposals are required to increase the municipalities' HDI, and decrease the proportion of poor population, Gini index, and Degree of urbanization. Regarding the Theil-L index, there is still a need for a more in-depth study to identify the reasons that the concentration of income reduces crime, contrary to expectations.

Using property crimes data as a spatial reference in addition to the census data, Andresen and Ha [68] used geographically weighted regression to investigate the effects of immigration measures on various classifications of property crimes in the census sectors of Vancouver, Canada. The authors identified that the estimated parameters vary in space, even though the covariate effects are not always relevant at the local level. In this article, we found a similar result to explain homicide rates in Pernambuco. It was identified that the HDI variable (Figure 7) was negatively related to homicide rates in most cities of Pernambuco. For example, the weights of the coefficients are more determinants in the regions of Zona da Mata, Metropolitan Region of Recife, and Agreste Pernambucano (north and east). Furthermore, in the south of the Zona da Mata, the coefficients have lower or positive weights. This indicates that, in this region, the HDI is not a significant explanation for homicides. This fact can help in the guidelines for actions to tackle homicides in the state, being able to concentrate its efforts in the regions with the greatest influence of each variable from the model.

6. Conclusions and Recommendations

The aim of this article was to investigate the spatial analysis of homicides in the state of Pernambuco, Brazil, between the years 2016 to 2019. The results allowed us to conclude that the statistical grouping methods and regressions were satisfactory for the analysis of homicides. Thus, this research can contributed to the literature in understanding the factors associated with lethal violence in the Northeast Region of Brazil.

In summary, the results indicated that public policies for prevention of homicides should be centered on raising the municipalities' HDI, that is, education, income, and longevity. In this sense, tackling poverty and income inequality are also fundamental, which are significantly associated with the increase in homicides.

It is important to note that this research has limitations that should be on the agenda for new studies on the subject. First of all, the results must be understood for the context of the state of Pernambuco, where the analyses were carried out. However, this methodology should be expanded to other units of the Federation to verify the degree of generalization of the results. Secondly, the predictor variables date from 2010 and are referring to the last census. In that way, new studies should consider more variables with the upcoming years, resulting in a better understanding of the social/spatial determinants of lethal violence in Brazil. Thirdly, regional studies towards the public policy of prevention should assess how the Integrates Security Areas (ISA) are important to explain crime rates reduction in Pernambuco [69]. Finally, future works should focus on the behavior of the Theil-L index, given that the result of this research was the opposite of what was expected; even though, it was corroborated by the findings of another study [65]. To solve this gap, qualitative studies must be carried out in the regions where this phenomenon occurs, as well as the addition of new variables of inequality in the models for quantitative approaches.

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4 CONSIDERAÇÕES FINAIS

A dissertação foi composta por dois capítulos na forma de artigos. Ambos os capítulos tiveram como objetivo geral realizar uma análise espacial dos homicídios para a região Nordeste do Brasil, ano de 2010 e para o estado de Pernambuco, de 2016 a 2019. Foram utilizados o Índice de Moran, Regressão Linear Múltipla e a Regressão Geograficamente Ponderada.

Os resultados, apresentados no Capítulo 2 do primeiro artigo, foram utilizados métodos espaciais para realizar a análise espacial dos homicídios na região Nordeste do Brasil sob a perspectiva da teoria da desorganização social. Estudos utilizando essa teoria, ainda é considerada escassa e, pode ser instrutivo devido ao alto grau de violência letal no Brasil. Em geral, os resultados indicaram que o efeito das minorias raciais e da heterogeneidade étnica está positivamente relacionada ao aumento das taxas de homicídios. Como também permitiram concluir que os métodos estatísticos de agrupamento e regressão foram satisfatórios para análise dos homicídios. Desse modo, esta pesquisa contribuiu com a literatura no entendimento dos possíveis fatores associados aos homicídios na Região Nordeste.

Já no Capítulo 3, que apresenta os resultados do artigo dois, foi possível concluir que a criminalidade no território pernambucano encontra-se concentrada na Região Metropolitana do Recife (RMR), Zona da Mata e Agreste, como indicado na análise espacial, através do levantamento de agrupamentos do fenômeno em questão. Assim, este artigo permitiu destacar que, as variáveis econômicas, sociais e de infraestrutura urbana são relevantes na determinação dos índices de criminalidade no Estado de Pernambuco.

Em síntese, os resultados indicam que as políticas públicas de prevenção de homicídios devem estar centradas na elevação do IDH dos municípios, ou seja, educação, renda e longevidade. Esses resultados encontrados mostraram que políticas públicas e de segurança seriam mais eficazes em reduzir a violência na região Nordeste se contribuírem com a geração de emprego e com as reduções das desigualdades de renda, principalmente nos grandes centros. Ademais, o combate à violência deve ser uma política regional (e não apenas municipal) uma vez que a violência de cidades vizinhas tem impacto positivo sobre as taxas de homicídios de um determinado município.

Esta dissertação revestiu-se de importância, na medida em que apresentou a distribuição espacial dos homicídios na região Nordeste no primeiro artigo e no estado de Pernambuco, dando vista às regiões que se destacaram com altos e baixas taxas de homicídios, além de demonstrar a interrelação entre municípios vizinhos e, fundamentalmente, relacionam-se às taxas de homicídio e as variáveis socioeconômicas, demográficas e de infraestrutura urbana. A intenção desta dissertação não foi esgotar o tema, mas contribuir para o avanço das discussões dessa problemática atual, bem como fornecer subsídios para adoções de políticas públicas de combate e prevenção dos homicídios nos municípios da região Nordeste. Isso ocorre com base nas associações do crime e nas suas especificidades regionais que podem influenciar no efeito desejado da política pública, caso suas particularidades não sejam consideradas.

Por fim, trabalhos futuros devem enfocar o comportamento do índice Theil-L, visto que o resultado do artigo 2 foi o oposto do esperado, no entanto, corroborou com o estudo de Bezerra et al., (2012). Para contornar essa lacuna, estudos qualitativos devem ser realizados nas regiões onde esse fenômeno ocorre, bem como a adição de novas variáveis de desigualdade nos modelos para abordagens quantitativas.

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