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Spatial Modeling for Homicide Rates Estimation in Pernambuco State-Brazil

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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 Teivāns-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 Teivāns-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, Dağlar 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).

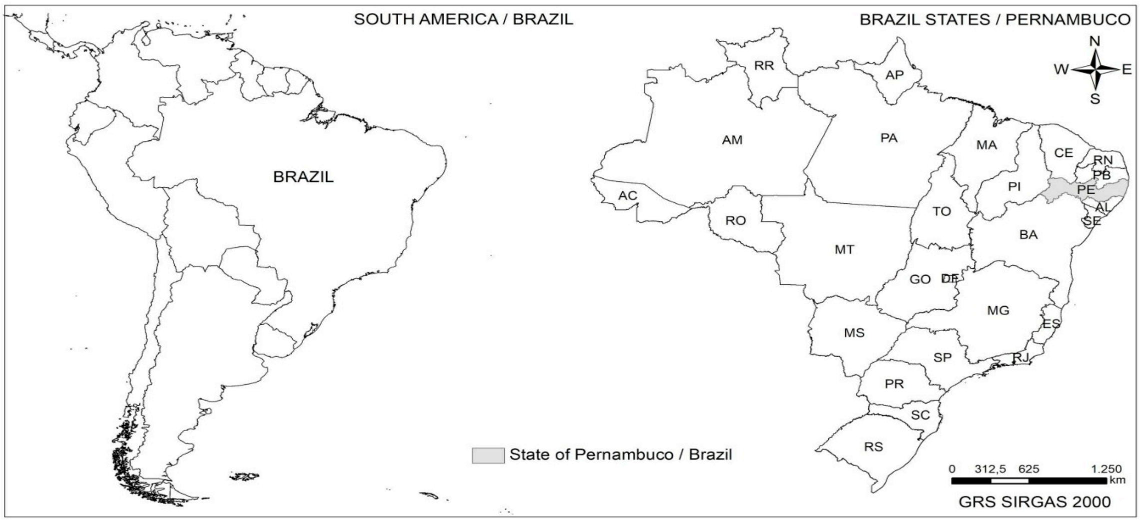

Figure 1. Location of the state of Pernambuco.

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 km^2. 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.

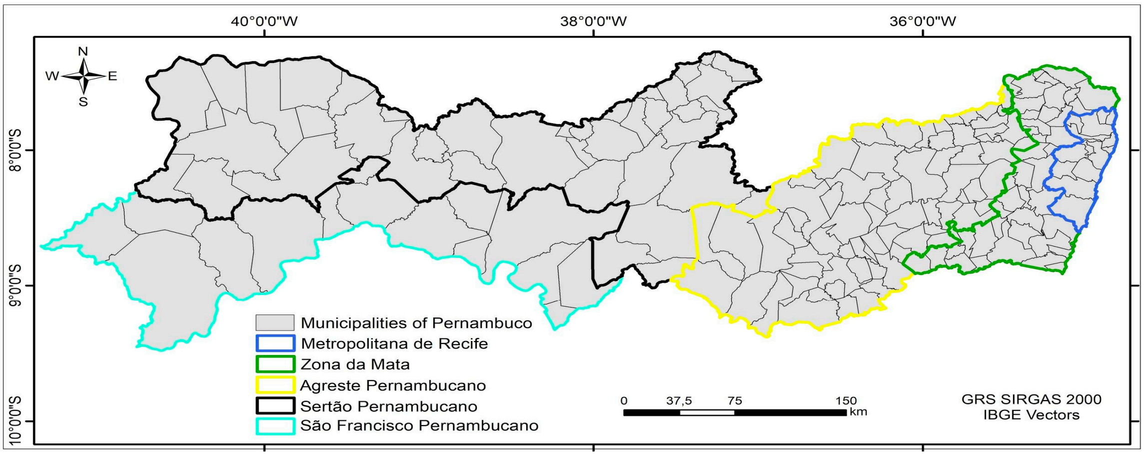

Figure 2. Location of Pernambuco's mesoregions.

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.

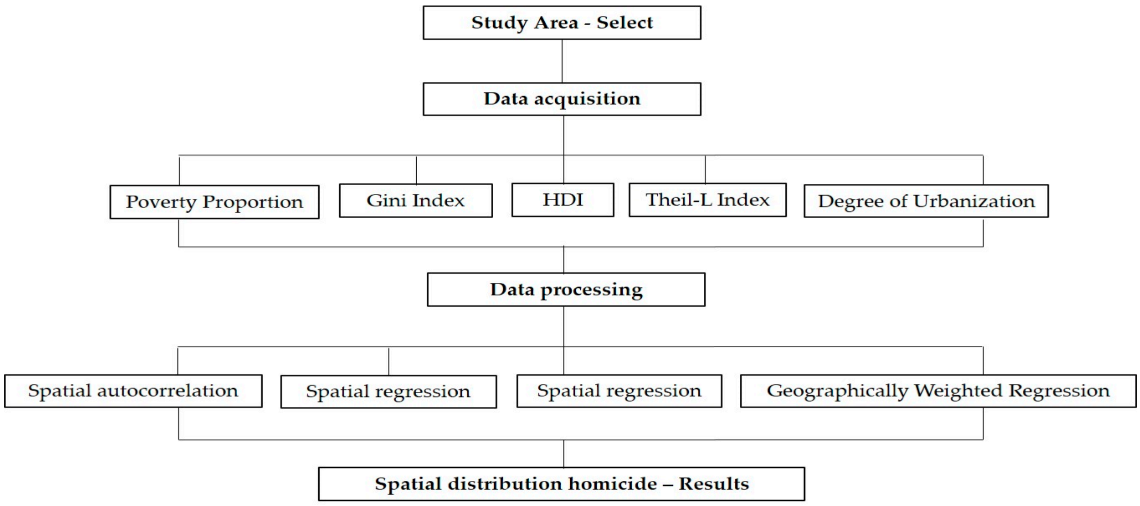

Figure 3. Synthesis of the methodological procedure.

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	Percentage 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	It is a measurement 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	It is a synthetic 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).

$$y_i = \beta_0(u_i, v_i) + \sum_{i=1}^{n} x_{i,k}\beta_k(u_i, v_i) \tag{1}$$

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 β_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).

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

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.

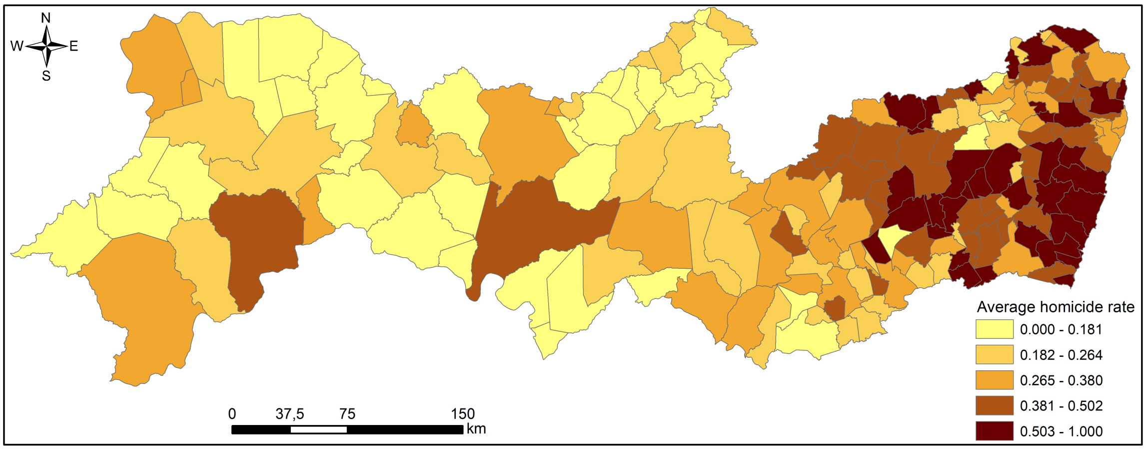

Figure 4. Homicide rates in the state of Pernambuco.

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.

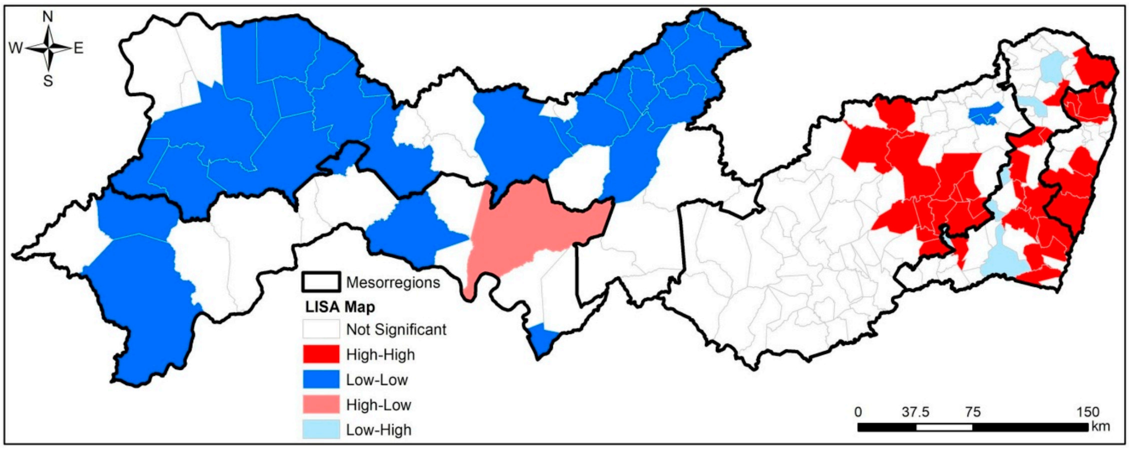

Figure 5. LISA map (Average homicide rate).

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 citiesof Pernambuco was the main objetive. 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 Teivāns-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
R^2	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
R^2	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.

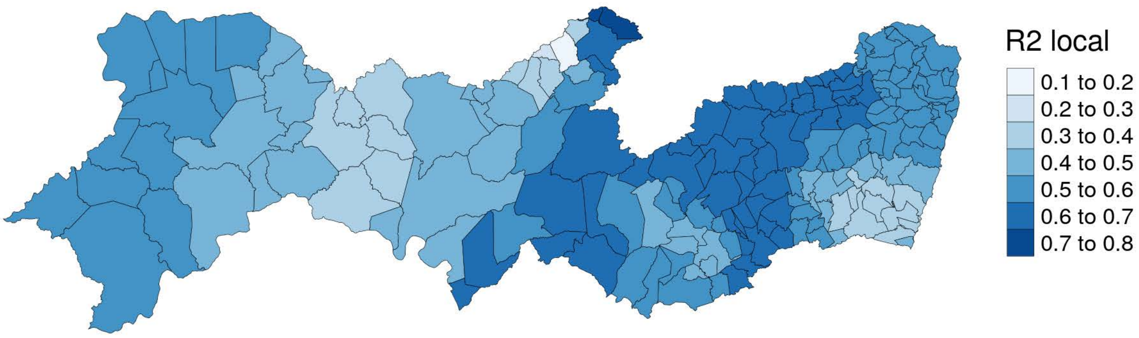

Figure 6. Distribution of local R^2 for the GWR model.

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.

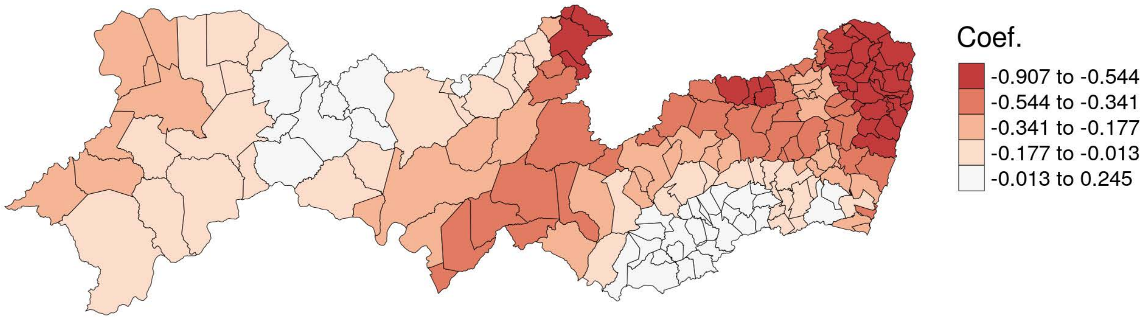

Figure 7. Distribution of the local coefficients of the GWR model (HDI).

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.

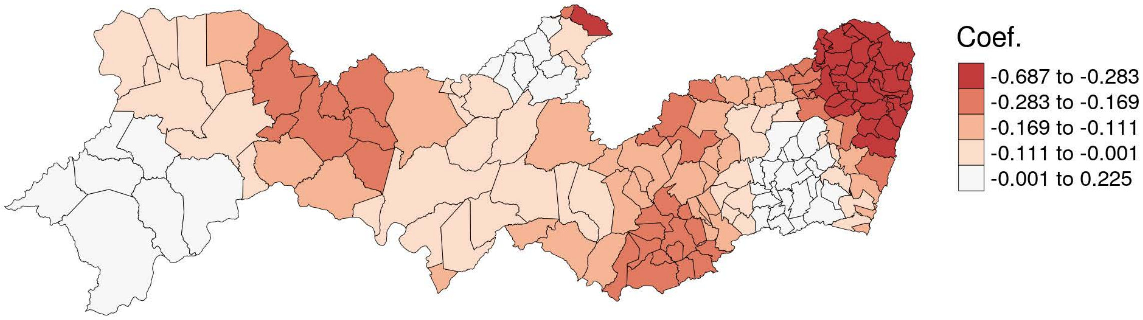

Figure 8. Distribution of the local coefficients of the GWR model (Theil-L Index).

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

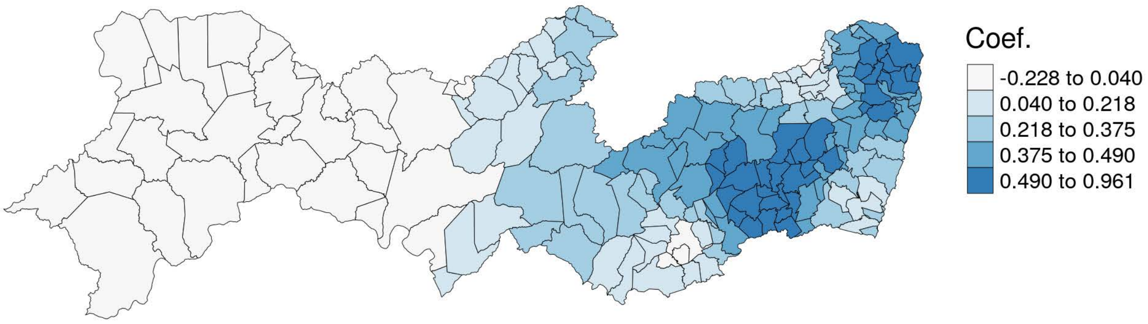

Figure 9. Distribution of the local coefficients of the GWR model (Degree of urbanization).

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.

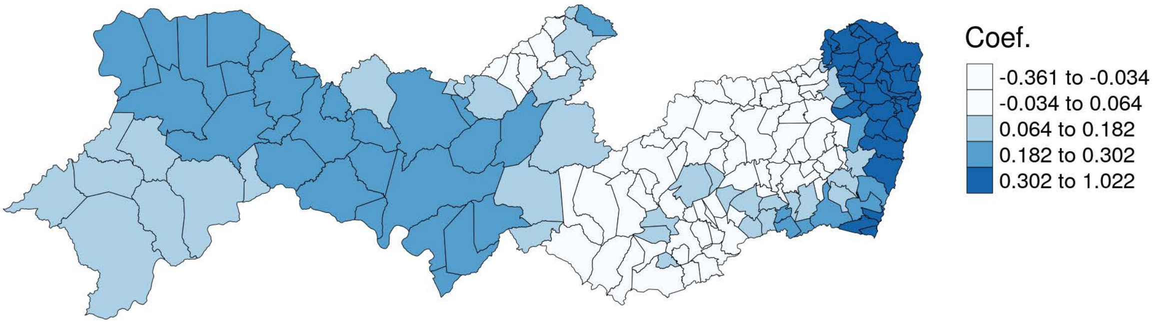

Figure 10. Distribution of the local coefficients of the GWR model (GINI Index).

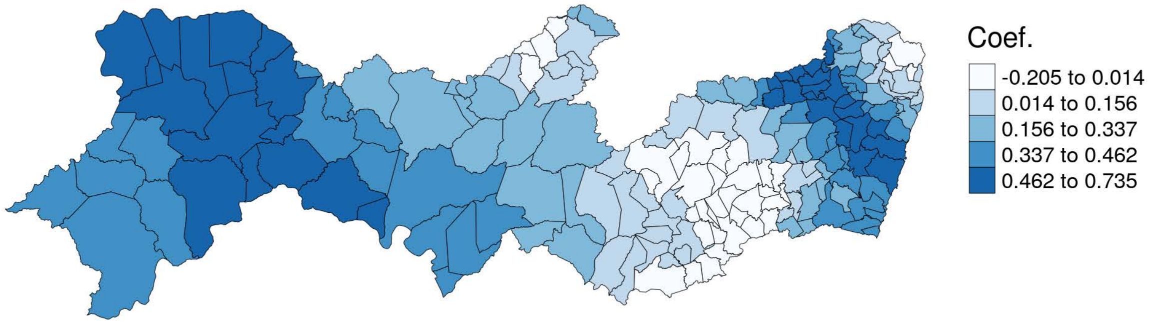

Figure 11. Distribution of the local coefficients of the GWR model (Poverty Proportion).

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, Poverty Proportion and Gini Index influence the variation in homicide rates in Pernambuco. The variable 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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