A SPACE-TIME MODEL FOR CRIME IN NEIGHBORHOODS OF FORTALEZA: THE INFLUENCE OF COMMON FACTORS AND NEIGHBORHOOD EFFECT

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ABSTRACT

One of the most common analyses in crime studies is the identification of spatial patterns. However, the observed spatial dependence may be influenced by cycles and trends in the economy and public safety policy, which can complicate the detection of spillover effects that spread between neighborhoods (Pesaran et al., 2015). To account for such characteristics, this paper employs an empirical model that estimates spatial patterns in crime rates while controlling for the influence of common factors in the data. Using theft and robbery data for Fortaleza, Brazil, the results suggest that there is a strong common trend in crime rates in the Central-Western region of the city and intense spatial clustering formations of theft crimes in the peripheral districts and robbery crimes in the upscale region. Moreover, there does not appear to be a clear relationship between these spatiotemporal patterns and neighborhood socioeconomic indicators.

Keywords: spatial patterns; crime concentration; common factors; Fortaleza;

Classificação JEL: C21, C23, C38.

1. Introduction

The high and persistent crime rates in Fortaleza are often highlighted in the press and society of Ceará. Despite recent community policing strategies and administrative improvements, crime rates have not substantially decreased (Lima, 2017; Araújo, 2019). Fortaleza is Brazil's second most violent city in terms of homicide rates and the ninth most violent city in the world, according to the 2022 report published by the Statista Research Department. Additionally, it is the 6th city in the country with the highest records of theft and robbery, according to the site "Where Was Stolen"[1].

Some authors argue that the lack of police intelligence and its late implementation have been among the main reasons for the decline in the efficiency of public security in Brazil (RIOS, 2008; GOMES, 2009). The police in the state of Ceará did not have an efficient intelligence system until the late twentieth century, but they mitigated this situation in the 2000s with the implementation of an intelligence course taught by the State University of Ceará - UECE. However, the process of recruiting, training, and qualifying professionals to work in the context of implementing new technologies demanded a significant amount of time and resources (Brasil, 2004).

Police intelligence activity is crucial for the construction and dissemination of studies and analysis of criminal information, which is important for public security. It subsidizes police actions and investigations, identifies the phase of violence, and possible failures in public safety programs. It also helps decision-makers understand crime trends by tracing the regions of concentration of criminal actions and groups, and the relationships between crimes committed and territory (Sánchez et.al., 2018).

This study contributes to the police administration literature by presenting a spatio-temporal model for crime in Fortaleza. The model reveals the degree of connection between neighborhood crime rates that result from common forces affecting crime in the city as a whole, identifying a spatial diffusion component of crime that spills over into each region. In Brazil, research centers such as the Center for the Study of Crime and Public Safety at the University of Minas Gerais have gained prominence in the early 2000s in the development of techniques and tools for crime analysis and the use of official statistics and surveys (Costa and Lima, 2018).

Currently, the State of Ceará has an Integrated Public Security Center (CISP) with an updated data system. However, it still presents a timid application of statistical analysis tools, compared to the states of Minas Gerais, São Paulo, and Rio de Janeiro, despite having an early system of statistical analysis of crime.

The identification of spatial patterns in crime occurrence is crucial to understand how crime behaves spatially in large cities and how socio-economic factors influence its spatial distribution (Shaw and McKay, 1976; Eck and Weisburd, 1995; ANSELIN, 1998; Almeida, Haddad, and Hewings, 2005, Anselin, Cohen, Cook, Gorr and Tita, 2000).

Some studies have found that crime rates tend to be higher in "transition zones," which correspond to the boundary between the suburbs and the areas where the commercial and industrial centers of cities are located (Park and Burgess, 1925). Studies in this field have found that crime clusters are generally formed in socially disorganized regions that remain constant over time (Shaw and McKay, 1942). The observation of changes in spatial dependence occurs as crime-fighting in large metropolises disperses criminal activity, with the presence of spillovers from large cities to smaller regions that have high social vulnerability (Ackerman, 1998).

In Stockholm, vandalism and vehicle robbery practices were found to exhibit similar spatial patterns at the neighborhood level (Ceccato et al., 2002), while in Vancouver this similarity was observed for vehicle robbery and violent crime (Andresen, 2011). Other work has highlighted specific patterns for distinct crimes[2], such as vehicle robbery, residential robbery, and burglary (Roncek and Maier, 1991).

Hillier and Sahbaz (2008) observed a distinct pattern of spatial behavior among some crimes in London. It was analyzed that home robberies were distributed throughout the urban area, while street robberies were concentrated in the main streets of the area. In the city of Cambridge, a significant spatial concentration of robbery crimes was observed in places predominantly frequented by young people (BRANTINGHAM and BRANTINGHAM, 1995).

In the field of spatial conditioning of crime, spatio-temporal econometric models have been used to capture the action of heterogeneity and spatial dependence (ANSELIN, 1988; CLIFF and ORD,

1. Link to the site “where I was robbed”: https://www.ondefuiroubado.com.br/fortaleza/CE
2. Studies have observed an interaction between demographic characteristics and certain routine activities that occur at night and outside of the home in the occurrence of property crimes (Miethe, Stafford, & Long, 1987).

1972; ALMEIDA 2012). Studies conducted in Colombo concluded that 10% of the variation in criminal incidents is explained by spatial dependence (ANSELIN, 1998). In the State of Rio Grande do Sul, it was found that spatial dependence[3] is significant in the models estimated for robbery and theft rates, but not for the homicide rate (Oliveira, 2008).

However, the spatial dependence observed in these studies may be affected by cyclical changes in the economy and security policies, which can influence all regions of the city. Ignoring these factors may result in biased estimates of spatial correlations (PESARAN et al., 2015).

This paper proposes to investigate the behavioral patterns of robbery and theft crime rates in Fortaleza between 2009 and 2019, using a space-time econometric model that accommodates common effects and neighborhood effects estimated by the Principal Component Analysis (PCA) method. Additionally, this study aims to determine the correlations between spatial units and compare them with the approach that only considers distance to determine neighboring units. Only 113 hybrid neighborhoods in the city will be considered as neighborhood breakups after 2010.

There is a scarcity of studies that discuss the hypothesis of the sources of dependencies in space (BAILEY, HOLLY and PESARAN, 2016), and this study aims to fill a gap in the spatial crime literature by analyzing the level at which dependencies between different spatial units are observed due to the influence of common factors.

This study aims to infer patterns of spatial association of how crime in Fortaleza interacts in space over time, by separating the relationship between spatial units due to the effect of common factors from what is purely spatial (STONE, 1947). The goal is to isolate the influence of these factors and provide decision-makers with new insights into the nature of crime spillover connections.

Previous studies have investigated the relationship between violence, demographics, and human development in Fortaleza. These studies have shown that the homicide rate is inversely associated with the level of human development of neighborhoods, with a concentration of crimes in the Western region of the city, where there is a predominance of neighborhoods with the lowest HDIs (Carvalho, Medeiros and Oliveira, 2016). Three areas with high homicide rates were identified where spatial dependence was significant within a limited radius of up to 2 km (Oliveira and Simonassi, 2019). Evidence suggests that locations characterized by high rates of violence are spatially correlated with more vulnerable locations in terms of socioeconomic, demographic, and urban disorder (Dantas and Favarin, 2021). There is a strong spatial relationship between the location of homicide crimes and the existence of slums in the vicinity of the event (Marques et.al, 2013).

Crime has a significant impact on various aspects of society, including foreign investment, education, health, business, civil rights, and quality of life. Children and adolescents residing in regions with high crime rates tend to have low school performance (TEIXEIRA, 2011). Insecurity can increase the prices of products and services up to 30% due to security-related expenses (Atlas of Violence, 2019). Fear of violence is also a factor taken into consideration by individuals when choosing tourist destinations (TUTISUFF, 2011).

To conclude, it is important to highlight the significance of studies in the field of spatial behavior of crime for the city of Fortaleza. These studies can help to inform and make governmental policies for crime mitigation more efficient. Despite being the 5th largest city in Brazil by population, Fortaleza is still a relatively poor city and needs economic advancements to bring about social changes.

This paper is divided into five sections, with this introduction being the first. The second section provides a brief analysis of the socioeconomic landscape and the structure of public security in Fortaleza. The third section describes the applied methodological framework. The fourth section presents the main results obtained. Finally, the conclusions are drawn, and the contributions of this work to the topic are discussed.

2. Geographic and Socioeconomic Overview and the Public Security Structure of Fortaleza

Fortaleza is the capital of the state of Ceará, located in the Northeast region of Brazil, with a land area of 312,353 km² divided into 121 neighborhoods[4]. It has the 5th largest population in the country, with 2.7 million inhabitants in 2021, and the Gross Domestic Product (GDP) was estimated in

3. There are applications of Bayesian multivariate spatial modeling in the literature that provide a framework for analyzing spatial correlations between several dependent variables (Wang and Wall, 2003). As for example, studies that check spatial patterns of robbery, theft, violent and vehicle crime (Quick et.al., 2018).
4. The division of Fortaleza by neighborhoods can be found in annex 1. The military structure are shown in annex 3.

2020 to be around R$ 65.16 billion, making it the largest GDP in the Northeast region. Figure 1 shows a map of Fortaleza's neighborhoods and their population size (panel a), average income 2010 (panel b), HDI 2010 (panel c), and employment measure (panel d).

In contrast to population size, which is generally higher in the periphery and/or Western region, the neighborhoods with better average income and HDI are concentrated in the top center of the map. This heterogeneity can be seen through the variability of the average income, which ranges from $111.94 to $1,916.07. The neighborhoods with the highest average income are in the top center of the map (Figure 1, panel b), near the coast, where there is a large concentration of businesses, offices, shopping centers, tourist attractions, and public offices. Coincidentally, these are the neighborhoods where the population has the best life expectancy, educational level, greatest employment opportunities, and the highest incomes, providing the highest HDI (Figure 1, panel c).

The employment links have a somewhat more decentralized spatial distribution, revealing a few points of concentration of jobs (Figure 1, panel d). In addition to the strong clustering of employment links in the top center of the map, which comprises the Center region, there is also a considerable concentration in the Center-South region of the city because it is an alternative commercial hub for the population living in the South region, which also has a cluster of companies and offices.

Comparing the level of development of the neighborhoods of Fortaleza with the national average, it is observed that the seven neighborhoods with the highest HDI in Fortaleza are above the national average (0.724) and all are located in the Central-Eastern region, while the seven neighborhoods with the worst HDI levels are concentrated in the Western region. This same scenario is reflected in income and employment generation, despite Fortaleza being the largest economy in the Northeast region, and is linked to the condition of inequality and poverty present in Fortaleza and in Brazil in general.

Before presenting an overview of crime in Fortaleza, it is first necessary to describe the organization of the policing/security system of the neighborhoods. With respect to the security division, Fortaleza has 10 Integrated Security Areas (AIS), as seen in Figure 2 (panel a). The divisions of the AIS aim to optimize the operational activity carried out by the security agencies, based on better efficiency in the allocation of police teams in crime prevention and investigation (SSPDS-CE).

Regarding the crime scenario in Fortaleza, Figure 2 presents the rates of robberies and thefts for Fortaleza between 2009 and 2019, through their averages and growth rates. Panels b) and c) with the averages indicate that the neighborhoods of the Midwest region (AIS 1, 3, 4, 5, 6, and 8) maintain throughout the analyzed period the highest notifications of these crimes.

When the average growth rates of robbery and theft are analyzed for this period, the spatial scenario is different. Panels d) and e) show that AIS 3, 7, 8, and 9 have the highest increases in notifications, being regions where populous neighborhoods with low levels of income, employment, and HDI are located, as seen above. The spatial analysis of socioeconomic conditions and crime makes it evident that the neighborhoods located in the Midwest and South regions of Fortaleza have the worst quality of life indices and present the highest growth rates of thefts and robberies in the last decade.

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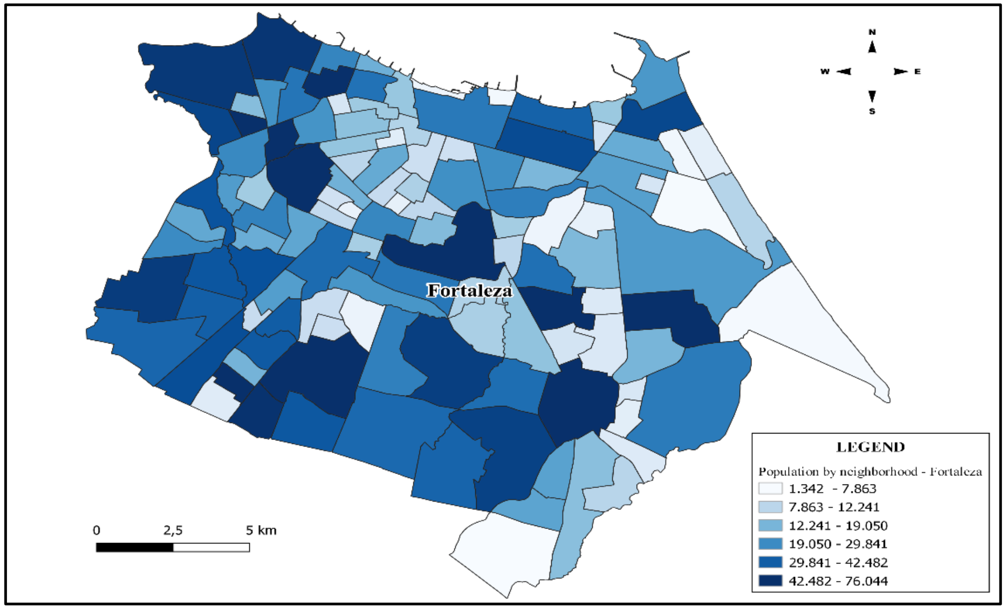
5. The level of employment is measured through the variable employment links, made available by the Annual Social Information Report (RAIS) database.

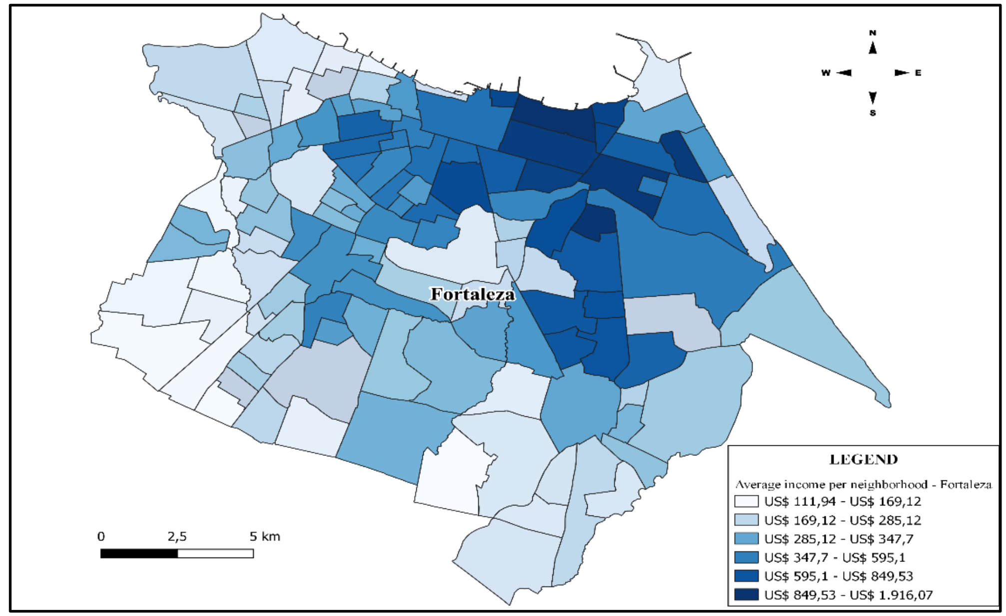
6. Annex 10 presents the original series for the two crime indicators: theft rates (2010-2019) and robbery rates (2009-2019), in Fortaleza. The database is from the Secretary of Security and Social Defense of the State of Ceará (SSPDS-CE), through police reports collected in the police stations of Fortaleza

Figure 1: Socioeconomic Overview

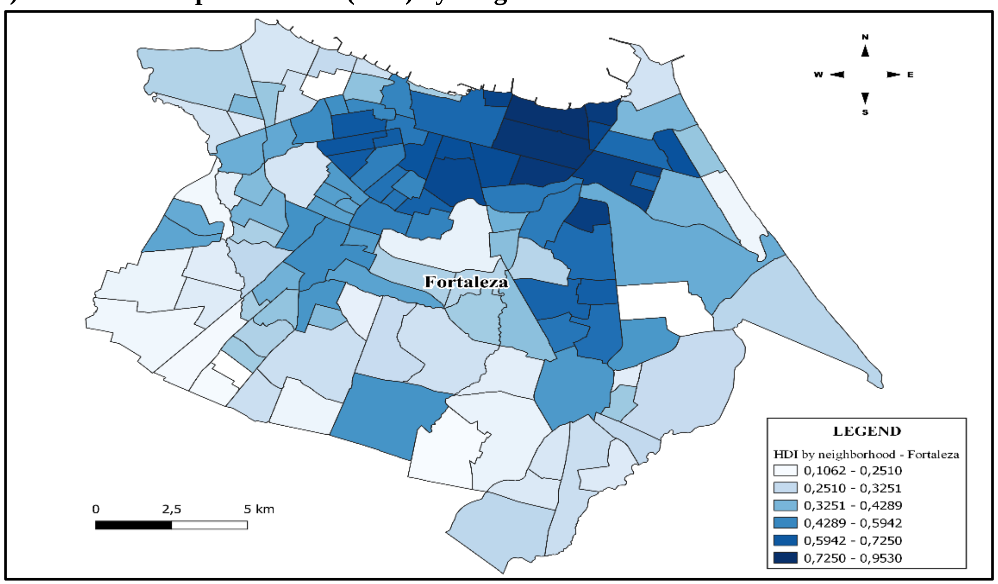
a) Population by neighborhood in Fortaleza – Census 2010.



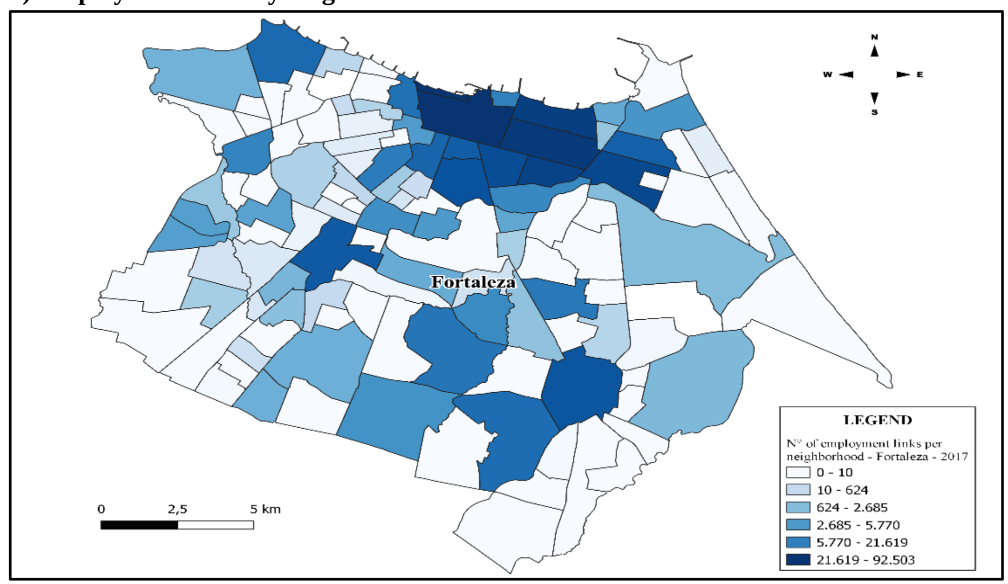
b) Average income per neighborhood of Fortaleza – Census 2010.



c) Human Development Index (HDI) by Neighborhood of Fortaleza – Census 2010

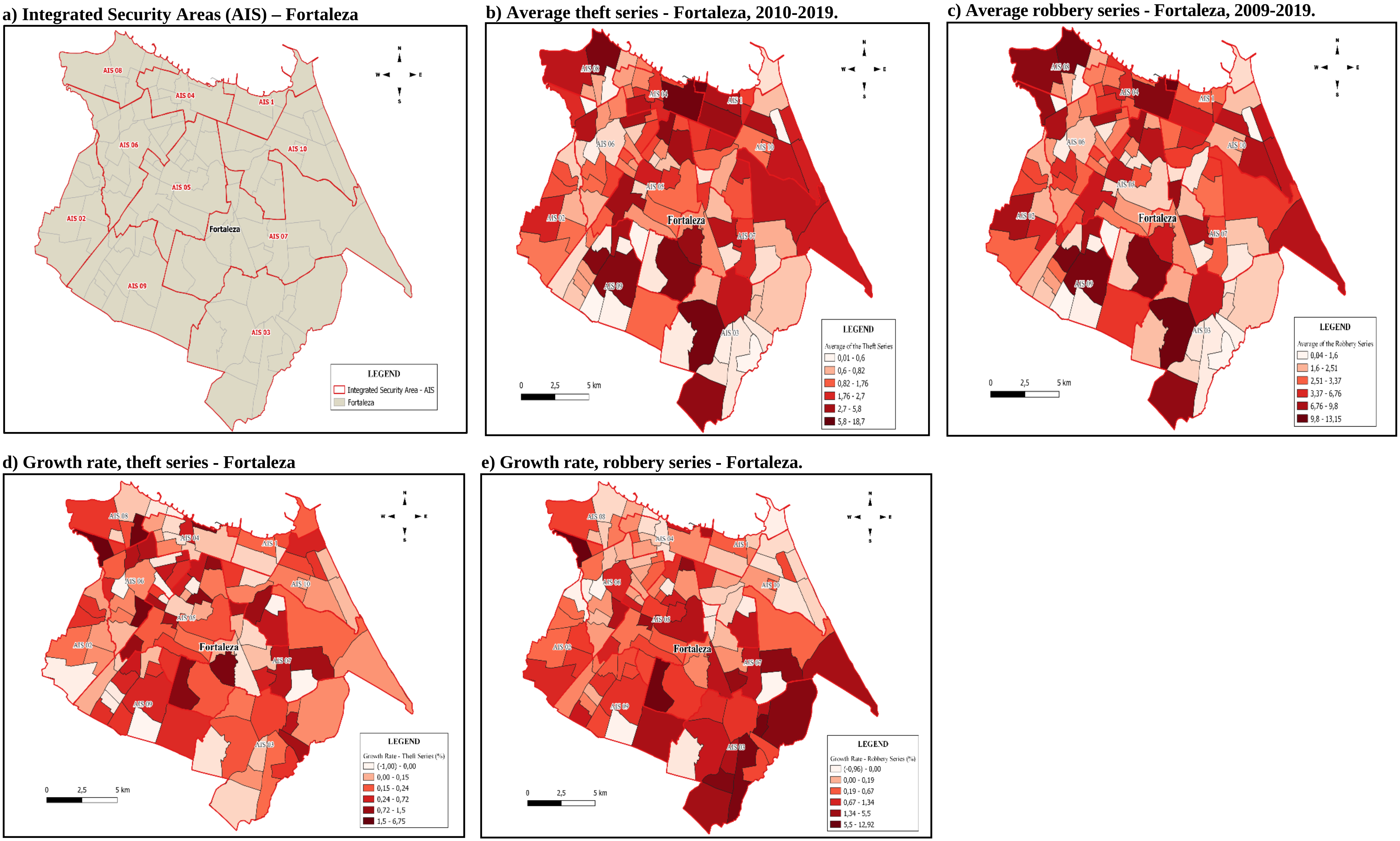


d) Employment links by neighborhood in Fortaleza - 2017.



Sources: IBGE, Census 2010. RAIS/MTE 2017. Prepared by the authors.

Figure 2: Crime Indicators for Fortaleza



Source: Prepared by the authors.

3. Methodology

For the methodological purpose suggested in this paper, an econometric model is used that decomposes the joint behavior of crime rates into a factor common to all neighborhoods that are administratively divided into 10 AISs, and a component that describes the spillover effects of each specific AIS. According to Chudik, Pesaran, and Tosetti (2011), this structure would be more suitable for the study of spatial effects by separating the influence of common factors (called strong correlation) from the specific spatial effect of each neighborhood (corresponding to what they defined as weak correlation). The adopted model would thus have the following general structure:

$$\pi_{irt} = a_{ir} + \gamma_{ir} f_{gt} + \beta'_{ir} F_{rt} + \lambda_{ij} + \psi^{+}_{ij} + \psi^{-}_{ij} + \xi_{irt} \qquad (1)$$
$$i = 1,2, \dots, N_r; r = 1,2, \dots, R; t = 1,2,3, \dots, T,$$

Where: $\psi = (\psi_1, \psi_2, \dots \dots, \psi_N)'$, represents the associated coefficients that can take on ψ^{+}_{ij} and ψ^{-}_{ij}. π_{irt} is the variable of interest (theft/robbery rates), f_{gt} is the global factor, $F_{rt} = (f_{1t}, \dots, f_{m_r t})$ is a vector m_r x 1 of AIS factors for r = 1, 2, ..., m_r; $\beta_{ir} = (\beta_{i1}, \beta_{i2}, \dots, \beta_{im_r})'$ and γ_{ir} are factor loadings associated with f_{gt} and F_{rt}, Wx_{ot} denotes the i-th row of the standardized spatial matrix N x N. λ_{ij}, ψ^{+}_{ij} and ψ^{-}_{ij} are the diagonal matrices of size N x N with λ_{ij} as their diagonal elements. λ_{ij} represents the effect of spatial common factors, ψ^{+}_{ij} represents positive spatial correlations and ψ^{-}_{ij} represents negative spatial correlations.

The literature on the application of factor analysis and principal component analysis methods has been the subject of debate (Dancey & Reidy, 2006; Tabachinick & Fidell, 2007). It is important to note that factor analysis imposes assumptions on the underlying factors of the data, and incorrect formulation of the model can lead to poor performance. Principal component analysis, however, does not make any a priori assumptions about the covariance matrix of the residuals. Therefore, this method was chosen for the estimation of the first part of the model.

It is worth noting that principal component analysis has several desirable properties, including the importance of each principal component being a linear combination of all other variables, their independence, and the estimation of the maximum information, which captures all the variation in the data (Johnson & Wichern, 1998; Hongyu, 2015). These properties make it suitable for separating strong cross-correlation errors in large panels (Pesaran, 2004).

However, the method also has its limitations, such as sensitivity to the variability of the variables, double absences, outliers, and missing data. Studies on panel data have highlighted the need to separate the cross-sectional dependence into weak and strong components (Forni & Reichlin, 1998; Chamberlain & Rothschild, 1983). Monte Carlo simulations have been used to examine and compare the performance of unobserved principal component-based estimators in the presence of strong factor loadings and weak and/or semi-strong common factors. The results showed satisfactory performance in separating weak and strong cross-sectional dependence (Bai, 2009). For further discussion on this topic, see Chudik, Pesaran, and Tosetti (2011).

In summary, principal component analysis was chosen for the first part of the model due to its desirable properties in capturing the maximum information and separating strong cross-correlation errors. However, its sensitivity to variable variability and other limitations must be taken into account. It is important to separate cross-sectional dependence into weak and strong components, and studies have shown that unobserved principal component-based estimators perform well in such situations.

An alternative approach was proposed in the study conducted by Bailey, Holly, and Pesaran (2014), which aimed to estimate the impact of common factors on changes in housing prices across Metropolitan Statistical Areas (MSAs) in the United States. To achieve this, a two-step procedure was used to identify the degree of cross-sectional correlation and apply de-factorization to the present factor loadings.

The authors concluded that ignoring common spatial factors that influence price behavior could bias spatial inferences about the variability of house prices. Moreover, de-factoring common effects allows for a more consistent analysis of spatial spillover effects, whether positive or negative, which are essential in spatial econometric studies.

In general, the principal components method extracts all strong cross-sectional dependence due to unobserved common factors in the error term of model (1) in the space-time model. By controlling these factors, the spatial weight matrices can be estimated, capturing the isolated effect of spatial variability in each neighborhood (weak correlation) and the communal spatial effect, which results from shocks that affect all neighborhoods. Therefore, the proposed approach in estimating model (1) is to separate the weak and strong spatial correlations of robbery and theft rates in Fortaleza's neighborhoods to provide new insights into crime behavior in the city.

The first part of the model that corresponds to hierarchical factors, f_{gt} and F_{rt}, is estimated sequentially using the principal components analysis (PCA) method. Assuming only one global factor and regional factors present in each AIS, f_{gt} corresponds to the strongest principal component extracted from the dataset, and each F_{rt} corresponds to the strongest principal components extracted from the data in each AIS separately. The hierarchical factors f_{gt} and F_{rt} are extracted by performing rescaling on the variance matrix of the data by the PCA method, obtaining factor loadings that are strongly correlated among all AIS.

There are alternative methods for extracting these factors. For example, Bai and Ng (2002) propose a selection by the first "n" principal components (PC), through the selection criterion based on the information criteria (IC)[7], which specifies the maximum number of factors that present strong variability in the residuals and that are controlled through the extraction of these principal components (de-factorization). This means that when applying de-factorization to the residuals using the PCA method, a dimensional reduction of the covariance matrix is being performed in order to observe only the weak variability belonging to each AIS.

The general assumption for model fitting in equation (1) is the presence of a strong cross-sectional correlation, as highlighted by Bai (2003). To verify this characteristic in the set of theft and robbery crime series, the same estimation procedure proposed by Bailey, Holly, and Pesaran (2014) is followed. The two-step procedure for diagnosing the degree of cross-sectional correlation is detailed below:

The first step is the Pesaran CD test, which assesses the nature of cross-sectional dependencies to analyze the possible presence of strong correlation. If a strong dependency is confirmed, one can proceed to the second step which consists of applying de-factorization of the main variability present in the associated factor loadings.

This two-step test deals with analyzing the mean of the correlation coefficients of the residuals. The null hypothesis is that the residuals of π_{irt} are weakly correlated. If this hypothesis is rejected, it indicates that the residuals of the model are strongly correlated. In that case, de-factoring such effects as discussed earlier is possible. In summary, the test is structured as follows:

(i) If the null hypothesis of weak dependence is not rejected, one can proceed to the second part of the model, which corresponds to the spatial analysis that is estimated through the residual lags.

(ii) If the null hypothesis of weak dependence is rejected, then one should model the strong dependence implied by the test result using the factor model discussed earlier.

The objective is to verify that the residuals of model (1), denoted by $\hat{\xi}_{it} = \left(\hat{\xi}_{1t}, \hat{\xi}_{2t}, \dots, \hat{\xi}_{Nt}\right)'$ are weakly correlated by applying the CD test.

Bailey, Kapetanios and Pesaran (BKP) (2014), proposed the method of the cross-sectional dependence exponent, α, to analyze the degree of spatial dependence when the null hypothesis of weak dependence is rejected, given the following condition: $1/2 < \alpha \leq 1$. The closer to unity, the more strongly correlated the residuals will be. In this sense, α corresponds to the highest loading factor present (analysis of this method in Appendix 6). Once the presence of strong cross-sectional dependence is confirmed, the principal components method (PCA)[8] can be applied, which will extract unobserved common factor

7. For Nascimento (2020), information criteria (IC) trade off the benefit of including an additional factor against the cost of greater sample variability arising from the additional estimation of another parameter.

8. According to Bai (2003), even if the data show limited cross-sectional dependence and the presence of heteroscedasticity in the error, the estimation by PCA is considered consistent.

(de-factorization), and then the CD test and the cross-sectional dependence exponent test can be reapplied to check if the de-factorization was successful.

For interested parties, an alternative method for extracting common factors that are not observed by the cross-sectional averages method is presented in appendix 9, including its methodology and the respective results for comparison. The main strategy is to reduce the regression equation by de-factorizing the cross-sectional means of the variables so that these means act as proxies for the common factors. By subtracting these averages, the serial correlation of the model's residuals can be controlled. In the literature, the two methods have often shown very close estimations (BAILEY, KAPETANIOS and PESARAN, 2014). The results for this alternative method are available in appendix 9.

The second part of the model, which corresponds to the spatial analysis, is estimated through the lags of the residuals of equation (1), $\hat{\xi}_{irt}$. According to the structure below:

$$\hat{\xi}_t = a_\xi + \Lambda_1 \hat{\xi}_{t-1} + \Psi_0^+ \widetilde{W}_{cs}^+ \hat{\xi}_t + \Psi_0^- \widetilde{W}_{cs}^- \hat{\xi}_t + \Psi_1^+ \widetilde{W}_{cs}^+ \hat{\xi}_{t-1} + \Psi_1^- \widetilde{W}_{cs}^- \hat{\xi}_{t-1} + \zeta_t \quad (2)$$

Where: $a_\xi = (\alpha_{1\xi}, \alpha_{2\xi}, \dots, \alpha_{N\xi})'$ is the vector of intercepts N x 1. $\Lambda_j, \Psi_j^+ \, and \, \Psi_j^-$ are diagonal N x N matrices with $\lambda_{ij}, \psi_{ij}^+ \, and \, \psi_{ij}^-$ as their diagonal elements for each i. In this sense, Λ = diag(λ), where $\lambda_1 = (\lambda_{11}, \lambda_{21}, \dots, \lambda_{N1})'$ represents the common factors (time effect). Ψ_0^+= diag(ψ_0^+), Ψ_0^-= diag(ψ_0^-), Ψ_1^+=diag(ψ_1^+), Ψ_1^-=diag(ψ_1^-), where, ψ_s^+=($\psi_{1s}^+, \psi_{2s}^+, \dots, \psi_{Ns}^+$) ′, ψ_s^-= ($\psi_{1s}^-, \psi_{2s}^-, \dots, \psi_{Ns}^-$)′, for s = 0 and 1. ($\widetilde{W}_{cs}^+$ and $\widetilde{W}_{cs}^-$) are the contemporaneous and first-order lagged positive and negative spatial correlation matrices, respectively; and $\zeta_t = (\zeta_{1t}, \zeta_{2t}, \dots, \zeta_{Nt})'$ is the error term.

In this context, λ_1 captures the strong spatial correlation that arises from common factors, that is, exogenous shocks that affect the variability of theft and robbery rates among the neighborhoods of Fortaleza. Ψ_0^+ and Ψ_0^-, represent the effect of positive and negative contemporaneous spatial correlations, respectively. Positive correlations indicate spillover of crime from one neighborhood i to its neighbors, while negative correlations indicate that a neighborhood i concentrates crime to itself, reducing crime in neighboring neighborhoods.

Ψ_1^+ and Ψ_1^- represent the effect of positive and negative lagged spatial correlations, which reflect the spatial variability of crime rates over a previous time interval. Thus, one can analyze the special behavior of crime across neighborhoods over time.

All spatial variability that is not captured by the hierarchical factors and the positive and negative correlations are measured in the error term, ζ_t.

Since this equation takes spatial heterogeneity into account, it assumes that the coefficients $\lambda_{ij}, \psi_{ij}^+ \, and \, \psi_{ij}^-$, and variance of the error, $\sigma_{\zeta_t}^2$ = var (ζ_t) may differ in i (across neighborhoods)

For consistent estimation of the parameters of equation (2): λ_{ij} , $\psi_{ij}^+ \, and \, \psi_{ij}^-$, an estimation method called the quasi-maximum likelihood method (QML) is proposed, which suggests using the following log-likelihood function:

$$\ell(\psi_0^+, \psi_0^-) \propto T ln|-\psi_0^+ W^+ - \psi_0^- W^-| - \frac{T}{2} \sum_{i=1}^{N} ln\left(\frac{1}{T} \tilde{x}_i' M_i \tilde{x}_i\right) \quad (3)$$

Where:

$\tilde{x}_i = x_i - \psi_{i0}^+ x_i^+ - \psi_{i0}^- x_i^-$, $M_i = I_T - Z_i(Z_i'Z_i)^{-1}Z_i'$, $Z_i = (x_{i,-1}, x_{i,-1}^+, x_{i,-1}^-)$, $\psi_0^+ = (\psi_{10}^+, \psi_{20}^+, \dots, \psi_{N0}^+)'$ e $\psi_0^- = (\psi_{10}^-, \psi_{20}^-, \dots, \psi_{N0}^-)'$.

Maximum likelihood estimation weights were used to account for spatial heterogeneity present in the positive and negative spatial weight matrices ($\tilde{x}_i = x_i - \psi_{i0}^+ x_i^+ - \psi_{i0}^- x_i^-$). This approach also considers the presence of residual correlation ($M_i = I_T - Z_i(Z_i'Z_i)^{-1}Z_i'$), which improves the consistency of the spatial weight matrix estimates.

The variance-covariance matrix obtained from equation (3), is presented in appendix 8.

It is worth noting that the literature commonly uses contiguity-based weight matrices (such as those of the type tower and queen), distance-based weight matrices, W_d, or pairwise correlations, $\hat{\rho}_{ij}$ (ANSELIN, 1988). However, in this work, distinct constructs were chosen to analyze spatial behavior.

For this work, it was chosen to construction spatial matrices that take into account the heterogeneity among the neighborhoods of Fortaleza. Instead of building homogeneous matrices with a fixed distance for all neighborhoods, was considered a variable distance that accommodates at least two neighboring neighborhoods. This has led to the construction of matrices in three scenarios: the distance between two neighborhoods (W_1), the distance between two neighborhoods multiplied by 1,5 (W_2), and the distance between two neighborhoods multiplied by 2 (W_3).

The construction of the spatial weight matrix follows a non-parametric approach, where the weight matrix is estimated without considering any homogeneity constraint on the spatial structure. For instance, Bhattacharjee and Holly (2011) estimated an unknown spatial weights matrix through statistical inference methods. Adopting this approach provides better understanding of the nature of spatial interactions in a highly heterogeneous environment.

Furthermore, the observations per neighborhood contained in the spatial correlation matrices are ranked in a descending manner on both the vertical and horizontal axis, according to the average number of criminal incidents (theft and robbery). In the neighborhood matrices, the vertical axis corresponds to the number of neighborhood connections and the horizontal axis corresponds to the neighborhood ID[9]

Additionally, was constructed spatial analyses of the association of the correlation-based contingency matrices $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$, with the distance-based weighting matrix, (W_1, W_2 and W_3). These analyses are found in Appendix 7.

3.1. Database

The data used in the proposed methodology were obtained from police reports (B.O)[10] collected in the police stations of Fortaleza, from 2009 to 2019, provided by the Secretariat of Security and Social Defense of the State of Ceará (SSPDS-CE). The variables of interest were theft and robbery, as they are indicators that record occurrences for a larger number of neighborhoods on a monthly basis, unlike homicide data where many neighborhoods have no monthly notifications.

However, theft and robbery data also present some difficulties for spatial analysis. For instance, theft and robbery occurrences are underreported due to various reasons, such as the distance from the police station, low confidence in the police investigation system, and fear of retaliation from the criminals. In addition, the spatial weight matrix could present many points with a value of 0 due to the presence of many neighborhoods with no occurrences.

According to SSPDS-CE, theft is defined as the number of cases of belongings stolen without violence or threat to the victim, while robbery is classified by the number of Violent Crimes against Property (CVP), except for robbery followed by death (*latrocínio*), which is counted as Intentional Lethal Violent Crimes (CVLI). Although Fortaleza currently has 121 neighborhoods, this study used an old spatial division that included 114 neighborhoods due to data collection in the early years of the series. Nevertheless, there are no missing areas as the change in the number of neighborhoods is due to disaggregations that occurred in previous years, which does not impact the analysis of the results found.

4. Results

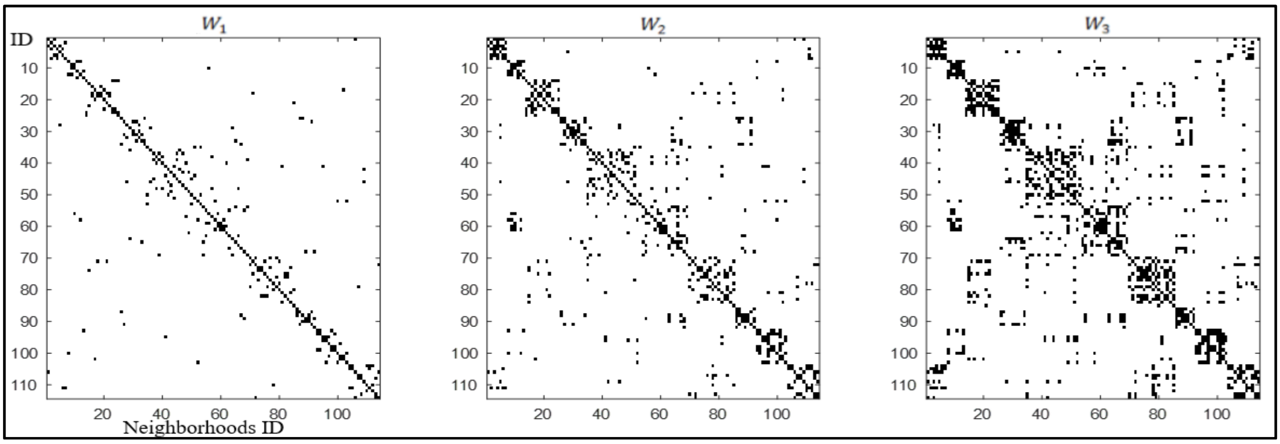
4.1. Analysis of Distance-Based Neighborhood Matrices

The neighborhood matrix map for the scenario W_3, indicates that spatially the neighborhood connection effects are concentrated among AIS 4, 5 and 6. The Midwest region shows high neighborhood connections and forms clusters with high rates of theft and robbery. Looking at the figures below, we can see from the dispersion of the distance matrices (W_1, W_2 e W_3) and the neighborhood effect that the number of non-zero elements increases as the radius (W_1, W_2 e W_3) within which neighborhoods are considered neighbors increases, in addition to showing significante clustering along the diagonal.

9. A table with the identification (ID) of the neighborhoods in the spatial weight matrices is provided in appendix 4.
10. The police report (B.O.) is a police document of notification by victims of criminal acts.

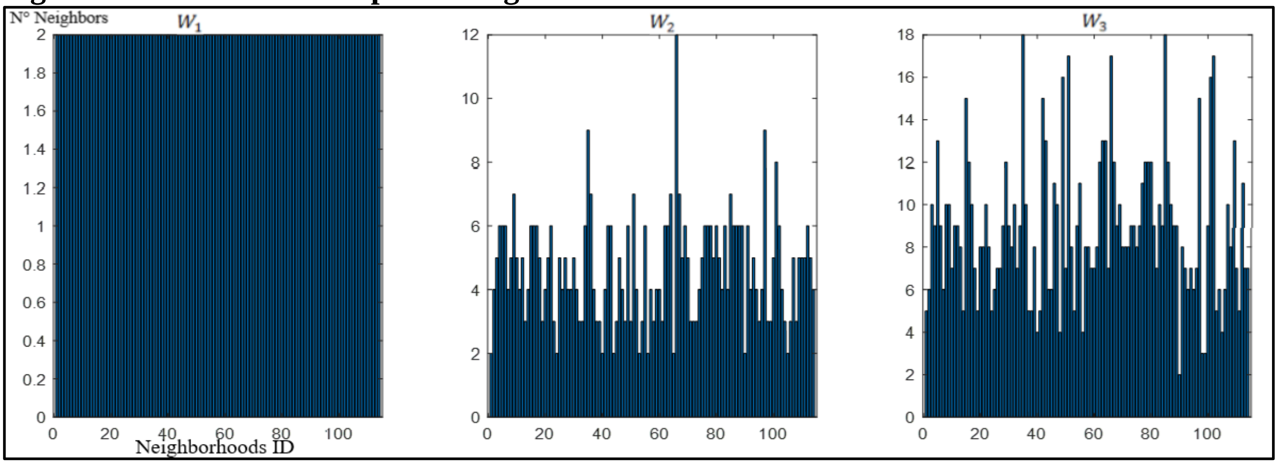
Figure 3 and Map 1, shows that this neighborhood grouping presents a greater spatial influence among the neighborhoods that are part of AIS 1,4,5,6 and 8. When the matrices W_2 and W_3 are considered, the number of neighborhood connections increases, and some neighborhoods go from 2 to 18 connections, as seen in Figure 4.

Figure 3: Distance-Based Spatial Weighting Matrices



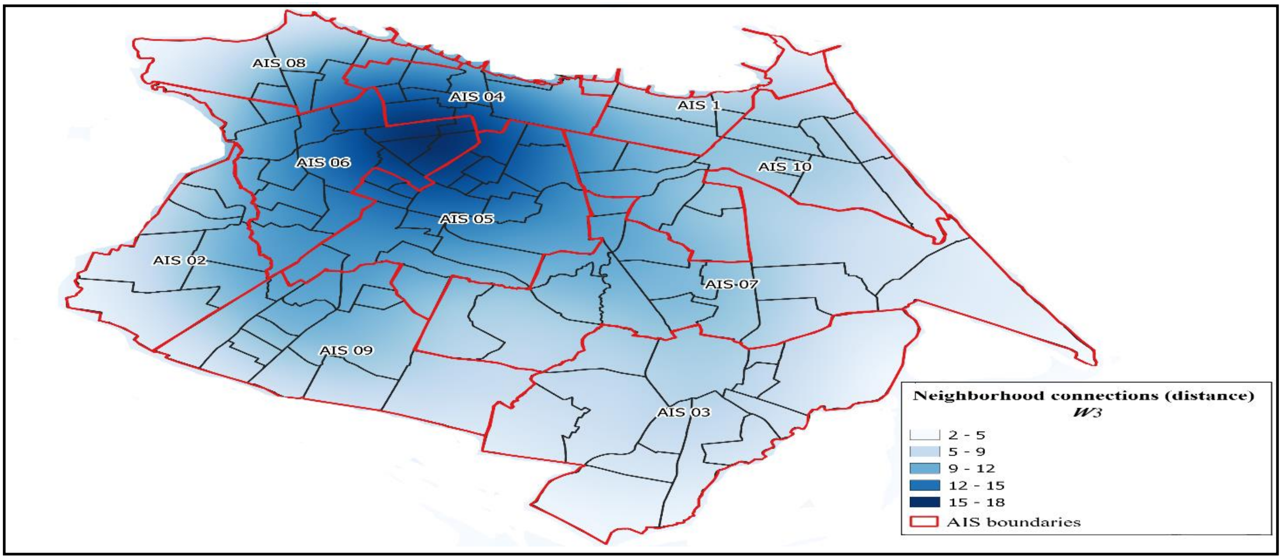
Source: Prepared by the authors.

Figure 4: Distance-Based Spatial Neighborhood Connections



Source: Prepared by the authors.

Map 1: Neighborhood Connections by Distance Matrix $W3$



Source: Prepared by the authors.

4.2. PCA De-factorization Results

As highlighted in the methodology, the degree of cross-sectional dependence in the changes in the rates of theft and robbery in the neighborhoods of Fortaleza is examined by calculating the Pesaran CD statistic for these variations, π_{ist}, without any de-factorization. The results obtained [CD_{π} = 140.75 ($\hat{\bar{\rho}}_{\pi} = 0.16$) for theft rate and CD_{π} = 243.78 ($\hat{\bar{\rho}}_{\pi} = 0.26$) for robbery rate] compared with a critical value of 1.96 at the 5% significance level, indicate that the test is statistically significant and suggest a high degree of cross-sectional dependence in the changes in robbery and theft rates, which may be due to regional and national common effects. Applying the method proposed by BKP, the exponent of the cross dependence was calculated (standard error in parentheses), [$\dot{\alpha}_{\pi}$ = 0.935 (0.02) for theft rate and $\dot{\alpha}_{\pi}$ = 0.967 (0.02) for robbery rate], which is very close to unity, suggesting that changes in the rates of theft and robbery are strongly correlated among the neighborhoods of Fortaleza.

Applying the principal component method (PCA) de-factorization, it can be seen that the resulting CD statistic is much reduced compared to the case without de-factorization, [decreasing from 140.75 to -1.14 in the rate of theft and 243.78 to -6.45 in the robbery rate], and gives a very small estimate for the average pairwise correlations, [$\hat{\bar{\rho}}_{\hat{\xi}}$ = -0.001 to theft rate and $\hat{\bar{\rho}}_{\hat{\xi}}$ = -0.007 for robbery rate], suggesting that the method was able to eliminate much of the strong cross-sectional dependency that existed. Furthermore, the estimate of the exponent of the cross-sectional dependence, which was $\dot{\alpha}_{\pi}$ = 0.935 (0.02) for theft rate and $\dot{\alpha}_{\pi}$ = 0.967 (0.02) for robbery rate, is reduced respectively to $\dot{\alpha}_{\pi} =$ 0.702 (0.01) and 0.601 (0.02).

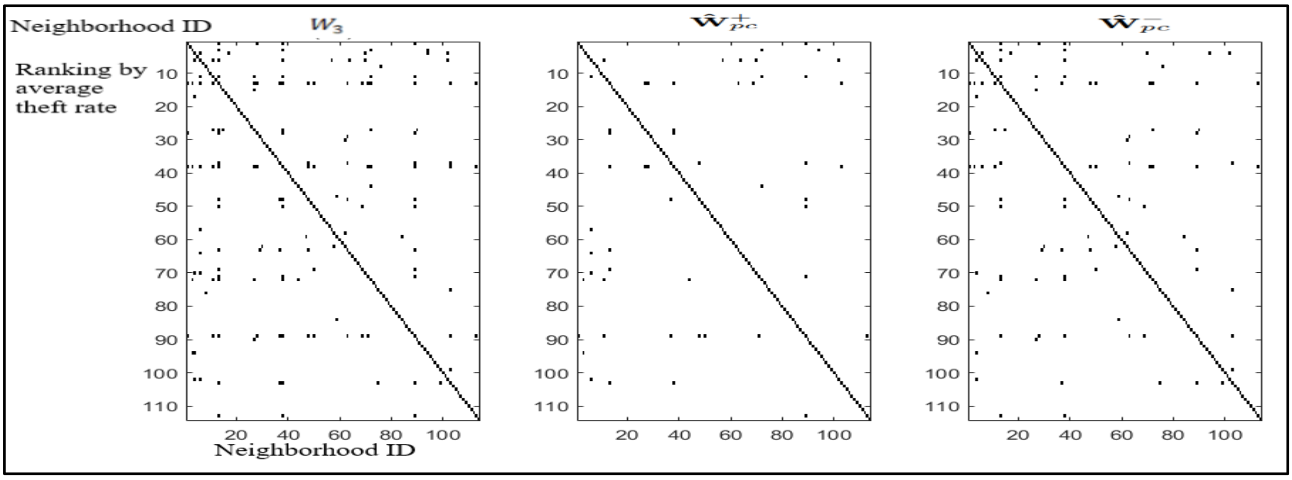
Note that in this case one is close to the threshold value of 1/2, representing weak cross-sectional dependence. It is clear that the more factors that are added, the strength of the cross-sectional dependence of the resulting residuals progressively decreases. Therefore, the defactorization procedure was able to eliminate almost all of the strong cross-sectional dependence that existed in the theft and robbery rates, and what remains may be due to local dependencies that need to be modeled using spatial techniques. After applying the defactorization, one is in the condition of analyzing the correlation matrix of pairs ij.

4.3. Analysis of Distance-Based Neighborhood Matrices and Correlation

In the figures presented below, observe the scatter plots of the distance matrices W_d and correlation matrices W_{pc}, as well as the neighborhood effect. Can see in Figures 5 and 7, when comparing the dispersion of W_3 with the correlations W_{pc}^{+} and W_{pc}^{-}, it becomes clear thath geographic proximity is not the only factor that drives spatial connections between neighborhoods. There are significant positive and negative correlations that occur away from the diagonal, indicating considerable connections.

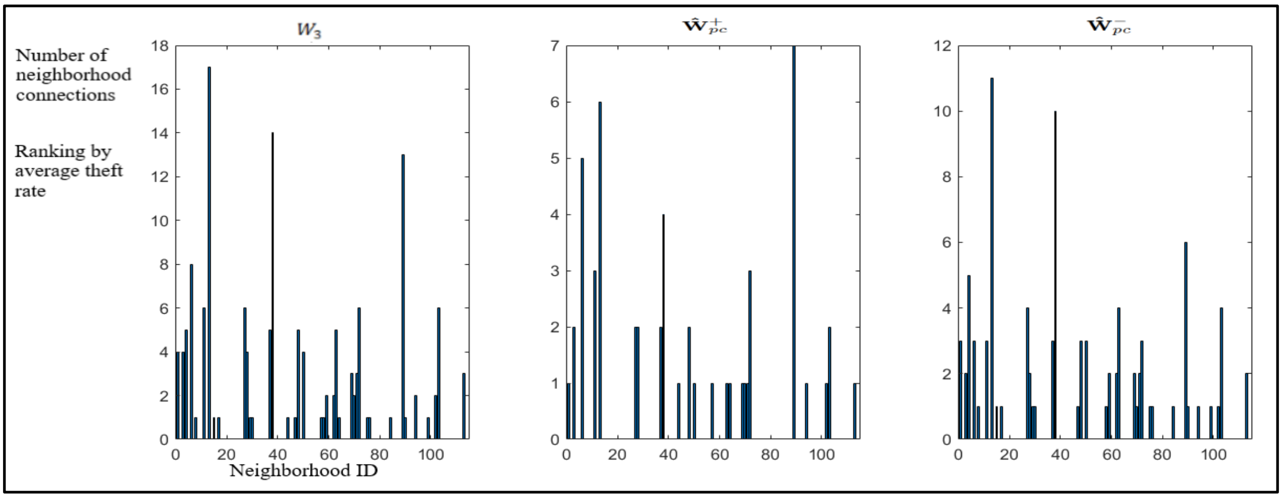
Regarding the theft rate, the matrix W_3 shows a greater spatial influence among neighborhoods in AIS 6 to 7, while for the robbery rate, this spatial cluster expands to neighborhoods in AIS 1 and 5. As shown in Figures 6 and 8, negative correlations have a higher degree of spatial influence and number of neighbors compared to positive correlations, indicating a considerable degree of spatial concentration of the theft and robbery rates. In Map 2, we have a better visualization of the neighborhood connections resulting from spatial correlations. The Midwest Region of Fortaleza has the highest neighborhood connections, indicating that it is a region with considerable spatial dependence on crime, even after eliminating common factors.

Figure 5: Spatial Weights Matrices - Distance and Correlation Based Connections (PCs) – Theft Rate.



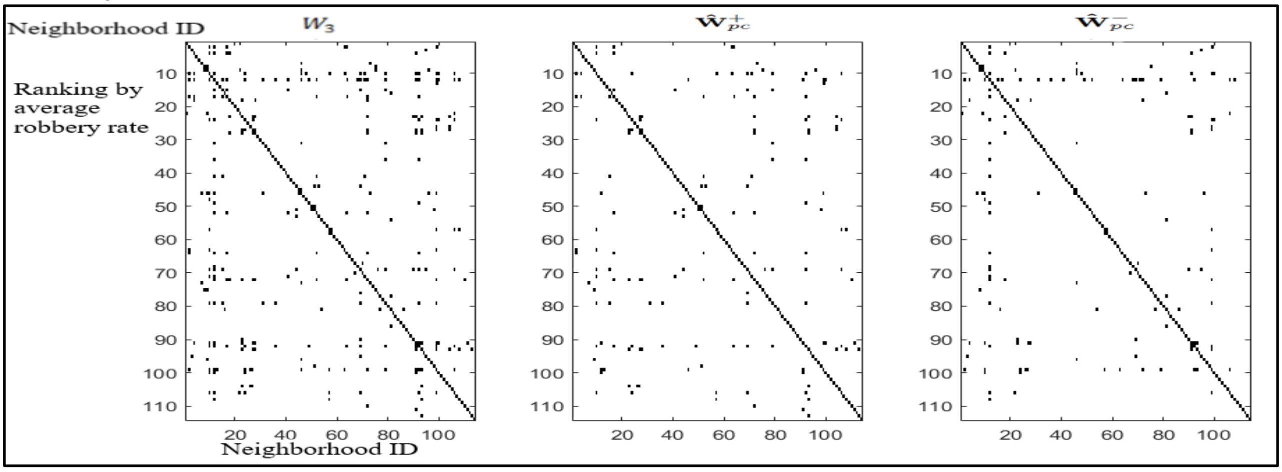
Source: Prepared by the authors.

Figure 6: Spatial Neighborhood Connections Based on Distance and Correlation (PCs) - Theft Rate.



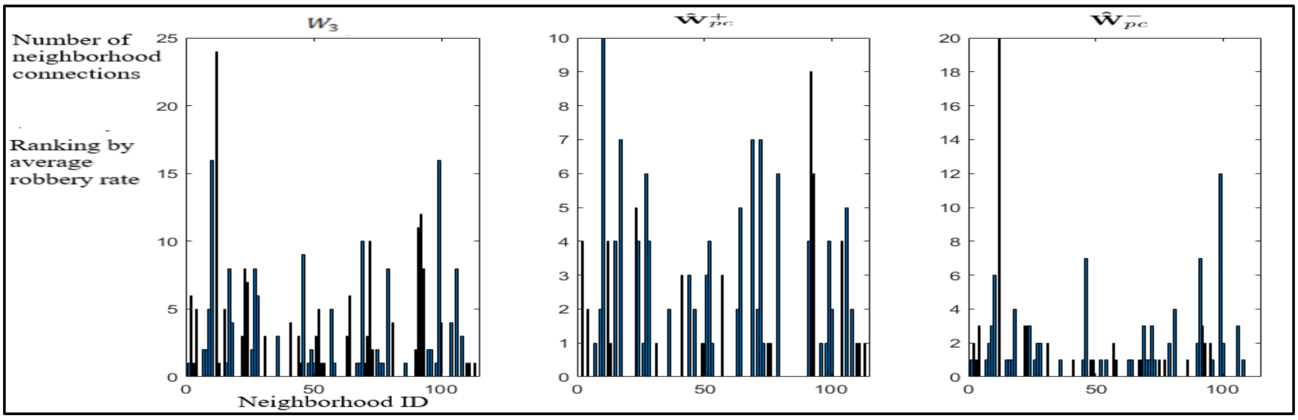
Source: Prepared by the authors.

Figure 7: Spatial Weights Matrices - Distance and Correlation Based Connections (PCs) - Robbery Rate.



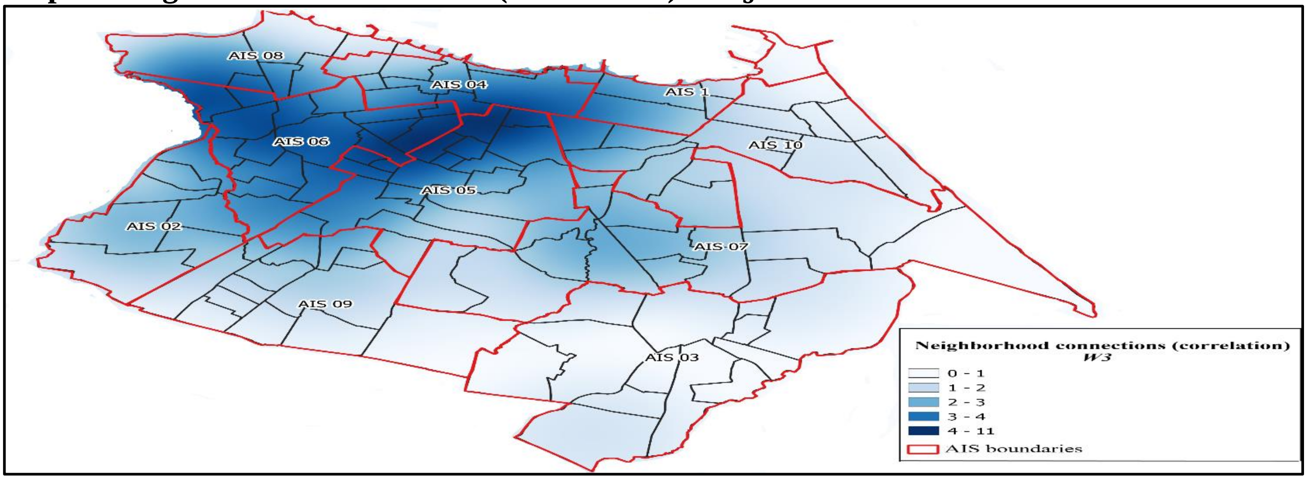
Source: Prepared by the authors.

Figure 8: Spatial Neighborhood Connections Based on Distance and Correlation (PCs) - Robbery Rate.



Source: Prepared by the authors.

Map 2 - Neighborhood Connections (Correlation) – W_3



Source: Prepared by the authors.

4.4. Space-Temporal Model Estimates

Table 1 displays the mean and median coefficients: $\hat{\lambda}_{i1}, \hat{\psi}^{+}_{i0}, \hat{\psi}^{-}_{i0}, \hat{\psi}^{+}_{i1}, \hat{\psi}^{-}_{i1}$ *and* $\hat{\sigma}_{\zeta i}$, along with their corresponding standard errors in parentheses and the proportion of neighborhoods with statistically significant parameters at the 5% level.

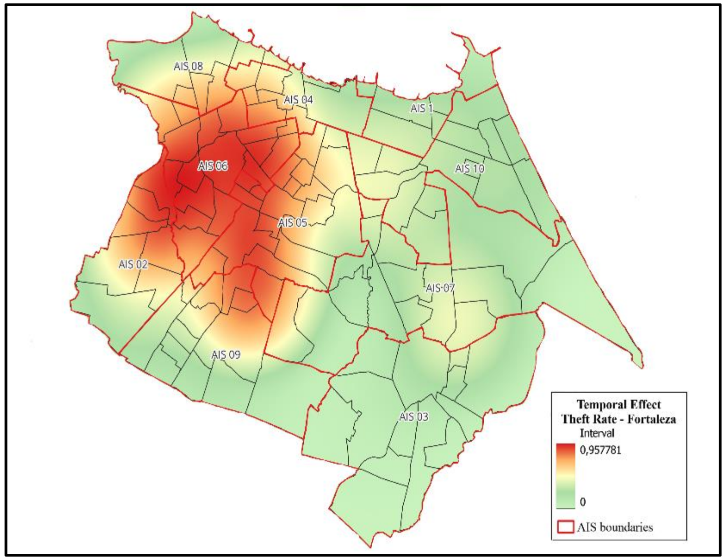
Table 1: QML Estimates from the Space-Temporal Model - Theft and Robbery Rates.

Theft Rate						
	$\boldsymbol{\lambda_1}$	$\boldsymbol{\psi_0^+}$	$\boldsymbol{\psi_0^-}$	$\boldsymbol{\psi_1^+}$	$\boldsymbol{\psi_1^-}$	$\boldsymbol{\sigma_\zeta}$
	Calculated on non-zero parameter coefficients					
Median	0.1466	0.0762	-0.3206	0.0494	0.0109	20.0807
Mean Group Estimates	0.1765	0.1138	-0.3628	0.0512	-0.0626	25.4161
	(0.0137)	(0.0679)	(0.0658)	(0.0372)	(0.0568)	(1.6743)
% significant (at 5% level)	42.1%	45.8%	61.1%	0.0%	22.2%	-
Number of non-zero coef.	114	24	36	24	36	114
Robbery Rate						
Median	0.2124	0.2232	-0.1889	0.0598	0.0273	28.7505
Mean Group Estimates	0.2198	0.2093	-0.2878	0.1538	-0.0351	32.9126
	(0.0127)	(0.0473)	(0.0562)	(0.0687)	(0.0596)	(2.3152)
% significant (at 5% level)	61.4%	46.8%	53.7%	14.9%	18.5%	-
Number of non-zero coef.	114	47	54	47	54	114

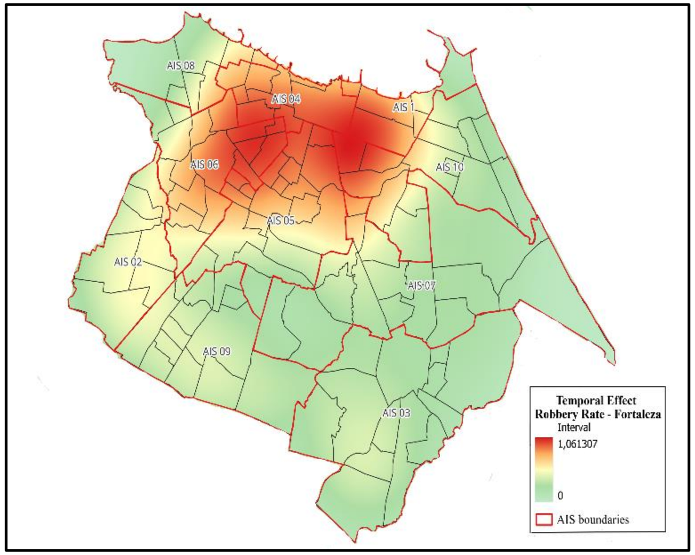
Source: Prepared by the authors.
* (): standard error
* %: proportion of neighborhoods with statistically significant parameters at the 5% level.

Figure 9: A spatial analysis for Fortaleza

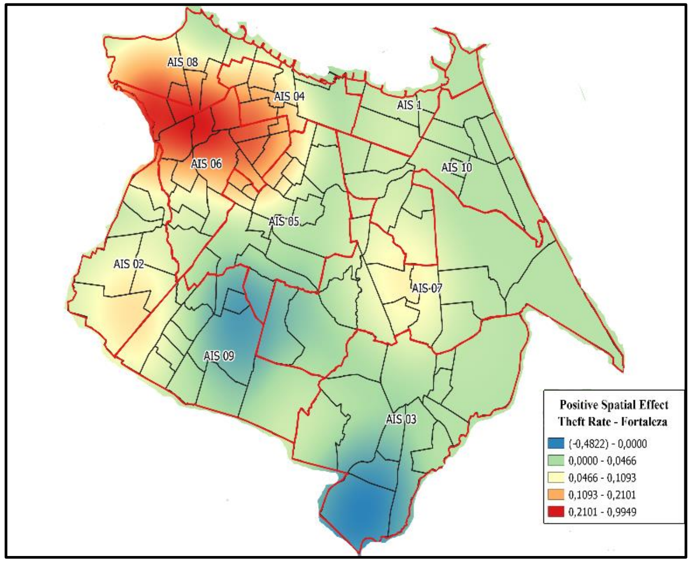
a) Time Effect (Common Factors) - Theft Rate - Fortaleza



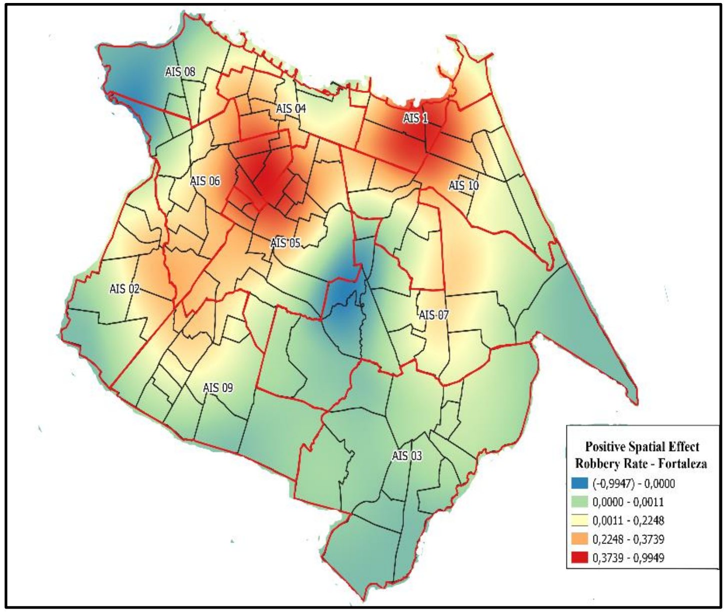
b) Time Effect (Common Factors) - Robbery Rate - Fortaleza



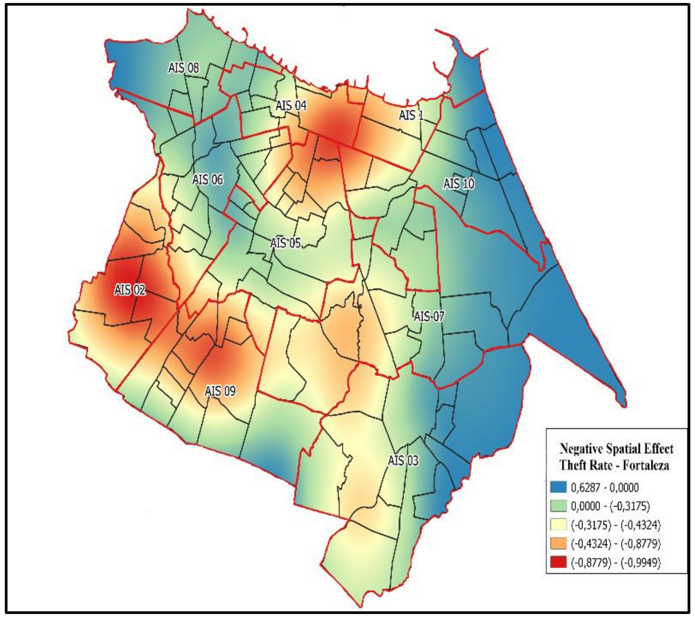
c) Positive Contemporary Spatial Effect - Theft Rate - Fortaleza



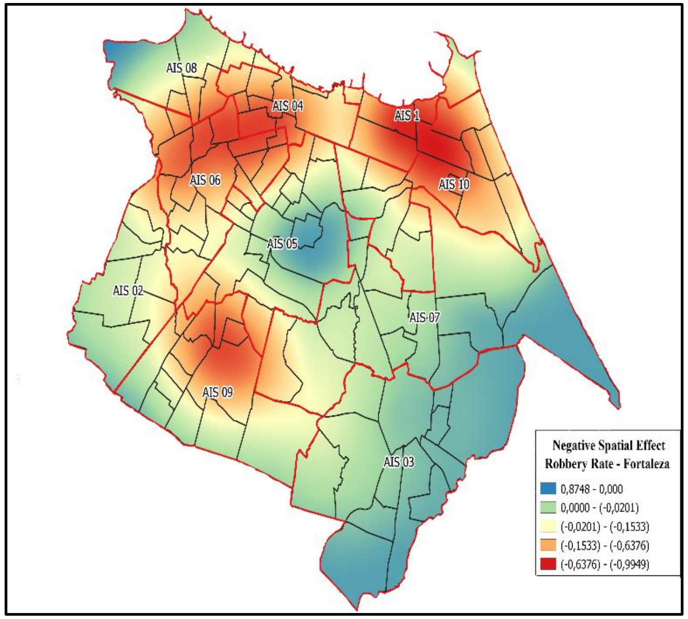
d) Positive Contemporary Spatial Effect - Robbery Rate - Fortaleza



e) Negative Contemporary Spatial Effect - Theft Rate - Fortaleza



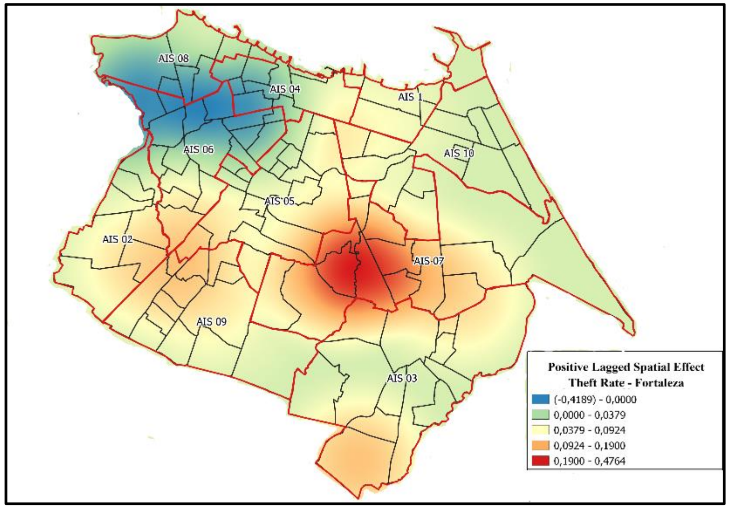
f) Negative Contemporary Spatial Effect - Robbery Rate - Fortaleza



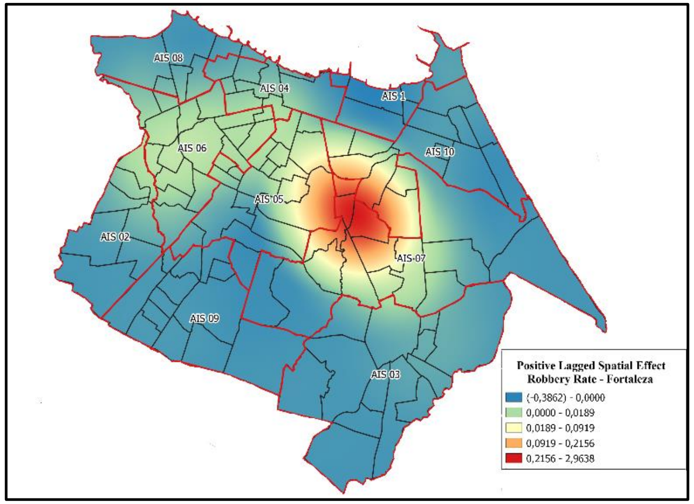
Source: Prepared by the authors.

Figure 10: Lagged spatial effects and ranking of neighborhoods with the highest temporal effects (common factors).

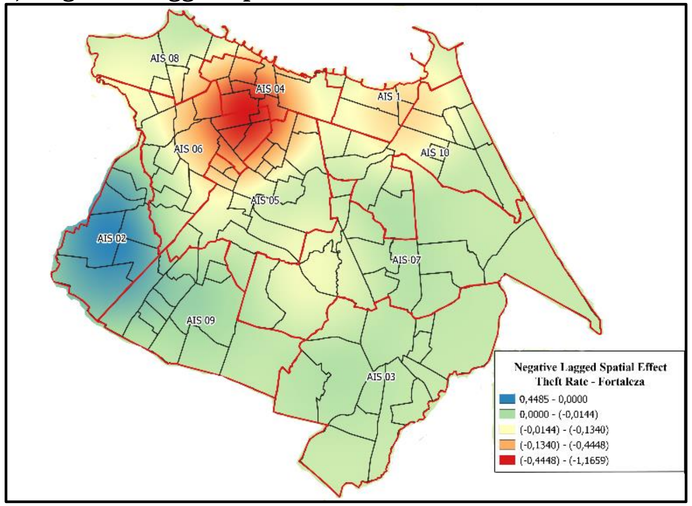
a) Positive Lagged Spatial Effect - Theft Rate - Fortaleza



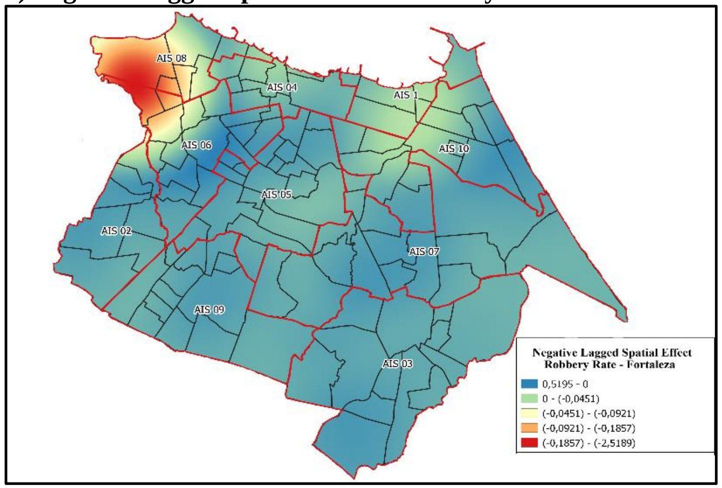
b) Positive Lagged Spatial Effect - Robbery Rate - Fortaleza



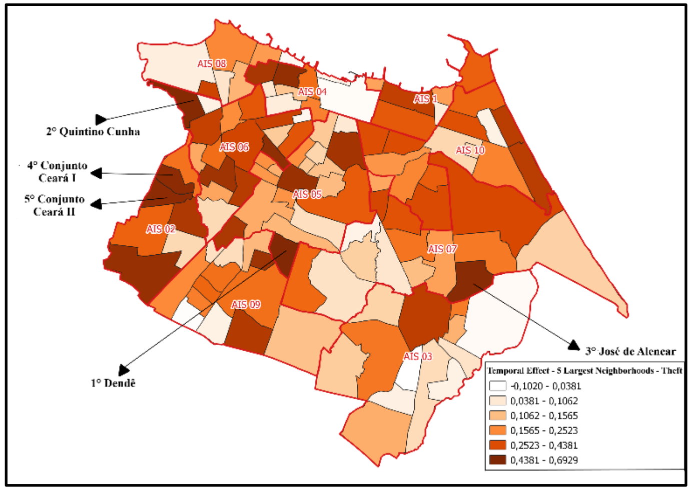
c) Negative Lagged Spatial Effect - Theft Rate - Fortaleza



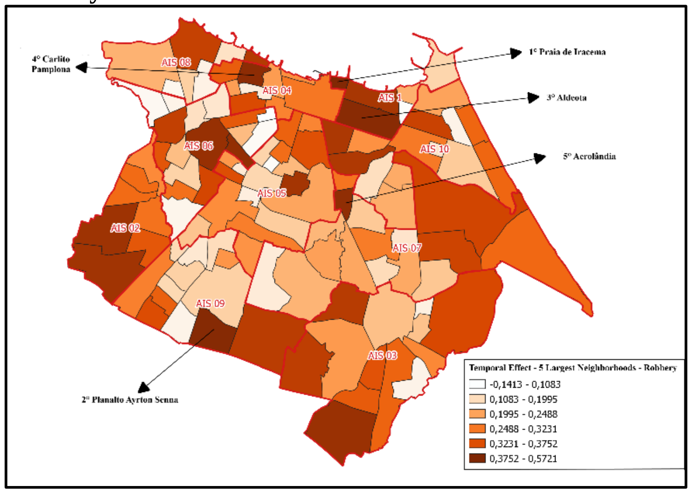
d) Negative Lagged Spatial Effect - Robbery Rate - Fortaleza



e) The Five Neighborhoods with the Highest Persistence of Theft Crime



f) The Five Neighborhoods with the Highest Persistence of Robbery Crime



Source: Prepared by the authors.

For the theft rate, only the mean estimates λ_1 e ψ_0^- are significant. The common factor effect of 0.17 (0.01), is significant in 42,1% of the neighborhoods, and the negative contemporaneous effect, $\hat{\psi}_0^- = -0.36\ (0.06)$, is significant in 61,1% of the neighborhoods, indicating that theft crimes are spatially concentrated.

Regarding the robbery rate, the mean estimates λ_1, ψ_0^+, ψ_0^- and $\psi_1^{;+}$are significant. The magnitude of common factors, $\hat{\lambda}_1$, is 0.22 (0.01), which is larger than that observed for the theft rate, indicating a stronger influence of common factors on robbery rates. On average, negative contemporaneous spatial effects, $\hat{\psi}_0^- = -0.28\ (0.05)$, have a larger magnitude than positive spatial effects, $\hat{\psi}_0^+ = 0.20\ (0.04)$, indicating a predominance of the concentration of robbery crime. The positive lagged spatial effect, $\hat{\psi}_1^+ = 0.15\ (0.06)$, has significant magnitude, suggesting a considerable degree of spatial persistence of robbery in the region.

In Figures 9 and 10, we present a spatial analysis[11] for Fortaleza and the ranking of the five neighborhoods with the highest common effects (temporal effect). In panels (a) and (b), the temporal effects on the rates of robbery and theft by Social Influence Area (AIS) of Fortaleza are presented. It can be observed that for the robbery rate, the persistence of common factors is concentrated with greater magnitude in AIS 2, 4, 5, 6, and 9, located in the Midwest region, exhibiting a strong spillover from AIS 6 to the neighboring areas. There is also an interconnection of clusters from AIS 4 and 5 towards the Eastern region.

For the robbery rate, the factor effect is more evenly distributed among the regions of Fortaleza, but it is also intensified in the West region, with a greater spillover from AIS 6 into neighboring areas. In comparison with the robbery rate, the cluster between AIS 6, 5, and 4 extends to the downtown area of the city, as does AIS 1. Overall, this intensification of robberies throughout the city indicates that it is the most commonly committed crime, with the presence of common factors concentrated throughout the Northern region, where the city center and neighborhoods with the highest incomes are located.

In panels (c) and (d), the positive contemporaneous spillover effect of the theft and robbery rates is shown. For the theft rate, a spillover effect is observed in the Western Region of the city, between AIS 4, 6 and 8, and another in AIS 2. In the Eastern Region, there is a weak spillover in AIS 7. By spatial analysis, neighborhoods in AIS 6 present a strong degree of spillover of theft in neighboring neighborhoods located in AIS 2, 4, 5, and 8. In the neighborhoods of Mondubim, Maraponga of AIS 9, Dendê of AIS 5, and Pedras, Ancuri, and Paupina of AIS 3, a reverse effect is observed, indicating that these neighborhoods concentrate the crimes of theft.

For the robbery rate, there is a strong spillover in the Eastern region (prime area of Fortaleza). This spillover occurs in the neighborhoods located in AIS 1 and influences neighboring neighborhoods in AIS 4, 7, and 10. The spillover present in the West region focuses on the neighborhoods located in AIS 5 and 6 and extends to influence AIS 2, 4, and 9. Interestingly, the spillover occurs in a connection from the North region to the southernmost neighborhoods of the city. There is a strong separation of these clusters into prime neighborhoods and the periphery.

In panels (e) and (f), the negative contemporaneous spatial effect of the theft and robbery rates is shown. For the theft series, we observe three strong clusters of crime concentration. The first is in the North Central region, the second in the South region, and the third is formed by neighborhoods in AIS 9. There is also the presence of a cluster with lower intensity among neighborhoods in AIS 3 and 7. It is worth noting that the large cluster in the South region borders municipalities that are industrial hubs in the state, such as the city of Maracanaú, while the cluster in the North region comprises the Downtown area, a commercial hub.

For the robbery rate, the distribution of clusters is different. We can also observe three strong clusters: the first in the Central-Eastern region of the city which encompasses the neighborhoods of AIS 1 and 10, the second in the Western region, and the third located in AIS 9. We can see that the clusters of theft concentration are located in heterogeneous regions of the city, such as the Western (periphery) and Eastern (prime region).

In Figure 10, panels (a), (b), (c) and (d) show the positive and negative spatial weight lags for theft and robbery rates. The theft rate displays a strong spillover from neighborhoods in AIS 7 to neighboring regions, while neighborhoods in AIS 4, 6 and 8 show a reverse effect, indicating spatial

11. Annexes 11 and 12 present tables and maps of the spatio-temporal model estimates for all AIS in Fortaleza

persistence of theft crime in these areas. Regarding the robbery rate, a strong spillover is observed in AIS 7 and a smaller one in AIS 6 that spills over into AIS 5. In AIS 1, 8 and 10, a reverse effect is displayed, indicating spatial persistence of robbery crime in these regions. The negative lags for theft and robbery are not significant.

In panels (e) and (f), the five neighborhoods with the highest persistence of common factors in the rates of robbery and theft, respectively, are presented. For theft, the neighborhood with the highest persistence is Dendê, located in AIS 5, followed by Quintino Cunha in AIS 8, José de Alencar in AIS 7, and Conjunto Ceará I and II in AIS 2. Most of these neighborhoods are concentrated in the West region of Fortaleza, although there is a persistence pole in neighborhoods of AIS 3, 7, and 10, located in the South and East regions. Concerning the robbery rate, it is observed that the East region (prime area) has three of the five neighborhoods with the highest persistence factors. Praia de Iracema located in AIS 1 leads the ranking, followed by Planalto Ayrton Senna in AIS 9, Aldeota in AIS 1, Carlito Pamplona in AIS 4, and Aerolândia in AIS 7.

5. Conclusions

Using the rates of theft and robbery in the city of Fortaleza, this paper sought to distinguish between strong and weak cross-sectional dependence, through a model that accommodates the effect of common factors and the association between spatial units. To this end, a two-stage estimation was carried out, and in the first stage the CD test for cross-sectional dependence was performed to verify the existence of weak sectional dependence. Since the null hypothesis of weak cross-sectional dependence was rejected, the second stage was to implicitly model the strong cross-sectional dependence by means of a factor analysis, the principal components method (PCA). The residuals of the model, referred to as de-factorized observations, were used to estimate possible connections between pairs of cross-sectional units.

The results of the spatial weight matrices indicate a significant effect of spatial correlation and distance (W_1, W_2 e W_3), collaborating with the interpretation that there is contamination of crime in a region and in neighboring regions. When the spatial influence is analyzed in the weight matrices it is observed that the effect is concentrated among the neighborhoods of the AIS 1, 4, 5, 6 and 10. It is verified that when the distance radius of the matrices (W_2 e W_3), is multiplied, the number of neighborhood connections increases, some neighborhoods go from 2 to 18 connections, for example, the Center neighborhood.

Furthermore, it is observed that the neighborhood effect for theft and robbery is heterogeneous across AIS. For the theft rate, matrix W_1 shows a greater spatial influence between neighborhoods in AIS 6 and 7, while for the theft rate this spatial cluster increases for neighborhoods in AIS 1, 2, 7 and 8. When the matrices W_2 and W_3 are considered, the increase in dependence between these neighborhoods is seen. The negative correlations have a higher degree of spatial influence and number of neighbors compared to the positive correlations, indicating a considerable degree of spatial concentration of robbery and theft rates. The West Region of Fortaleza holds the highest neighborhood connections, even after separating out the influence of common factors.

In general, the estimates from the spatio-temporal model suggest that there is considerable temporal and dependency structure in the changes in rates of theft and robbery in the neighborhoods of Fortaleza over the analyzed period. The results make it evident that the rates of robbery and theft in the Midwest region of the city are strongly influenced by common factors, and this influence can stem from economic shocks, as in times of growth and recession, as well as from state security policies that aim to combat these types of crime.

This is demonstrated by the strong overflow of temporal effects in AIS 4, 5, and 6 for the theft rate, and in AIS 1, 4, 5, 6, and 7 for the robbery rate. As these regions concentrate the main commercial, financial, and industrial centers of Fortaleza, they are more vulnerable to the movement of economic activities, and also receive special attention from the state in terms of security policies.

Analyzing spatial effects, it is observed that theft crimes are spatially correlated, occurring more frequently in economically attractive regions from the point of view of the broken windows theory of the Chicago School, that is, regions with a lack of state tutelage. While for the crime of robbery, this hypothesis does not hold, observing the presence of significante clusters in the prime region of the city, with strong intensification between the neighborhoods Praia de Iracema, Aldeota and Meireles. It is worth mentioning that the two last mentioned neighborhoods have strong commercial and financial influence in the city, which can explain the attraction of criminal practices. In summary, it is observed that the crime of robbery has advanced frequently in all regions of the city, regardless of the socioeconomic status of the neighborhoods.

One hypothesis for the theft crimes to be concentrated in the Western region of the city is the fact that the peripheral region is the place where there is the greatest lack of policing and the predominance of housing in "villages", which facilitates the practice of theft actions by bandits without the owner of the property catching the act. This is a more costly action to carry out in the Eastern region of Fortaleza, due to the greater ostensive police presence and the predominance of residential buildings with private security. Despite the expected greater benefit of criminal action in prime regions (Viapiana, 2006).

The results for spatial correlations found in this work converge with the evidence observed by Carvalho, Medeiros, and Oliveira (2016), Oliveira and Simonassi (2019), and Dantas and Favarin (2021), in which they observe a concentration of crimes in the western region of Fortaleza. This region presents the worst levels of income, formal jobs[12], HDI, and a greater scarcity of police stations. In addition, we observe overflows of the rates of robbery and theft in the regions closer to the city center (AIS 4), the so-called "transition zones" evidenced by Park and Burgess (1925). The significant positive lagged spatial effect indicates that there is spatial persistence of crime in these areas over time.

One difference with the results of the work done for Fortaleza that uses the CVLI rate, is that the spatial spillovers of homicide are concentrated in AIS 2, while the spillovers of robbery and theft seen for this work are concentrated in AIS 1, 4, 5, 6 and 8 after removing the influence of common factors. This reinforces the assumption that spatially there is a heterogeneity of the practice of violence across city regions, in which certain regions become attractive for a specific type of crime, meeting the theory of criminal patterns (Brantingham and Brantingham, 2010). In this sense, it is necessary for the state to understand which regions predominate the actions of theft and in which areas the practice of robbery is more frequent.

Thus, by filling a gap in the literature on the spatial dependence of crime, this work also seeks to contribute to public policies that aim to achieve the best management decisions in public security, whether in the ostensible action of distributing the staff of police officers throughout the city, in the police knowledge of the region they are working in, or in administrative programs (incentive plans for generating results, training for police officers) with the intention of promoting greater results in terms of improving criminal indicators in the most critical regions.

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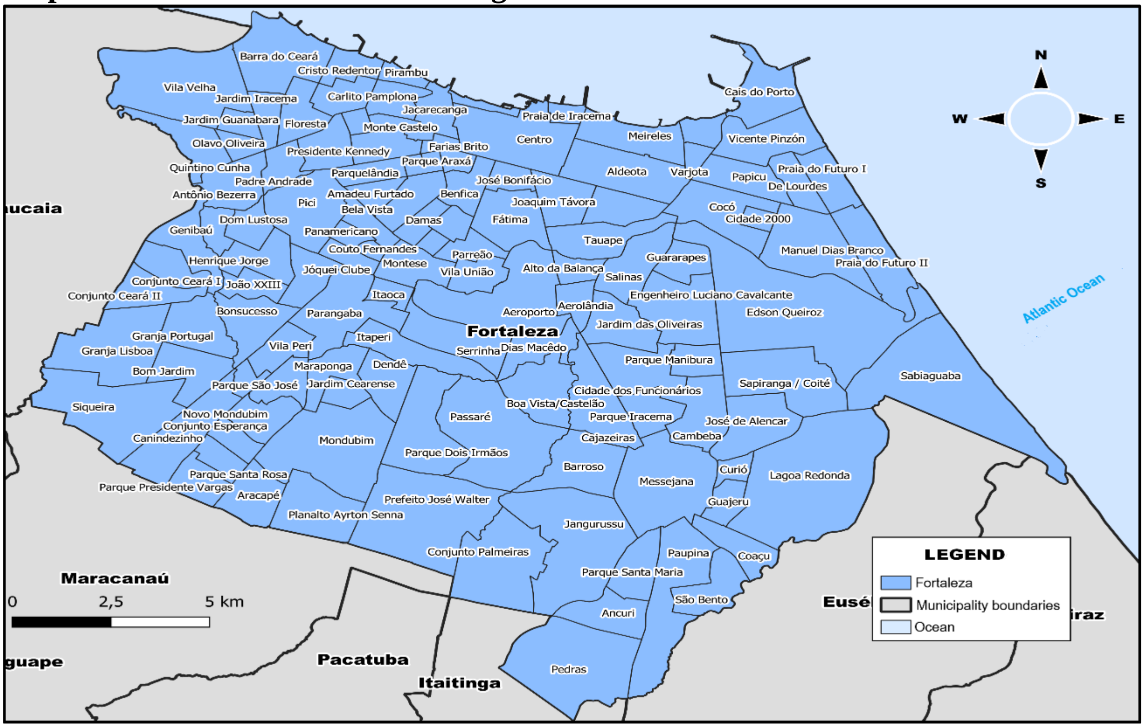
ANNEXES

ANNEX 1 – Territorial Division of the Neighborhoods of Fortaleza

Map: Territorial Division of the Neighborhoods of Fortaleza

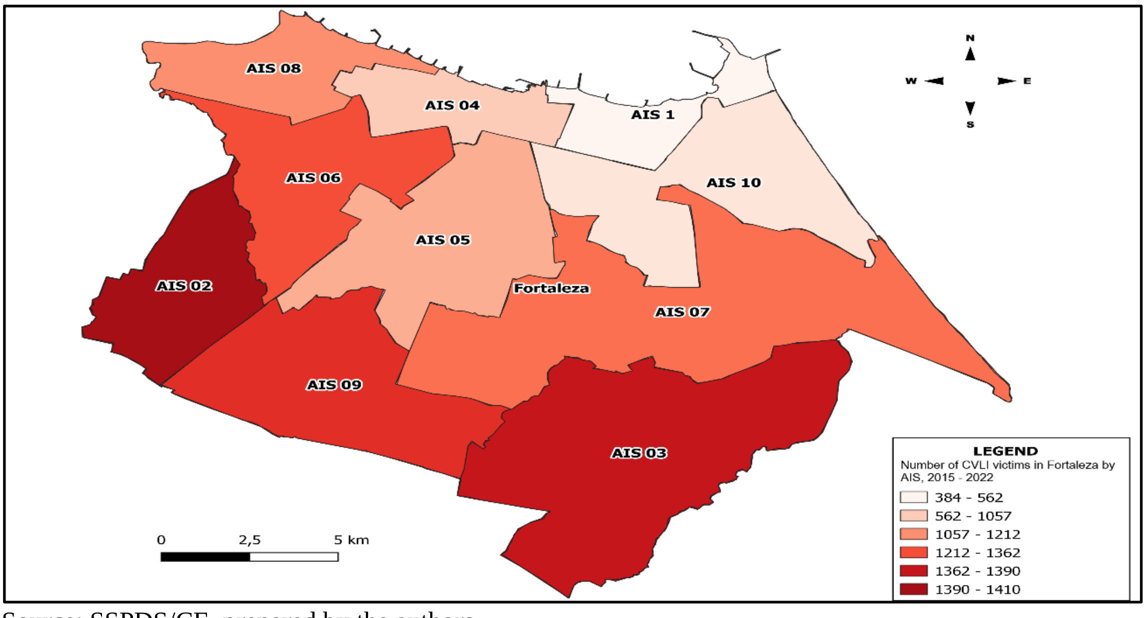


Source: Fortaleza Municipal Government, prepared by the authors.

ANNEX 2 - Panorama of CVLI, Theft and Robbery Crimes in Fortaleza by AIS, from 2015 to 2022.

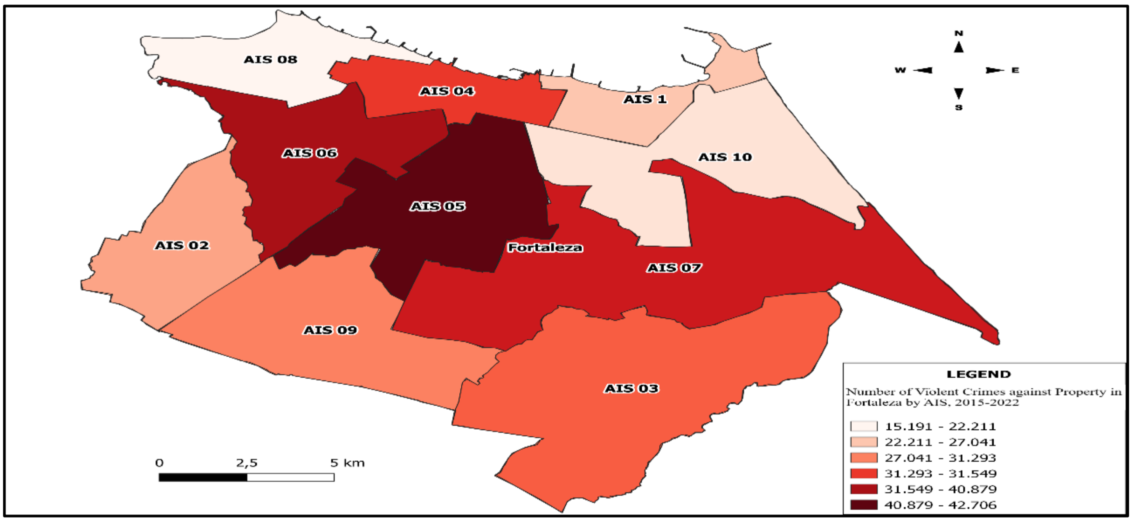
Over the last eight years (2015-2022), Fortaleza has registered more than 9.000 lethal and intentional violent crimes (CVLI), with over 65% of these records concentrated in the western region. In addition, there were more than 215.000 notifications of thefts and 285.000 violent crimes against property (CVP).

Map 1: Number of Victims of Intentional Lethal Violent Crime in Fortaleza by AIS, 2015-2022.



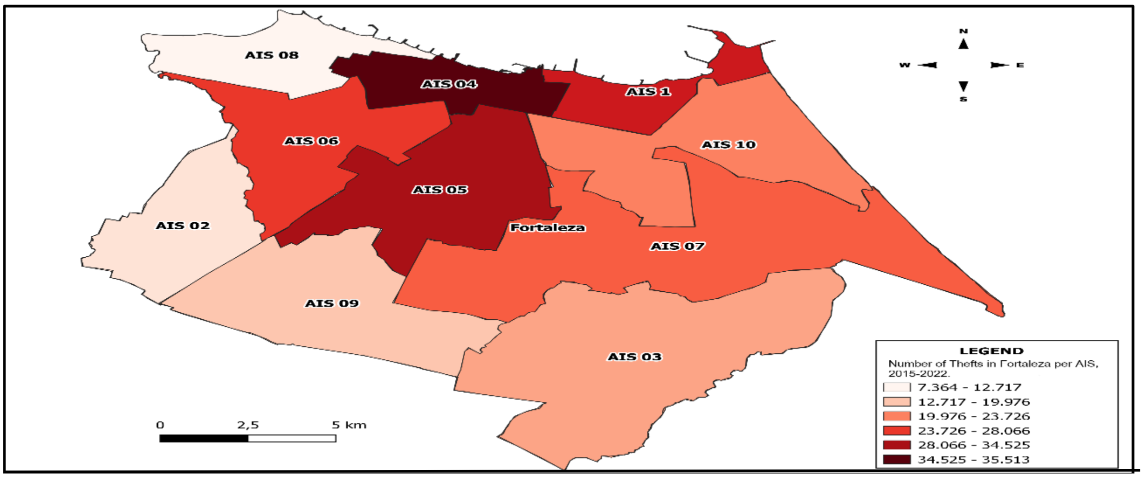
Source: SSPDS/CE, prepared by the authors.

Map 2: Number of Violent Crimes against Property in Fortaleza by AIS, 2015-2022.



Source: SSPDS/CE, prepared by the authors.

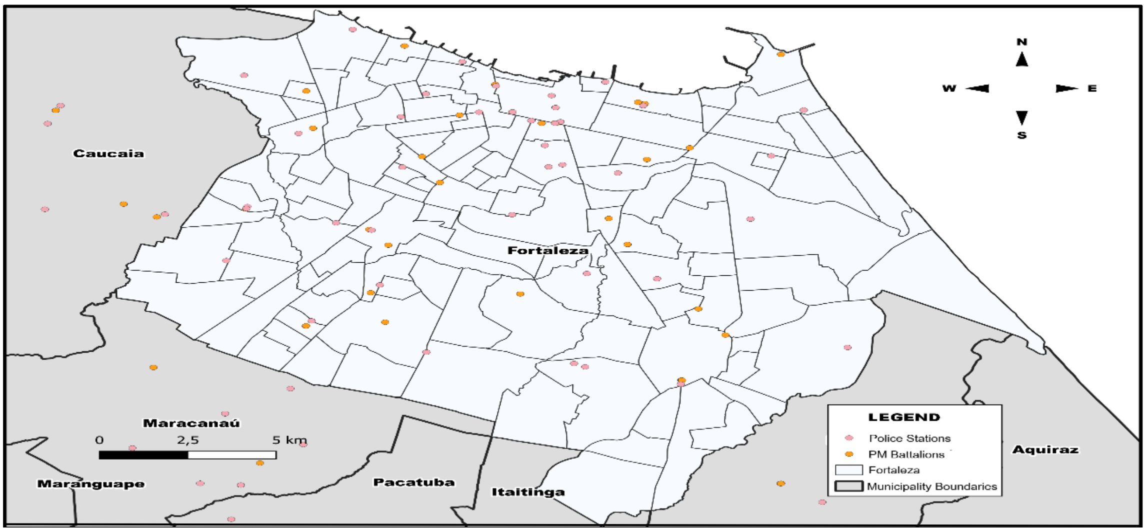
Map 3: Number of Thefts in Fortaleza per AIS, 2015-2022.



Source: SSPDS/CE, prepared by the authors.

ANNEX 3 - Military Structure - Distribution of Police Stations and Battalions in Fortaleza

Map: Distribution of Police Stations and Battalions of the Military Police in Fortaleza



Source: Secretariat of Public Security and Social Defense of the State of Ceará (SSPDS-CE), prepared by the authors.

In the northern part of the city, especially in the central neighborhood and its surroundings, there is a concentration of specialized police stations, whereas the periphery is the region with the lowest concentration of police stations. The community bases of the military police aim to reduce these deficits.

ANNEX 4 - Identification of the neighborhoods in the Distance Matrix Figures

Table: Neighborhood ID in the Spatial Weights Matrices

Order	AIS	Neighborhood	Order	AIS	Neighborhood
1	1	Aldeota	58	6	Bonsucesso
2	1	Cais do Porto	59	6	Dom Lustosa
3	1	Meireles	60	6	Henrique Jorge
4	1	Mucuripe	61	6	João XXIII
5	1	Praia de Iracema	62	6	Jóquei Clube
6	1	Varjota	63	6	Padre Andrade
7	1	Vicente Pinzon	64	6	Parque Araxá
8	2	Bom Jardim	65	6	Parquelândia
9	2	Conjunto Ceará	66	6	Pici
10	2	Genibaú	67	6	Presidente Kennedy
11	2	Granja Lisboa	68	6	Quintino Cunha
12	2	Granja Portugal	69	6	Rodolfo Teófilo
13	2	Siqueira	70	7	Aerolândia
14	3	Ancuri	71	7	Alagadiço Novo (José de Alencar)
15	3	Barroso	72	7	Alto da Balança
16	3	Coaçu	73	7	Boa Vista (Castelão\Mata Galinha)
17	3	Conjunto Palmeiras	74	7	Cajazeiras
18	3	Curió	75	7	Cambeba
19	3	Guajerú	76	7	Cidade dos Funcionários
20	3	Jangurussu	77	7	Dias Macedo
21	3	Lagoa Redonda	78	7	Edson Queiroz
22	3	Messejana	79	7	Jardim das Oliveiras
23	3	Parque Santa Maria	80	7	Lagoa Sapiranga (Coité)
24	3	Paupina	81	7	Parque Dois Irmãos
25	3	Pedras	82	7	Parque Iracema
26	4	Álvaro Weyne	83	7	Parque Manibura
27	4	Carlito Pamplona	84	7	Passaré
28	4	Centro	85	7	Sabiaguaba
29	4	Farias Brito	86	8	Barra do Ceará
30	4	Jacarecanga	87	8	Cristo Redentor
31	4	Monte Castelo	88	8	Floresta
32	4	Moura Brasil	89	8	Jardim Guanabara
33	4	São Gerardo	90	8	Jardim Iracema
34	4	Vila Ellery	91	8	Pirambu
35	5	Aeroporto	92	8	Vila Velha
36	5	Benfica	93	9	Canindezinho
37	5	Bom Futuro	94	9	Conjunto Esperança
38	5	Couto Fernandes	95	9	Jardim Cearense
39	5	Damas	96	9	Maraponga
40	5	Demócrito Rocha	97	9	Mondubim
41	5	Dendê	98	9	Parque Presidente Vargas

42	5	Fátima	**99**	9	Parque Santa Rosa
43	5	Itaoca	**100**	9	Parque São José
44	5	Itaperi	**101**	9	Planalto Ayrton Senna
45	5	Jardim América	**102**	9	Prefeito José Walter
46	5	José Bonifácio	**103**	9	Vila Manuel Sátiro
47	5	Montese	**104**	10	Cidade 2000
48	5	Panamericano	**105**	10	Cocó
49	5	Parangaba	**106**	10	Dionísio Torres
50	5	Parreão	**107**	10	Engenheiro Luciano Cavalcante
51	5	Serrinha	**108**	10	Guararapes (Patriolino Ribeiro)
52	5	Vila Peri	**109**	10	Joaquim Távora
53	5	Vila União	**110**	10	Manuel Dias Branco
54	6	Amadeu Furtado	**111**	10	Papicu
55	6	Antônio Bezerra	**112**	10	Praia do Futuro
56	6	Autran Nunes	**113**	10	Salinas
57	6	Bela Vista	**114**	10	São João do Tauape

Source: Prepared by the authors.

ANNEX 5 - Multiple Test developed in Bailey, Pesaran, and Smith (2014)

To test the statistically significant data of pairwise correlations of the defactor observations, ij, onde needs to consistently estimating the true positive rate and the false positive rate of zeros using the underlying matrix, W.

Bailey, Pesaran and Smith have established that the zeros of W = (wij) can be consistently estimated by:

$$\widehat{W}_{ij} = I\left(\left|\hat{\rho}_{ij}\right| > \frac{C_p(N)}{\sqrt{T}}\right) \qquad (1)$$

Where $C_p(N) = \Phi^{-1}\left(1 - \frac{p}{N(N-1)}\right)$, p is the pre-specified overall size of the test (set to 5%) and $\Phi^{-1}(.)$ is the inverse of the standard cumulative normal distribution. More specifically, consider the true positive rate (TPR) and the false positive rate (FPR) of ones / zeros in matrix W, as defined respectively by:

$$TPR = \frac{\sum_{i\neq j}\sum I(\widehat{w}_{ij} \neq 0, e\ \rho_{ij} \neq 0)}{\sum_{i\neq j}\sum I(\rho_{ij} \neq 0)} \qquad (2)$$

$$FPR = \frac{\sum_{i\neq j}\sum I(\widehat{w}_{ij} \neq 0, e\ \rho_{ij} = 0)}{\sum_{i\neq j}\sum I(\rho_{ij} = 0)} \qquad (3)$$

Bailey, Pesaran and Smith show that, under certain plausible regularity conditions, the TPR → 1 and FPR → 0 with N and T →1 with probability one, provided

$$\rho_{min} = min_{i,j}\left(\rho_{i,j}\right) > C_p(N)/\sqrt{T} \qquad (4)$$

One problem that can arise with the multiple testing approach is when you have a number of possible dependent tests and the goal is to control the size of the overall test. In this regard, it is necessary to impose the assumption that a family of null hypotheses exists, H_{01}, H_{02}, ...,H_{0n} together with the corresponding test statistics, Z_{1T}, Z_{2T}, ..., Z_{nT}, with separate rejection rules provided by:

$$P_r(|Z_{iT}| > CV_{iT}|H_{0i}) \leq p_{iT}, \qquad (5)$$

where CV_{iT} is some appropriately chosen critical value of the test and p_{iT} is the p-observed value for H_{oi}. Now consider the family-wise error rate (FWER) defined by:

$$FWER_T = P_r[U_{i=1}^{n}(|Z_{iT}| > CV_{iT}|H_{oi})] \quad (6)$$

If it is desired to control $FWER_T$ below a predetermined value p, then a reduction procedure is proposed by Holm (1979), which imposes no additional restrictions on the extent to which the underlying tests depend on each other.

If abstract from the subscript T and order the p-values of the tests such that: $p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(n)}$ are associated with the null hypotheses, H_{01}, H_{02}, ...,H_{0n}, respectively, Holm's procedure rejects H_{01} if $p_{(1)} \leq$ p/n, rejects H_{01} and H_{02} if $p_{(2)} \leq$ p/(n – 1), rejects H_{01}, H_{02} and H_{03} if $p_{(3)} \leq p/$(n – 2), and so on. Therefore, a solution to the problem of test dependency is obtained.

ANNEX 6 - Cross Dependency Exponent Method

The exponent of the cross dependency, α, is defined in terms of the scaled factor loadings, δ_i, present in the residuals of the spatio-temporal model. In this case, the degree of cross-sectional dependence due to the i-th factor can be measured by $\alpha_l = \frac{\ln(M_l)}{\ln(N)}$, and the overall degree of cross-dependence by $\alpha = max_l(\alpha_l)$. The exponent α gives the maximum number of units xit, $M = max_l(M_l)$, that are correlated in pairs. Suppose that only the first M_l elements of δ_{il} over i are non-zero, and note that

$$\bar{\delta}_{lN} = N^{-1}\left(\sum_{i=1}^{M_l} \delta_{il} + \sum_{i=M_l+1}^{N} \delta_{il}\right)$$

$$= \left(\frac{M_l}{N}\right)\left(M_l^{-1}\sum_{i=1}^{M_l} \delta_{il}\right) = N^{\alpha_l - 1}\mu_l$$

Where $\mu_l = M_l^{-1}\sum_{i=1}^{M_l} \delta_{il} \neq 0,\ and\ \ \alpha = max_l(\alpha_l)$.

ANNEX 7 - Contingency analysis of distance-based spatial weight matrices with correlation-based spatial weight matrices

The association analysis of correlation-based estimates, $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$, with the distance-based weighting matrix, $(W_1,\ W_2\ and\ W_3)$, can be performed using an upper triangular contingency table to analyze which of these matrices best fits the contingency analysis:

$$\begin{pmatrix} n_{11} & n_{10} \\ n_{01} & n_{00} \end{pmatrix} \qquad (1)$$

Where:

n_{11}: represents the number of times $\widehat{W}^{+}$ (or $\widehat{W}^{-}$) displays the entry 1 when W_d is displayed 1.
n_{00}: represents the number of times $\widehat{W}^{+}$ (or $\widehat{W}^{-}$) displays the entry 0 when W_d is displayed 0.
n_{01}: represents the number of times $\widehat{W}^{+}$ (or $\widehat{W}^{-}$) displays the entry 0 when W_d is displayed 1.
n_{10}: represents the number of times $\widehat{W}^{+}$ (or $\widehat{W}^{-}$) displays the entry 1 when W_d is displayed 0.

Then, $n_{11} + n_{00} +\ n_{01} + n_{10} = \frac{N\ (N\ -\ 1)}{2}$ = 2, e a estatística qui-quadrada de Pearson (1900), há um nível de significância de 5%, a ser comparado com um valor crítico de 3,84 é:

$$x^2 = \frac{1}{2}N(N-1)\left[\sum_{i,j=0}^{1}\frac{n_{ij}^2}{(n_i+n_j)} - 1\right] \qquad (2)$$

Also below are the contingency tables for i): $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$ versus W_1, ii): $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$ versus W_2 , iii) $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$ versus W_3 and Pearson's chi-square test. The contingency tables and chi-square tests show that the theft rate has a greater spatial association of $\widehat{W}_{pc}^{-}$ ($\widehat{W}_{pc}^{-}$ has more elements in common with W_1, W_2 and W_3 than $\widehat{W}_{pc}^{+}$, and the chi-square test statistics are highly significant for $\widehat{W}_{pc}^{-}$), indicating a spatial concentration of theft, while for the robbery rate there is a weakly greater association of $\widehat{W}_{pc}^{+}$ (the elements of $\widehat{W}_{pc}^{+}$ are most associated with the spatial weights of W_2 than $\widehat{W}_{pc}^{-}$, and the chi-square test statistics are highly significant for $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$), indicating robbery overflow. This scenario is intensified when analyzing the matrices W_3 for theft rate and W_2 for robbery rate.

Table 1: Contingency Table for $\widehat{W}_{pc}^{+}$ and $\widehat{W}_{pc}^{-}$ versus W_1, W_2 and W_3 – Theft and Robbery

	Theft Rate											
	W_1				W_2				W_3			
$\widehat{W}_{pc}^{+}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$
	1	1	25	**26**	1	2	24	**26**	1	3	23	**26**
	0	117	6298	**6415**	0	275	6140	**6415**	0	508	5907	**6415**
	$\sum_{cols}$	**118**	**6323**	**6441**	$\sum_{cols}$	**277**	**6164**	**6441**	$\sum_{cols}$	**511**	**5930**	**6441**
$\widehat{W}_{pc}^{-}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$
	1	5	42	**47**	1	11	36	**47**	1	16	31	**47**
	0	113	6281	**6394**	0	266	6128	**6394**	0	495	5899	**6394**
	$\sum_{cols}$	**118**	**6323**	**6441**	$\sum_{cols}$	**277**	**6164**	**6441**	$\sum_{cols}$	**511**	**5930**	**6441**
	Robbery Rate											
	W_1				W_2				W_3			
$\widehat{W}_{pc}^{+}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$
	1	6	70	**76**	1	15	61	**76**	1	18	58	**76**
	0	112	6253	**6365**	0	262	6103	**6365**	0	493	5872	**6365**
	$\sum_{cols}$	**118**	**6323**	**6441**	$\sum_{cols}$	**277**	**6164**	**6441**	$\sum_{cols}$	**511**	**5930**	**6441**
$\widehat{W}_{pc}^{-}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$		1	0	$\sum_{rows}$
	1	6	62	**68**	1	12	56	**68**	1	18	50	**68**
	0	112	6261	**6373**	0	265	6108	**6373**	0	493	5880	**6373**
	$\sum_{cols}$	**118**	**6323**	**6441**	$\sum_{cols}$	**277**	**6164**	**6441**	$\sum_{cols}$	**511**	**5930**	**6441**

Source: Prepared by the authors.

Table 2: Pearson's chi-square test

	Theft Rate		
	W_1	W_2	W_3
$\widehat{W}_{pc}^{+}$	0.58886	0.72969	0.46446
$\widehat{W}_{pc}^{-}$	20.4157	41.9833	44.1865

Robbery Rate			
$\widehat{W}_{pc}^{+}$	15.7183	44.5264	26.1214
$\widehat{W}_{pc}^{-}$	18.6794	29.7452	32.3318

Source: Prepared by the authors.

ANNEX 8 - Maximum Likelihood Estimator of the Spatial-Temporal Model Parameters

Inference on the individual coefficients of the spatio-temporal model are performed using secondary cross derivatives of the maximum likelihood function, with respect to $\theta = (\theta_1', \theta_2', \dots, \theta_N')'$, where $\theta_i = \left(\psi_{i0}^{+}, \psi_{i0}^{-}, \psi_{i1}^{+}, \psi_{i1}^{-}, \lambda_{i1}, \sigma_{u_i}^{2}\right)'$.

From the variance-covariance matrix of $\hat{\theta}_{ML}$ the maximum likelihood estimators of the model parameters are obtained:

$$\hat{\Sigma}_{\theta_{ML}} = \left[-\frac{1}{T}\frac{\partial^2 \ell(\hat{\theta}_{ML})}{\partial\hat{\theta}_{ML}\partial\hat{\theta}'_{ML}}\right]^{-1}$$

For the quasi maximum likelihood estimation (QML) of the parameters, it is assumed that $\zeta_{it} \sim$ IIDN (0; $\sigma_{\zeta_i}^2$), to i = 1; 2; ...; N.

ANNEX 9 - Cross Averaging Observation Defactorization Methodology and its Results

Consider irt as the rate of change of thefts and robberies in the iº neighborhoods located in the AIS r = 1; 2; ...; R, at time t, and consider the following hierarchical model:

$$\pi_{irt} = a_{ir} + \beta_{ir}\bar{\pi}_{rt} + \gamma_{ir}\bar{\pi}_t + \xi_{irt} \quad (1)$$
$$i = 1,2,\dots,N_r; r = 1,2,\dots,R; t = 2,3,\dots,T,$$

Where, $\bar{\pi}_{rt} = N_r^{-1}\sum_{i=1}^{N_r}\pi_{irt}$, $and\ \bar{\pi}_t = N^{-1}\sum_{r=1}^{R}\sum_{i=1}^{N_r}\pi_{irt}$, with N = $\sum_{r=1}^{R} N_r$. Rewriting the hierarchical model in a general form:

$$\pi_t = a + BQ_N\pi_t + \Gamma P_N\pi_t + \xi_t \quad (2)$$

Where π_t is a vector N x 1 of changes in rates of theft and burglary divided by neighborhoods, given by

$$\pi_t = (\pi_{11t}, \pi_{21t}, \dots, \pi_{N_1 1t};\ \pi_{12t}, \pi_{22t}, \dots, \pi_{N_2 2t}; \dots; \pi_{1Rt}, \pi_{2Rt}, \dots, \pi_{N_R Rt})'$$

Similarly for a, we have:

$$a = \left(a_{11}, a_{21}, \dots, a_{N_1 1}; a_{12}, a_{22}, \dots, a_{N_2 2}; \dots; a_{1R}, a_{2R}, \dots, a_{N_R R}\right)'$$

B and Γ are diagonal matrices N x N with elements ordered, respectively, by:

$$\beta_{11}, \beta_{21}, \dots, \beta_{N_1 1}; \beta_{12}, \beta_{22}, \dots, \beta_{N_2 2}; \dots; \beta_{1R}, \beta_{2R}, \dots, \beta_{N_R R},$$

and $\gamma_{11}, \gamma_{21}, \dots, \gamma_{N_1 1}; \gamma_{12}, \gamma_{22}, \dots, \gamma_{N_2 2}; \dots; \gamma_{1R}, \gamma_{2R}, \dots, \gamma_{N_R R},$

Q_N and P_N are projection matrices N x N such that $Q_N\pi_t$ represents the global average and $P_N\pi_t$ the average regional characteristic. More specifically, either τ_{N_r} a vector N_r x 1 of ones, and τ_N a vector N x 1 of ones, then:

$$P_N = \tau_N(\tau'_N, \tau_N)^{-1}\tau'_N, \quad (3)$$

$$\text{and } Q_N = \begin{pmatrix} P_{N_1} & 0 & \cdots & 0 & 0 \\ 0 & P_{N_2} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & P_{N_{R-1}} & 0 \\ 0 & 0 & \cdots & 0 & P_{N_R} \end{pmatrix} \quad (4)$$

where $P_{N_r} = \tau_{N_r}(\tau'_{N_r}\tau_{N_r})^{-1}\tau'_{N_r}$. It is assumed that R is fixed, and for each r, Nr/N tends to a non-zero constant with N → ∞. $P_{N_r}\pi_t$, to r = 1; 2; ...; R and $P_N\pi_t$, can be seen as global and regional factors that are consistently estimated by simple averages.
The changes in the rates of theft and robbery are then given by the residuals:

$$\hat{\xi}_t = \pi_t - \hat{a} - \hat{B}Q_N\pi_t - \hat{\Gamma}P_N\pi_t, \quad t = 2,\ldots,T \quad (5)$$

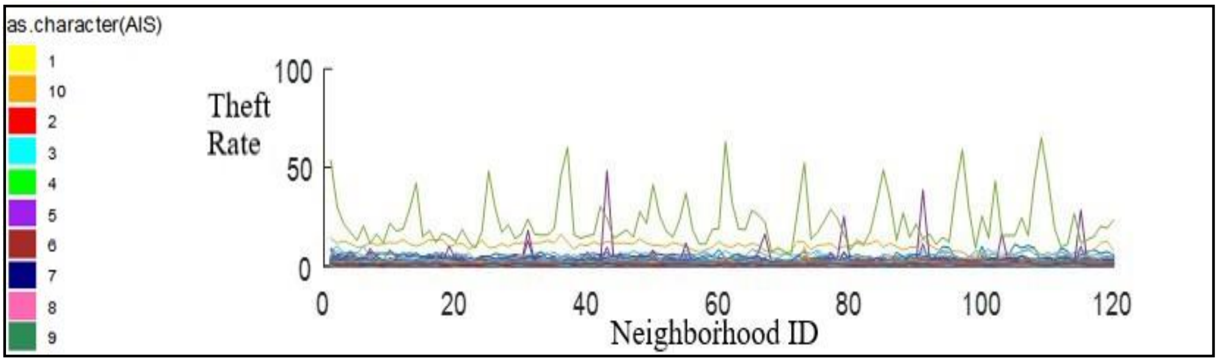
To check if the defactoring was successful, it is crucial to apply the CD test to the residues, $\hat{\xi}_t$.

Applying the methodology of transversal averages, the CD test is performed for the residuals, $\hat{\xi}_t$. The resulting CD statistic is very small compared to the case without defactoring, [decreasing from 140.75 to -3.41 in the rate of theft and 243.78 to -4.98 in the robbery rate], giving a very small estimate for the average pairwise correlations, [$\hat{\bar{\rho}}_{\hat{\xi}}$ = -0.003 for theft rate and $\hat{\bar{\rho}}_{\hat{\xi}}$ = -0.005 for robbery rate]. Furthermore, the estimate of the exponent of the cross-sectional dependence, which was $\dot{\alpha}_\pi$ = 0.935 (0.02) for theft rate and $\dot{\alpha}_\pi$ = 0.967 (0.02) for robbery rate is reduced, respectively to $\dot{\alpha}_\pi =$ 0.664 (0.02) and 0.791 (0.02); Note that in this case it is close to the threshold value of 1/2, representing a weak cross-sectional dependence.

ANNEX 10 - Series of Theft and Robbery Rates - Fortaleza, 2009 to 2019

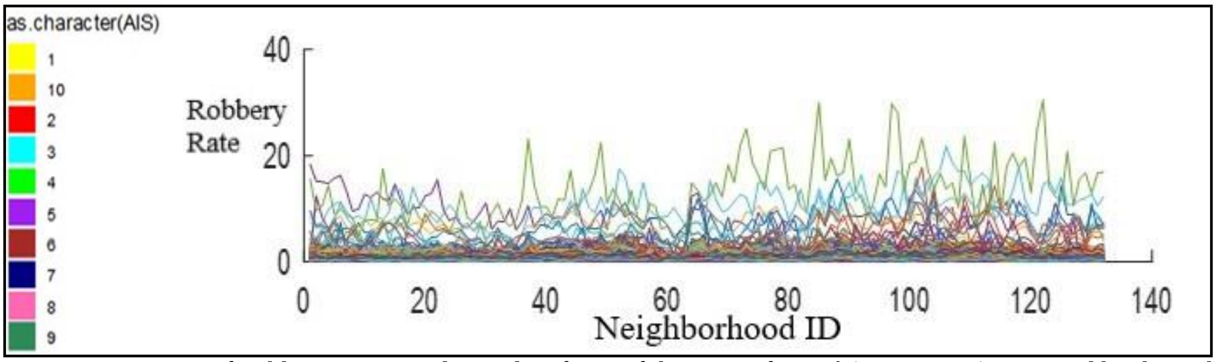
Theft: T=120 (2010-2019), 25 UNISEG´S;
Robbery: T=132 (2009-2019), 25 UNISEG´S;

Graph 1: Theft Rate



Source: Secretariat of Public Security and Social Defense of the State of Ceará (SSPDS-CE), prepared by the authors.

Graph 2: Robbery Rate



Source: Secretariat of Public Security and Social Defense of the State of Ceará (SSPDS-CE), prepared by the authors.

In the data on the rate of theft per 100 thousand inhabitants, the UNISEG'S of AIS 4 registered the highest variations of monthly occurrences, with some peaks above 50 occurrences, while the other UNISEG'S concentrated between rates of 0 to 10 theft. In the case of the robbery rates per 100 thousand inhabitants, despite the UNISEG'S of AIS 4 presenting the greatest variations, with a peak around 30 notifications, there is a greater variability of cases.

ANNEX 11 - Analysis of the Space-Temporal Model Estimations by AIS

Tables 11 and 12 show the mean and median estimates of the model parameters by AIS, along with the standard errors in parentheses and the proportion of neighborhoods with statistically significant parameters at the 5% level.

Starting with the analysis of theft rate, for AIS 1, 5, 6, 7, 8, 9, and 10 only the average estimate of λ_1 is statistically significant at the 5% level. Among these, AIS 1 and 5 show the highest average time effect, $\hat{\lambda}_1$, being respectively 0.20 (0.02) statistically significant in 57.1% of the neighborhoods in AIS 1, and 0.20 (0.03) statistically significant in 31.6% of the neighborhoods in AIS 5.

Analyzing the estimates of spatial effects by AIS, it is observed that AIS 2, 3, 4, 6, 7, 8, 9 and 10 present a greater negative contemporaneous connection effect. This suggested that these AIS consist of neighborhoods with high rates of theft/robbery that associate with neighbors that have much lower rates, resulting in a predominance of negative effects. In this case, there is a concentration effect of crime. For example, in AIS 4, the Centro neighborhood has a high rate of theft and robbery compared to its neighbors because of its inherent characteristics.

In contrast, AIS 5 shows a greater positive contemporaneous connection effect, indicating that there is a predominant clustering of neighborhoods with identical magnitudes, neighborhoods with high (low) rates of robbery and theft accompanied by neighbors with high (low) rates. This indicates a crime spillover effect. It is worth noting that AIS 5 and its neighbors AIS 4 and 6, have the highest rates of robbery and theft, according to SSPDS-CE, suggesting that these areas have clusters with strong positive connections. The presence of two large university campuses in this AIS (Benfica and Itaperi) may be influencing the presence of a strong positive effect. According to data from SSPDS-CE, in 2016, the Itaperi university campus alone recorded 70 occurrences of theft/theft. Finally, AIS 1 presents distinct predominance of the effects of spatial connections for theft rates (positive connection) and robbery (negative connection).

For AIS 4, only the average estimates of λ_1 and ψ_1^- are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is 0.14 (0.04) and is statistically significant in 33.3% of the neighborhoods. The magnitude of the lagged negative mean effect is - 0.07 (0.01) and has significance at 33.3%.

For AIS 2 and 3, only the average estimates of λ_1 and ψ_0^- are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is respectively 0.28 (0.07) and 0.06 (0.03) being statistically significant respectively in 66.7% and 16.7% of the neighborhoods. The contemporaneous negative connection spatial effect, [respectively of -0.36 (0.16) and -0.53 (0.22)], is statistically significant respectively in 100% and 33.3% of the neighborhoods, suggesting the predominance of negative connection spatial effects.

Analyzing the theft rates, for AIS 1, only the average estimates of λ_1, ψ_0^+, ψ_0^- and ψ_1^+ are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is 0.23 (0.05), being statistically significant in 71.4% of the neighborhoods. The magnitude and significance of the negative contemporaneous effect, -0.27 (0.12), is larger than the positive contemporaneous effect, 0.18 (0.07). The lagged positive connection effect, 0.09 (0.04), is smaller than the contemporaneous positive connection effect.

For AIS 2 and 9 only the average estimates, λ_1 and ψ_0^+, are statistically significant at the 5% level. The average time effect, $\hat{\lambda}_1$, is respectively 0.29 (0.04) and 0.21 (0.04), being statistically significant in 83.3% and 63.6%, of the neighborhoods. The magnitude of the average positive contemporaneous effect, [respectively of 0.04 (0.01) and 0.14 (0.07)], is significant in 66.7% and 25% of the neighborhoods.

For AIS 3 only the average estimates of λ_1, ψ_0^- and ψ_1^+ are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is 0.25 (0.03), being statistically significant respectively in 66.7% of the neighborhoods. The magnitude (in absolute value) of the negative contemporaneous spatial effect, -0.35 (0.12), is larger than the positive lagged spatial effect, 0.08 (0.03). Nevertheless, the positive lagged effect has higher significance, 33.3%.

In AIS 4, only the average estimate of λ_1, is statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is 0.25 (0.03), being statistically significant in 77.8% of the neighborhoods.

For AIS 5 and 10 only the average estimates of λ_1, ψ_0^+ and ψ_0^- are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is respectively 0.18 (0.03) and 0.24 (0.03) being statistically significant in 52.6% and 43% of the neighborhoods. In AIS 5 the magnitude of the average positive contemporaneous effect, 0.17 (0.06), is larger than the negative contemporaneous effect, -0.07 (0.02). While in AIS 10 the magnitude and significance of the negative connection contemporaneous effect, -0.28 (0.14), is greater than the positive contemporaneous effect, 0.12 (0.03).

For AIS 6,7 and 8, only the mean estimates, λ_1 and ψ_0^- are statistically significant at the 5% level. The size of the average time effect, $\hat{\lambda}_1$, is respectively of 0.18 (0.04), 0.21 (0.02) and 0.13 (0.05), and is statistically significant respectively in 44%, 68.8% and 43% of the neighborhoods. The contemporaneous negative connection spatial effect, [respectively of -0.22 (0.08), -0.22 (0.08 and -0.58(0.27)], is statistically significant respectively in 83.3%, 66.7% and 33.3% of the neighborhoods, suggesting the predominance of negative connection spatial effects.

Table 1: QML estimates of the Space-time model by AIS - Theft Rate

	Computed over non-zero parameter coefficients					
	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
	AIS 1					
Median	0.2053	0.0623	-0.1524	0.0479	-0.1187	27.1100
Mean Group Estimates	0.1749	0.0623	-0.3065	0.0479	-0.2097	25.7172
	(0.0357)	(0.1002)	(0.2452)	(0.0497)	(0.2410)	(6.7540)
% significant (at 5% level)	57.1\%	50.0\%	25.0\%	0.0\%	0.0\%	-
Number of non-zero coef.	7	2	4	2	4	7
	AIS 2					
Median	0.2693	0.2102	-0.5140	0.0251	0.2673	11.4882
Mean Group Estimates	0.2976	0.1783	-0.4721	0.0667	0.2296	11.5566
	(0.0712)	(0.0562)	(0.1559)	(0.0622)	(0.0822)	(1.4715)
% significant (at 5% level)	66.7\%	33.3%	100.0\%	0.0%	40.0\%	-
Number of non-zero coef.	6	3	5	3	5	6
	AIS 3					
Median	0.0821	-0.1506	-0.9433	-0.0015	0.0821	15.0494
Mean Group Estimates	0.0857	-0.1486	-0.9433	0.1000	0.0821	21.0219
	(0.0319)	(0.1932)	(0.517)	(0.1069)	(0.1238)	(6.1089)
% significant (at 5% level)	25.0%	66.7%	50.0%	0.0%	50.0%	-
Number of non-zero coef.	12	3	2	3	2	12
	AIS 4					
Median	0.0981	NaN	-0.3736	NaN	-0.3485	33.8299
Mean Group Estimates	0.1443	NaN	-0.3167	NaN	-0.3529	31.3137
	(0.0594)	(NaN)	(0.1215)	(NaN)	(0.1674)	(6.0324)
% significant (at 5% level)	33.3\%	NaN\%	33.3\%	NaN\%	0.0%	-
Number of non-zero coef.	9	0	3	0	3	9
	AIS 5					
Median	0.1125	0.0197	-0.2732	0.0556	0.0505	27.9102
Mean Group Estimates	0.1872	-0.0104	-0.3463	0.0429	0.0048	25.5907
	(0.0379)	(0.0438)	(0.1703)	(0.0229)	(0.0456)	(1.9714)

% significant (at 5% level)	26.3%	25.0%	60.0%	0.0%	0.0%	-
Number of non-zero coef.	19	4	5	4	5	19
	AIS 6					
Median	0.2407	0.5671	0.0052	-0.1848	-0.5348	19.4486
Mean Group Estimates	0.2476	0.5593	0.0694	-0.1625	-0.5135	22.1046
	(0.0424)	(0.2516)	(0.2070)	(0.1376)	(0.2777)	(3.1314)
% significant (at 5% level)	62.5%	50.0%	25.0%	0.0%	100.0%	-
Number of non-zero coef.	16	4	4	4	4	16
	AIS 7					
Median	0.1293	0.0832	-0.2596	0.1901	-0.0046	28.4278
Mean Group Estimates	0.1653	0.0697	-0.3441	0.1914	-0.0359	36.1100
	(0.0323)	(0.0875)	(0.1477)	(0.0833)	(0.0855)	(7.2473)
% significant (at 5% level)	43.8\%	20.0\%	66.7\%	0.0\%	16.7\%	-
Number of non-zero coef.	16	5	6	5	6	16
	AIS 8					
Median	0.1088	NaN	-0.2179	NaN	0.0503	12.8126
Mean Group Estimates	0.1024	NaN	-0.2179	NaN	0.0503	19.5838
	(0.0387)	(NaN)	(0.2145)	(NaN)	(0.0207)	(7.3542)
% significant (at 5% level)	14.3\%	NaN\%	50.0\%	NaN\%	0.0\%	-
Number of non-zero coef.	7	0	2	0	2	7
	AIS 9					
Median	0.1565	-0.1255	-0.6594	0.0633	0.0946	17.2379
Mean Group Estimates	0.1566	-0.0089	-0.6594	0.0511	0.0946	16.9428
	(0.0429)	(0.1874)	(0.2185)	(0.0281)	(0.1056)	(2.9534)
% significant (at 5% level)	45.5%	100.0%	100.0%	0.0%	0.0%	-
Number of non-zero coef.	11	3	2	3	2	11
	AIS 10					
Median	0.2138	NaN	-0.3139	NaN	0.1327	31.0303
Mean Group Estimates	0.1978	NaN	-0.4552	NaN	0.0966	33.8974
	(0.0239)	(NaN)	(0.2799)	(NaN)	(0.0566)	(3.7449)
% significant (at 5% level)	54.5\%	NaN\%	100.0%	NaN\%	0.0\%	-
Number of non-zero coef.	11	0	3	0	3	11

Source: Prepared by the Authors.

Table 2: QML estimates of the Space-time model by AIS - Robbery Rate

	Computed over non-zero parameter coefficients					
	λ_1	ψ_0^+	ψ_0^-	ψ_1^+	ψ_1^-	σ_ζ
	AIS 1					
Median	0.1995	0.4287	-0.3929	0.0189	-0.0589	26.2209
Mean Group Estimates	0.2618	0.3204	-0.4519	-0.0353	-0.0790	24.3389
	(0.0915)	(0.0829)	(0.1628)	(0.0534)	(0.2253)	(4.8192)
% significant (at 5% level)	71.4\%	85.7%	33.3%	0.0%	16.7%	-
Number of non-zero coef.	7	7	6	7	6	7
	AIS 2					
Median	0.2845	0.2380	-0.0663	0.0758	-0.0077	18.7186
Mean Group Estimates	0.3100	0.2380	-0.1729	0.0758	0.0271	20.8298
	(0.0341)	(0.0148)	(0.0909)	(0.0205)	(0.0732)	(2.5953)
% significant (at 5% level)	100.0%	100.0%	40.0\%	0.0%	40.0%	-

Number of non-zero coef.	6	2	5	2	5	6
			AIS 3			
Median	0.2869	0.1379	-0.1335	0.1097	0.0794	17.4480
Mean Group Estimates	0.2631	0.1577	-0.1635	0.1031	0.1077	30.3821
	(0.0325)	(0.0691)	(0.0804)	(0.0360)	(0.0479)	(12.7385)
% significant (at 5% level)	66.7%	50.0%	50.0%	50.0%	25.0%	-
Number of non-zero coef.	12	4	4	4	4	12
			AIS 4			
Median	0.2275	NaN	-0.3615	NaN	-0.0851	37.8780
Mean Group Estimates	0.2451	NaN	-0.2610	NaN	-0.1073	38.4611
	(0.0379)	(NaN)	(0.2922)	(NaN)	(0.1149)	(5.9001)
% significant (at 5% level)	77.8%	NaN%	100.0%	NaN%	0.0%	-
Number of non-zero coef.	9	0	5	0	5	9
			AIS 5			
Median	0.2072	0.3814	-0.0881	0.2157	-0.0451	31.8698
Mean Group Estimates	0.1894	0.5510	-0.0186	0.1537	0.0296	31.5846
	(0.0246)	(0.2240)	(0.4970)	(0.1735)	(0.0887)	(2.3993)
% significant (at 5% level)	63.2%	33.3%	33.3%	33.3%	0.0%	-
Number of non-zero coef.	19	3	3	3	3	19
			AIS 6			
Median	0.1654	0.0654	-0.1473	0.1303	0.0574	27.6103
Mean Group Estimates	0.1804	0.1372	-0.3690	0.1423	-0.1529	30.5527
	(0.0442)	(0.1006)	(0.1338)	(0.0762)	(0.2675)	(3.4760)
% significant (at 5% level)	43.8%	25.0%	50.0%	8.3%	20.0%	-
Number of non-zero coef.	16	12	10	12	10	16
			AIS 7			
Median	0.1924	0.1283	-0.2014	0.0504	0.0118	32.0066
Mean Group Estimates	0.2104	0.0600	-0.2618	0.5273	0.0217	42.1068
	(0.0257)	(0.1685)	(0.0870)	(0.3661)	(0.0704)	(8.4066)
% significant (at 5% level)	68.8%	37.5%	57.1%	37.5%	14.3%	-
Number of non-zero coef.	16	8	7	8	7	16
			AIS 8			
Median	0.1291	0.1913	-0.0585	0.0493	-0.0129	21.4687
Mean Group Estimates	0.1630	0.1913	-0.0248	0.0493	-0.2785	38.6097
	(0.0574)	(0.1991)	(0.2984)	(0.0665)	(0.3748)	(18.1460)
% significant (at 5% level)	28.6%	50.0%	33.3%	0.0%	33.3%	-
Number of non-zero coef.	7	2	3	2	3	7
			AIS 9			
Median	0.2103	0.2582	-0.3404	0.0271	0.0200	26.0451
Mean Group Estimates	0.2250	0.4118	-0.4159	0.0193	0.0312	25.6852
	(0.0420)	(0.1587)	(0.2168)	(0.0321)	(0.0669)	(4.3385)
% significant (at 5% level)	54.5%	66.7%	60.0%	0.0%	0.0\%	-
Number of non-zero coef.	11	3	5	3	5	11
			AIS 10			
Median	0.2126	0.1160	-0.2728	0.0653	0.0794	39.0829
Mean Group Estimates	0.2306	0.1819	-0.3788	0.0612	0.0863	42.1563
	(0.0316)	(0.0840)	(0.1258)	(0.0549)	(0.0230)	(6.3725)
% significant (at 5% level)	54.5%	33.3%	66.7%	0.0%	33.3%	-
Number of non-zero coef.	11	6	6	6	6	11

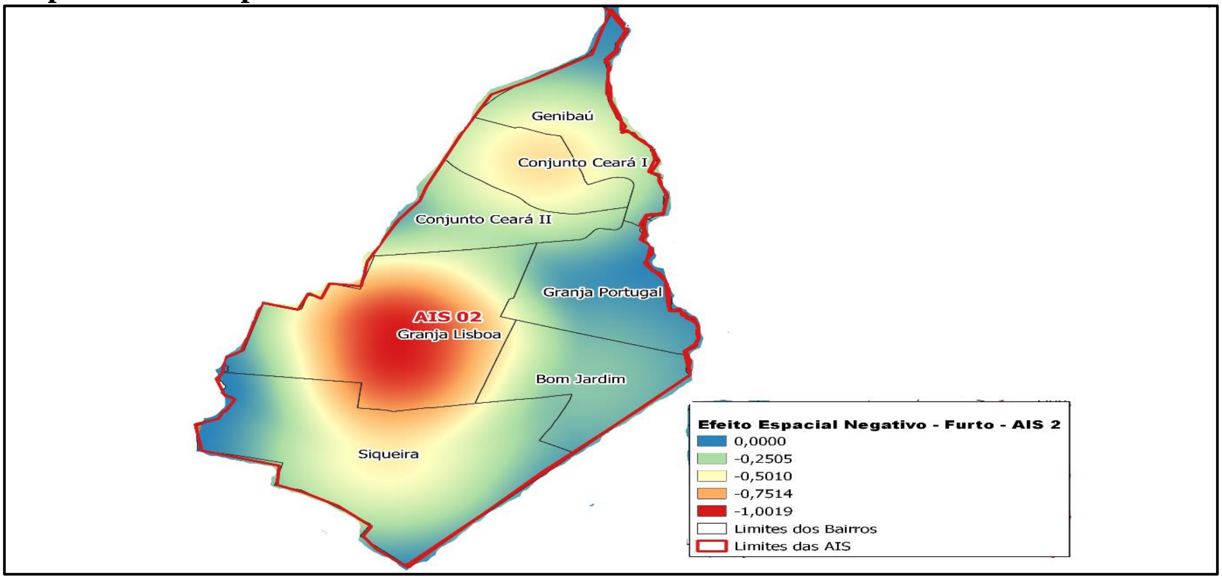
Source: Prepared by the Authors.

ANNEX 12 - Spatial Analysis by AIS

In this subsection, an analysis of positive and negative spatial effects by AIS is performed to observe the spatial behavior of crime within each area. This helps to understand which neighborhoods have greater spatial influence over the others in each region. The main results are presented below.

For the robbery rate, it was observed that AIS 2 and AIS 6 exhibit more than one spillover. In Map 1, it can be seen that in AIS 2, the biggest spillover occurs in the Siqueira neighborhood, influencing the Granja Lisboa, Bom Jardim, and Granja Portugal neighborhoods. There is also a cluster of lesser magnitude that overflows from the Genibaú neighborhood to the Conjunto Ceará I and II neighborhoods.

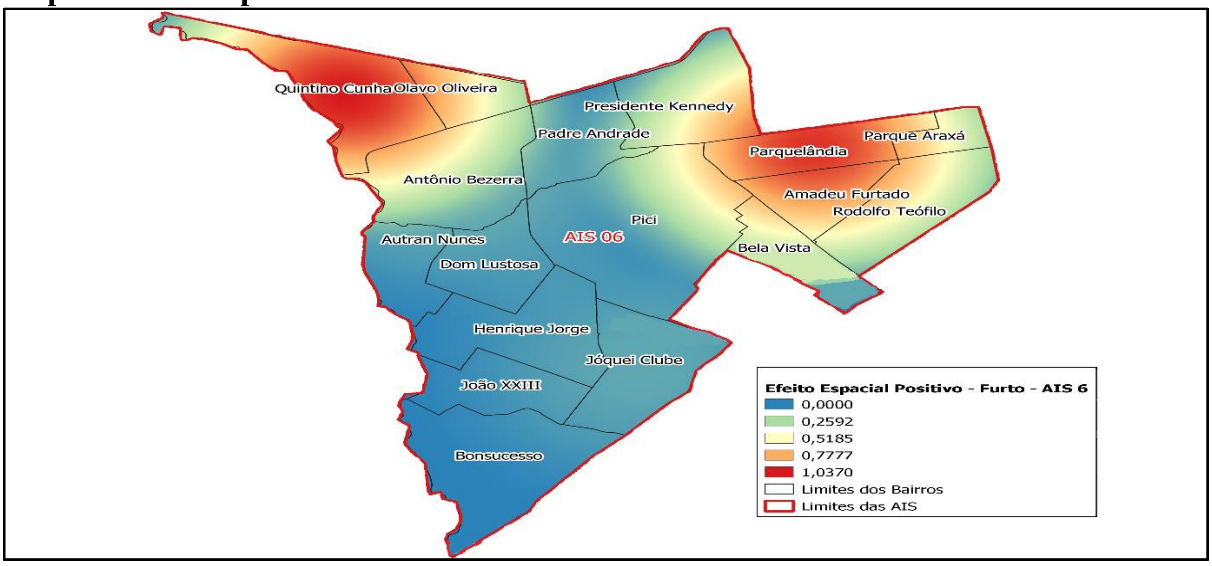
Map 1: Positive Spatial Effect - Theft Rate - AIS 2



Source: prepared by the authors.

In Map 2, it is possible to see that AIS 6 exhibits two strong overflow clusters. On the eastern side of this SIA, there is an overflow from the Parquelândia neighborhood into the neighborhoods of Parque Araxá, Amadeu Furtado, Rodolfo Teófilo, Bela Vista, Pici, Presidente Kennedy, and Padre Andrade. On the western side, there is an overflow from the Quintino Cunha neighborhood into the Olavo Oliveira, Padre Andrade, Antônio Bezerra, and Autran Nunes neighborhoods. The Jóquei Clube, Henrique Jorge, and João XXIII neighborhoods show a cluster of weak magnitude. In the other neighborhoods of this SIA, there is no positive spatial effect.

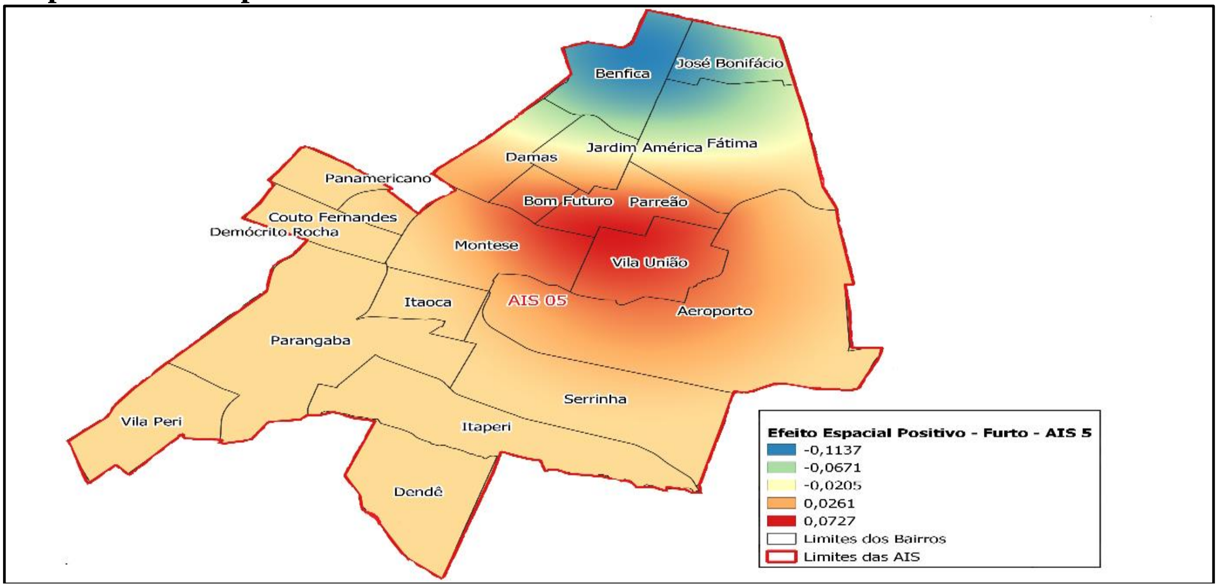
Map 2: Positive Spatial Effect - Theft Rate - AIS 6



Source: prepared by the authors.

In AIS 5, 7, and 9, there are extensive clusters of theft crime overflow. Maps 3, 4, and 5 respectively show the spatial behavior in each area. In AIS 5, the neighborhoods Vila União, Bom Futuro, and Parreão form a spatial cluster that overflows into the neighborhoods Aeroporto, Damas, Jardim América, Fátima, Serrinha, Itaoca, Parangaba, Itaperi, Serrinha, Dendê, Vila Peri, Demócrito Rocha, Couto Fernandes, and Panamericano. However, the neighborhoods Benfica and José Bonifácio have the opposite effect, with lower rates of theft crime.

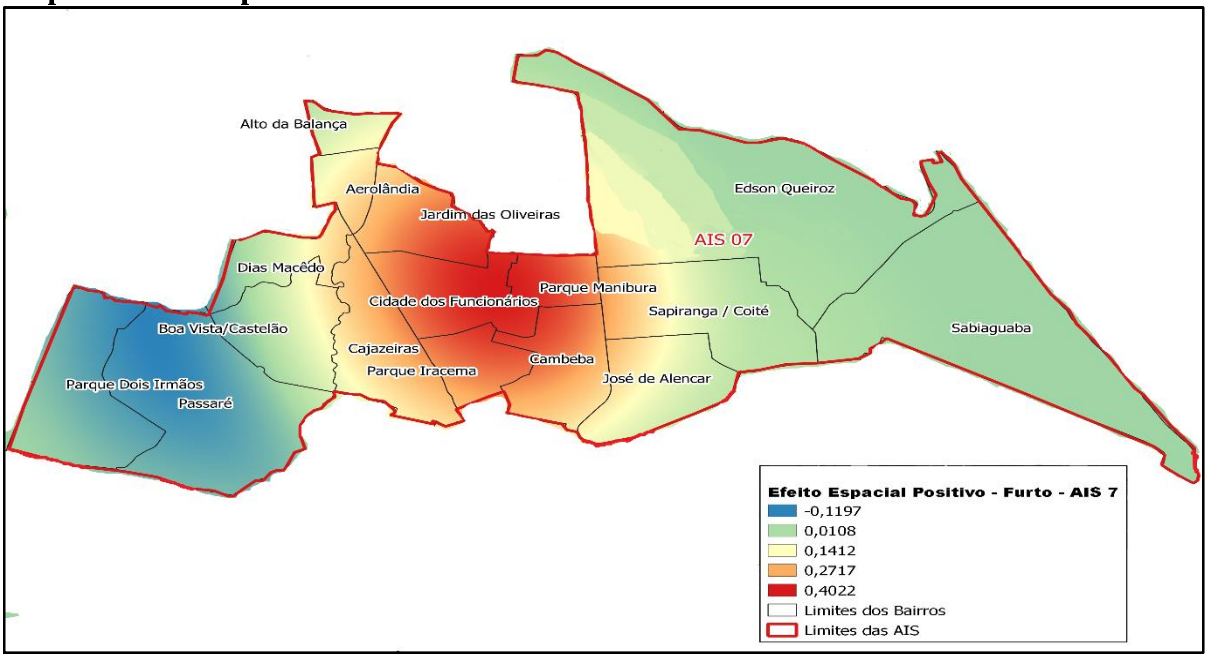
Map 3: Positive Spatial Effect - Theft Rate - AIS 5



Source: prepared by the authors.

In AIS 7, the overflow of theft crimes occurs in the center of the region, specifically in the neighborhood of Cidade dos Funcionários, which influences several adjacent neighborhoods such as Parque Manibura, Jardim das Oliveiras, Cajazeiras, Parque Iracema, Cambeba, Aerolândia, José de Alencar, Sapiranga, Dias Macêdo, Alto da Balança and Castelão. On the other hand, the neighborhoods of Parque Dois Irmãos and Passaré present a reverse effect, meaning that they have a higher concentration of theft crimes.

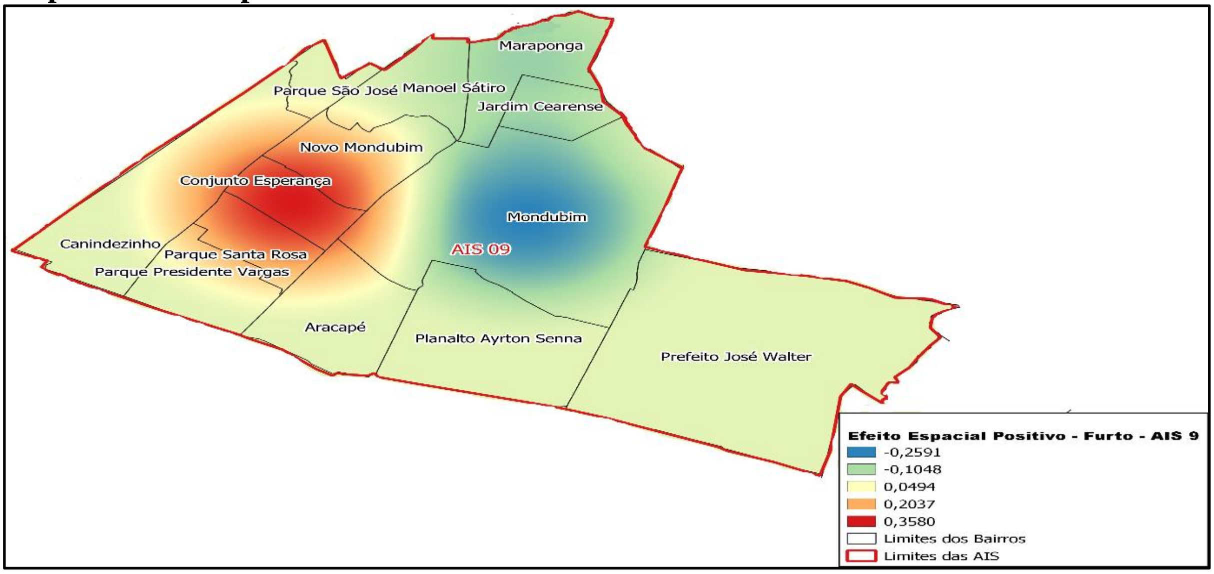
Map 4: Positive Spatial Effect - Theft Rate - AIS 7



Source: prepared by the authors.

In AIS 9, the overflow of crime occurs in the West region and influences the east side of the area, particularly in the Conjunto Esperança neighborhood, which in turn influences the neighborhoods of Novo Mondubim, Parque Santa Rosa, Canindezinho, Parque Presidente Vargas, Aracapé, Planalto Ayrton Senna, Parque São José, Manoel Sátiro and Prefeito José Walter. Additionally, there is a reverse effect of crime concentration in the Mondubim neighborhood that influences the Jardim Cearense and Maraponga neighborhoods.

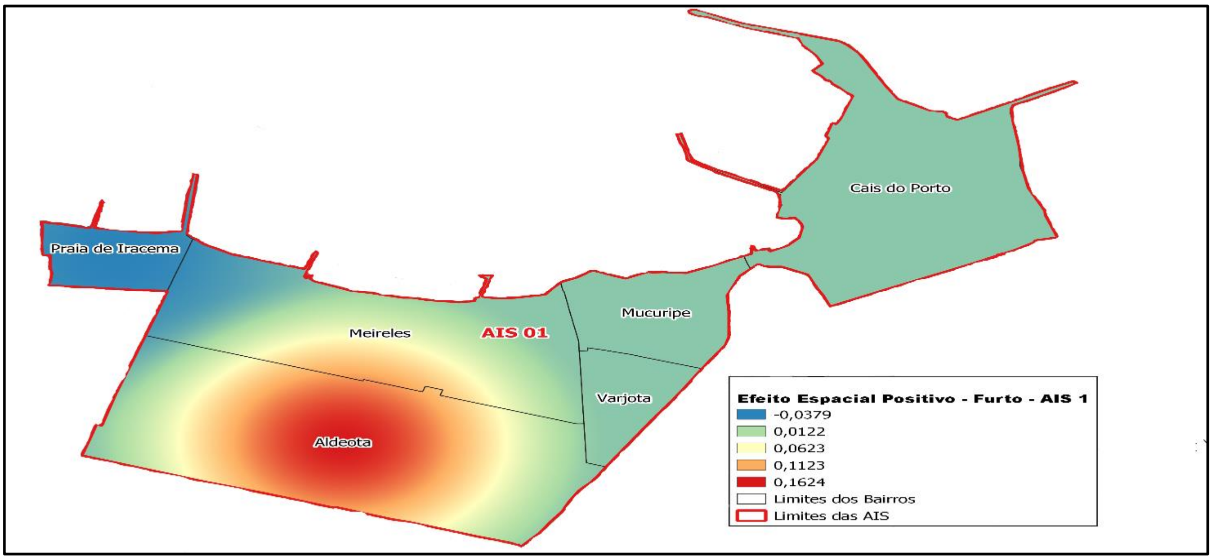
Map 5: Positive Spatial Effect - Theft Rate - AIS 9



Source: prepared by the authors.

In AIS 1 and 3, the overflow effect of the crime of theft has a smaller magnitude. Map 6 shows that in AIS 1, the overflow occurs in the Aldeota neighborhood and its influence is limited to the Meireles neighborhood, which also presents a reverse effect. In the other neighborhoods, the positive spatial effect is weak.

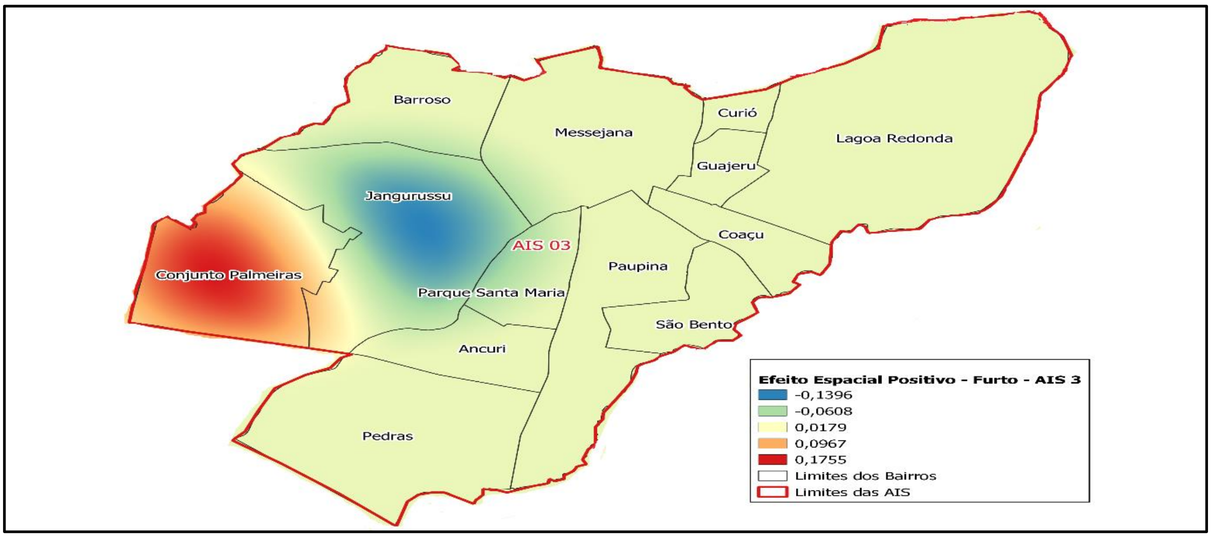
Map 6: Positive Spatial Effect - Theft Rate - AIS 1



Source: prepared by the authors.

In AIS 3, the concentration of theft in the Conjunto Palmeiras neighborhood is counteracted by the reverse effect of its neighboring neighborhood, Jangurussu, which also has a high rate of theft concentration, influencing the neighborhoods of Parque Santa Maria, Messejana, Ancuri, and Barroso.

Map 7: Positive Spatial Effect - Theft Rate - AIS 3



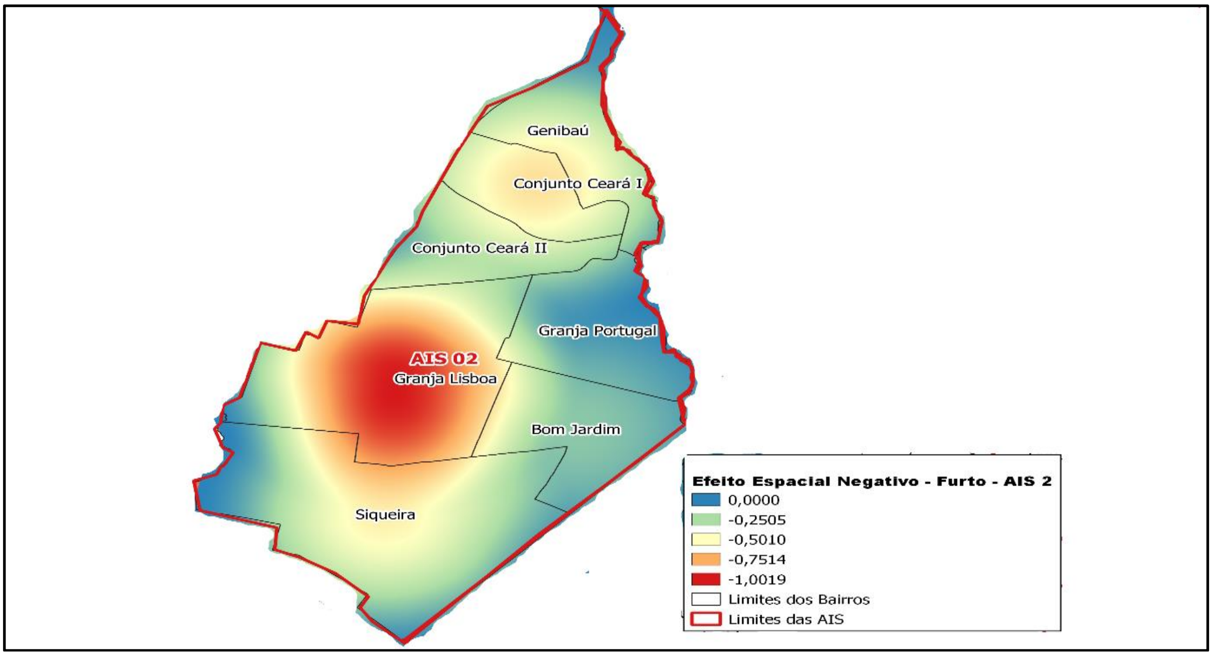
Source: prepared by the authors.

In terms of concentration effects, AIS 2 and 4 exhibit multiple theft clusters, indicating that these regions have neighborhoods with high rates of crime. Maps 8 and 9 depict these effects for the respective areas.

In AIS 2, there is a strong cluster centered on the Granja Lisboa neighborhood, which influences the neighborhoods of Siqueira, Bom Jardim, and Granja Portugal. This indicates that these neighborhoods jointly have high rates of theft. The other cluster present in this area includes the neighborhoods of Conjunto Ceará I and II and Genibaú, but with lower intensity.

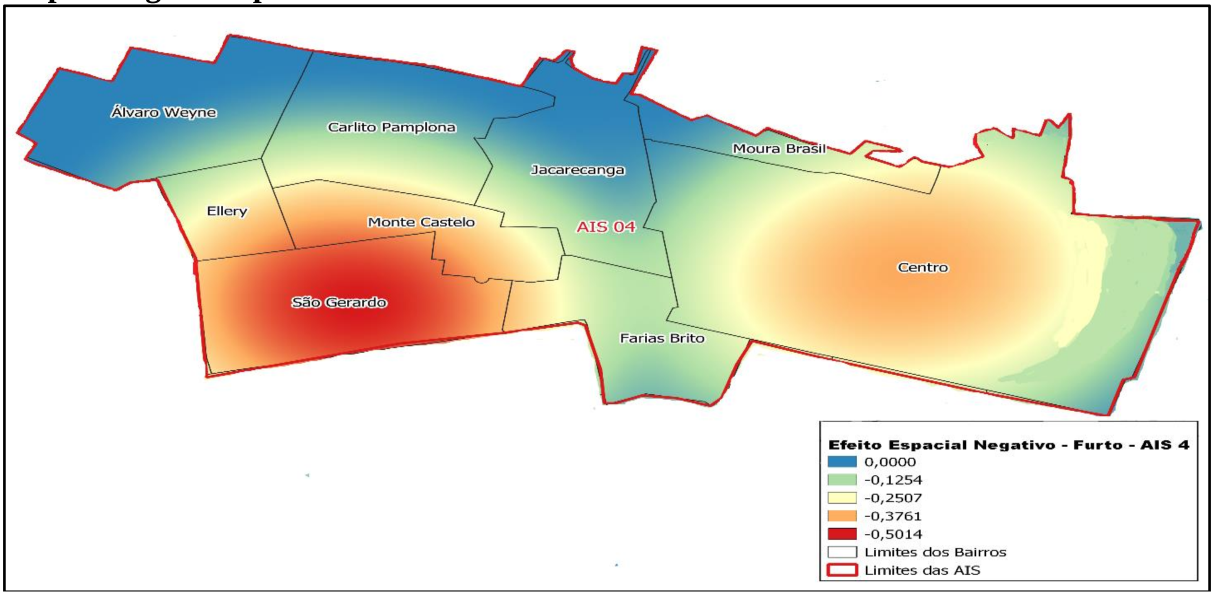
In AIS 4, the cluster with the highest magnitude focuses on the São Gerardo neighborhood, which influences its neighboring neighborhoods of Ellery, Monte Castelo, Carlito Pamplona, Farias Brito, and Jacarecanga. The second cluster focuses on the entire neighborhood of the Center and influences the neighborhoods of Moura Brasil, Farias Brito, and Jacarecanga.

Map 8: Negative Spatial Effect - Theft Rate - AIS 2



Source: prepared by the authors.

Map 9: Negative Spatial Effect - Theft Rate - AIS 4

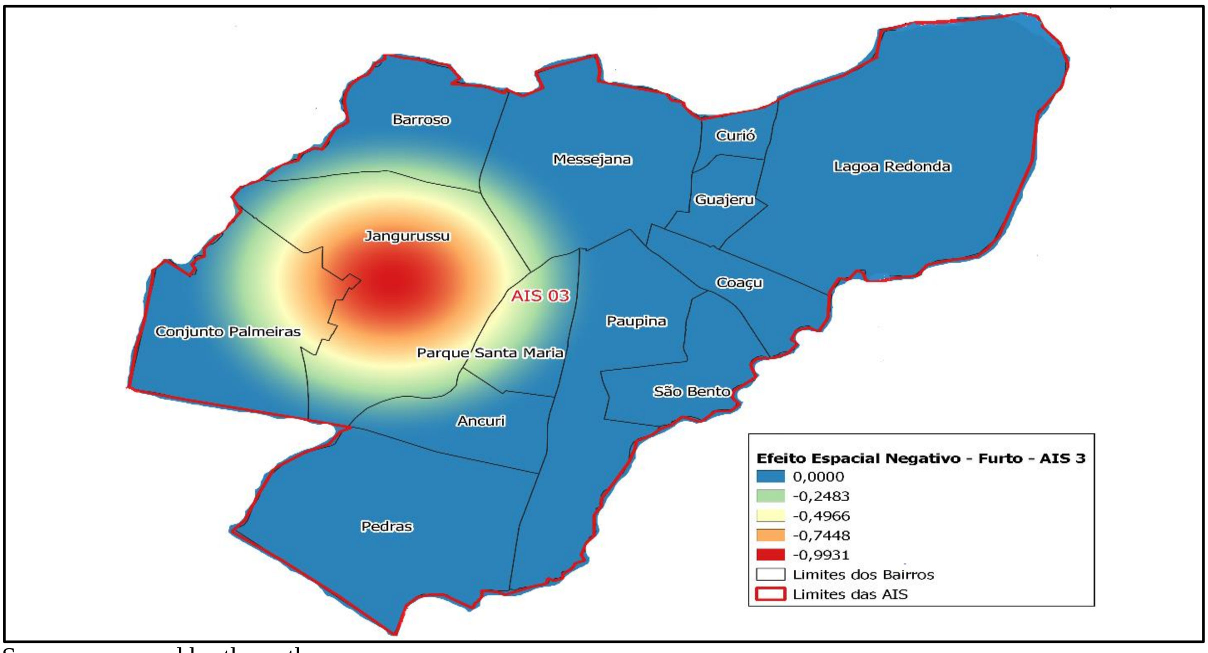


Source: prepared by the authors.

In contrast to AIS 2 and 4, which show a high concentration of theft across a large area, AIS 1, 3, and 5 exhibit a smaller spatial clustering effect among their neighborhoods. For instance, in AIS 3, as shown in map 32, Jangurussu neighborhood has the highest concentration of theft, with a weaker influence on adjacent neighborhoods such as Conjunto Palmeiras, Parque Santa Maria, Messejana, and Barroso. Conversely, the other neighborhoods display a predominant reverse effect.

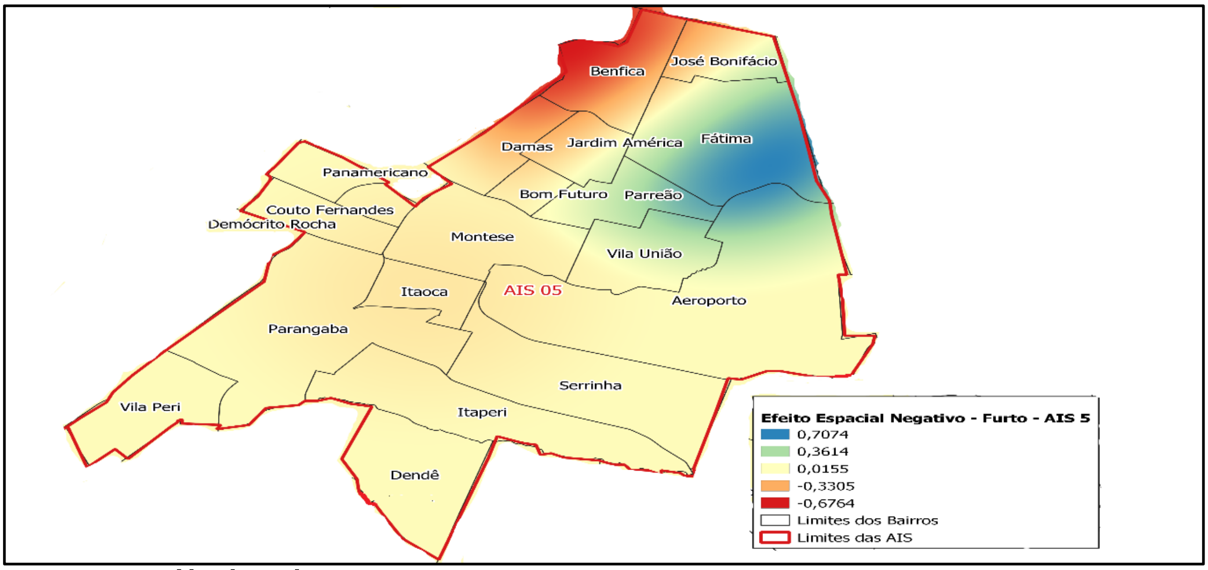
A similar pattern is observed in AIS 5, where Benfica neighborhood has the most significant concentration of theft, with a weaker impact on the neighboring areas of José Bonifácio, Damas, and Jardim América. Similarly, the other neighborhoods also exhibit a reverse effect, with Fatima neighborhood showing a strong overflow of theft.

Map 10: Negative Spatial Effect - Theft Rate - AIS 3



Source: prepared by the authors.

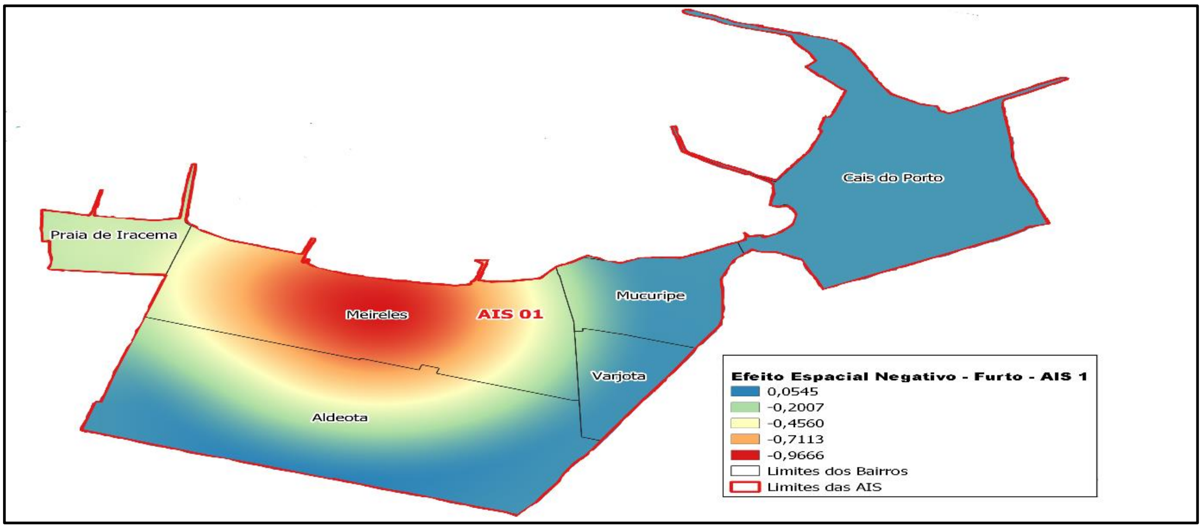
Map 11: Negative Spatial Effect - Theft Rate - AIS 5



Source: prepared by the authors.

In AIS 1, we observe a spatial concentration effect of theft in the Meireles neighborhood, which extends its influence to the neighboring neighborhoods of Aldeota, Praia de Iracema, Mucuripe, and Varjota. This influence is more intense in the Praia de Iracema neighborhood, whereas for the other neighborhoods, the weak influence of the concentration effect is contrasted by a predominant reverse effect.

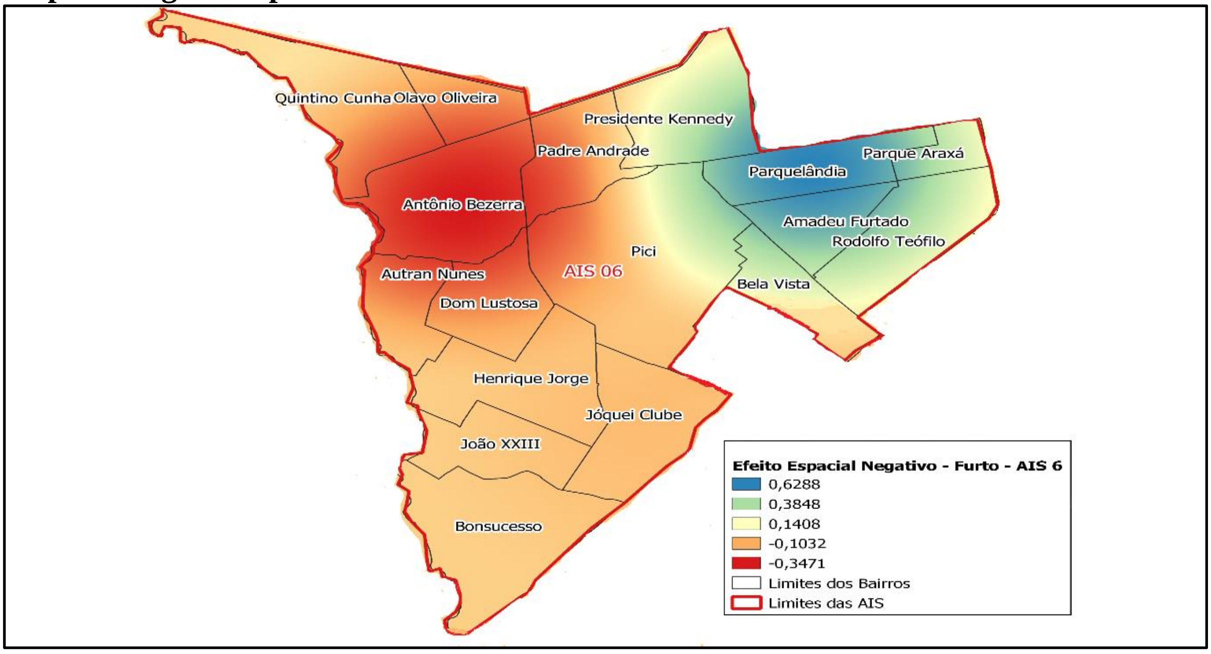
Map 12: Negative Spatial Effect - Theft Rate - AIS 1



Source: prepared by the authors.

In AIS 6, 7, 8, 9, and 10, we observe clusters with a high power of influence in these areas, indicating that these regions have neighborhoods with high rates of concentration of the crime of theft. In the case of AIS 6, it is observed that the incidence is in the Antonio Bezerra neighborhood and influences all the neighborhoods located in the West region of this area, such as Autran Nunes, Quintino Cunha, Olavo Oliveira, Pici, Padre Andrade, Dom Lustosa, Henrique Jorge, João XXIII, Jóquei Clube, and Bonsucesso. In the Eastern region of this area, a reverse effect is observed between the neighborhoods of Parquelândia, Parque Araxá, Amadeu Furtado, and Rodolfo Teófilo.

Map 13: Negative Spatial Effect - Theft Rate - AIS 6

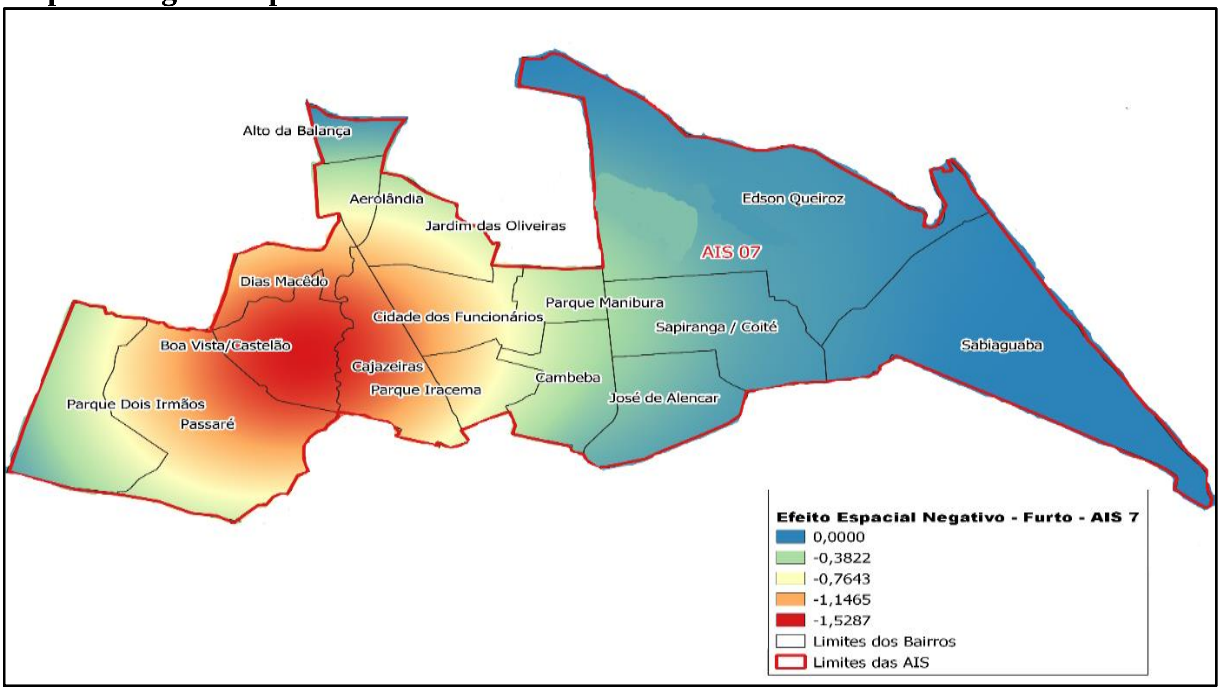


Source: prepared by the authors.

The concentration of crime in the West region is a recurring scenario in AIS 7 and 10. In AIS 7, the effect is centered on the Castelão neighborhood and spills over to its neighboring areas, such as Passaré, Dias Macêdo, Parque Dois Irmãos, Cidade dos Funcionários, Cajazeiras, Parque Iracema, Jardim das Oliveiras, Aerolândia, and Parque Manibura. Conversely, in the Eastern region, which includes neighborhoods like Edson Queiroz and Sabiaguaba, a reverse spatial effect is observed.

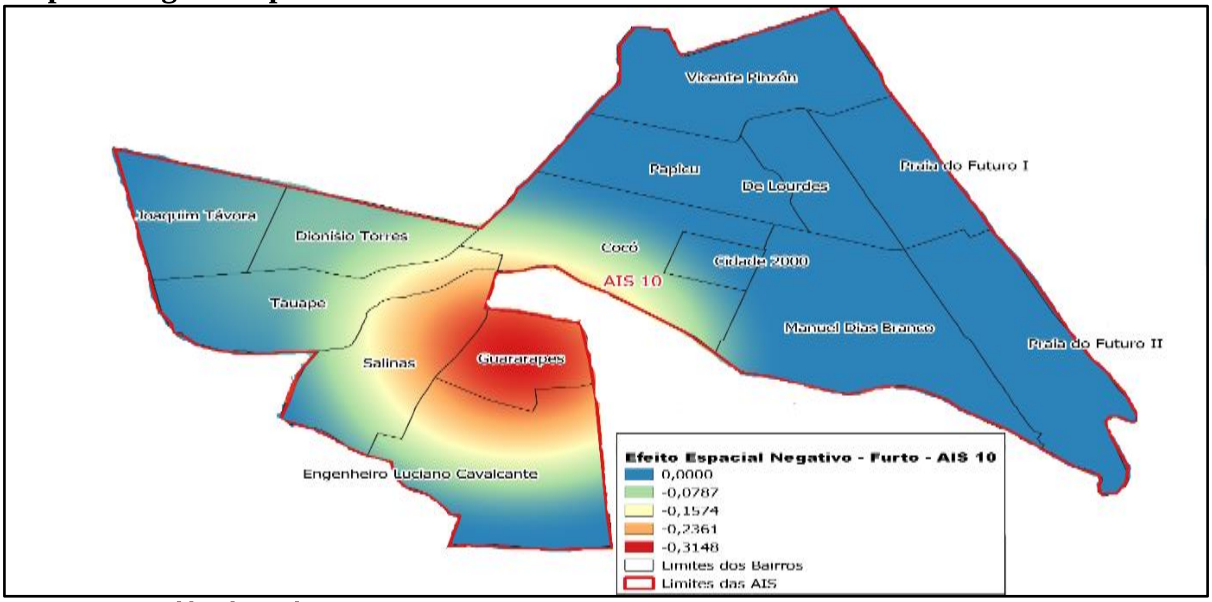
In AIS 10, the robbery cluster is concentrated in the Guararapes neighborhood and extends to Salinas, Tauape, Dionisio Torres, Cocó, and Engenheiro Luciano Cavalcante. However, the reverse effect predominates in the eastern neighborhoods of this area.

Map 14: Negative Spatial Effect - Theft Rate - AIS 7



Source: prepared by the authors.

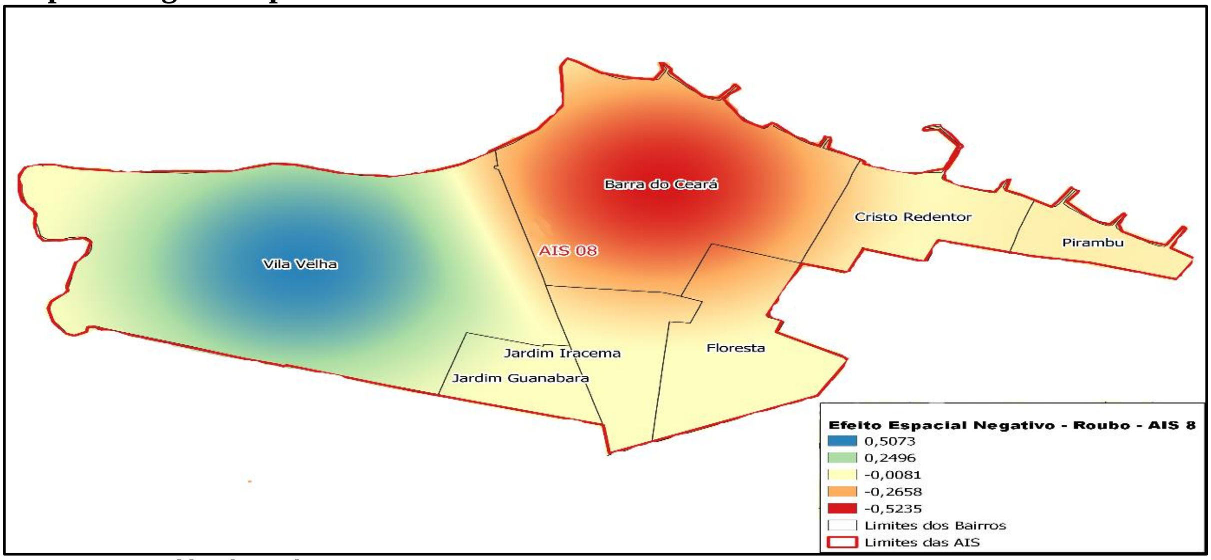
Map 15: Negative Spatial Effect - Theft Rate - AIS 10



Source: prepared by the authors.

Different from the other AIS areas, in AIS 8, the main cluster of robbery crimes is located in the eastern region, specifically in the Barra do Ceará neighborhood, which influences neighboring areas such as Cristo Redentor, Floresta, Jardim Iracema, Jardim Guanabara, and Pirambu. On the other hand, the Vila Velha neighborhood, located in the western region of this area, presents a reverse effect, indicating a concentration of robbery crimes in that area.

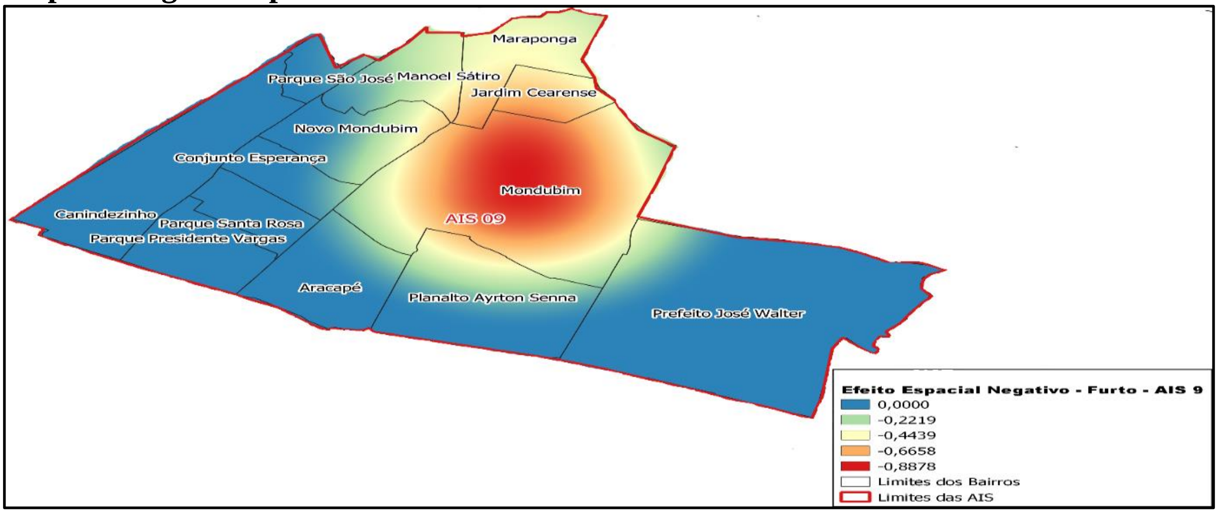
Map 16: Negative Spatial Effect - Theft Rate - AIS 8



Source: prepared by the authors.

In AIS 9, the major cluster is concentrated in the center of this area, precisely in the Mondubim neighborhood, and influences the neighborhoods of Jardim Cearense, Manoel Sátiro, Maraponga, Novo Mondubim, and Planalto Ayrton Senna. In contrast, the reverse effect is observed in the other neighborhoods.

Map 17: Negative Spatial Effect - Theft Rate - AIS 9



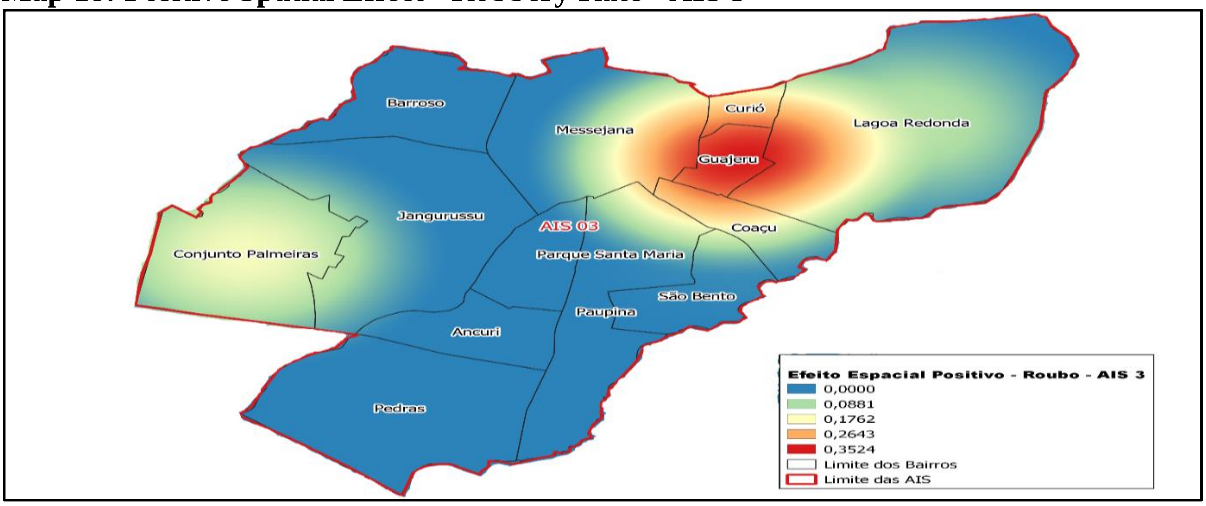
Source: prepared by the authors.

Regarding the robbery rate, it can be observed that in AIS 3, 6, and 10, there are multiple spillover effects that influence several neighborhoods within these areas. In AIS 3, the highest magnitude spillover occurs in the Guajeru neighborhood and overflows into the neighborhoods Messejana, Curió, Lagoa Redonda, Coaçu, São Bento, and Parque Santa Maria. The second spillover, of lower magnitude, affects the entire Conjunto Palmeiras neighborhood and overflows into the neighboring Jangurussu neighborhood. In the other neighborhoods, there is no spillover effect for robbery crimes.

In AIS 6, the largest spillover effect occurs in the Presidente Kennedy neighborhood and influences the Padre Andrade, Pici, Parquelândia, Parque Araxá, Amadeu Furtado, Rodolfo Teófilo, and Bela Vista neighborhoods. The second spillover of smaller magnitude occurs in the João XXIII neighborhood and overflows into the Henrique Jorge, Bonsucesso, and Jóquei Clube neighborhoods. In the other neighborhoods, a reverse effect is observed, indicating a concentration of robbery crimes, especially in the Antônio Bezerra and Quintino Cunha neighborhoods with the highest magnitudes.

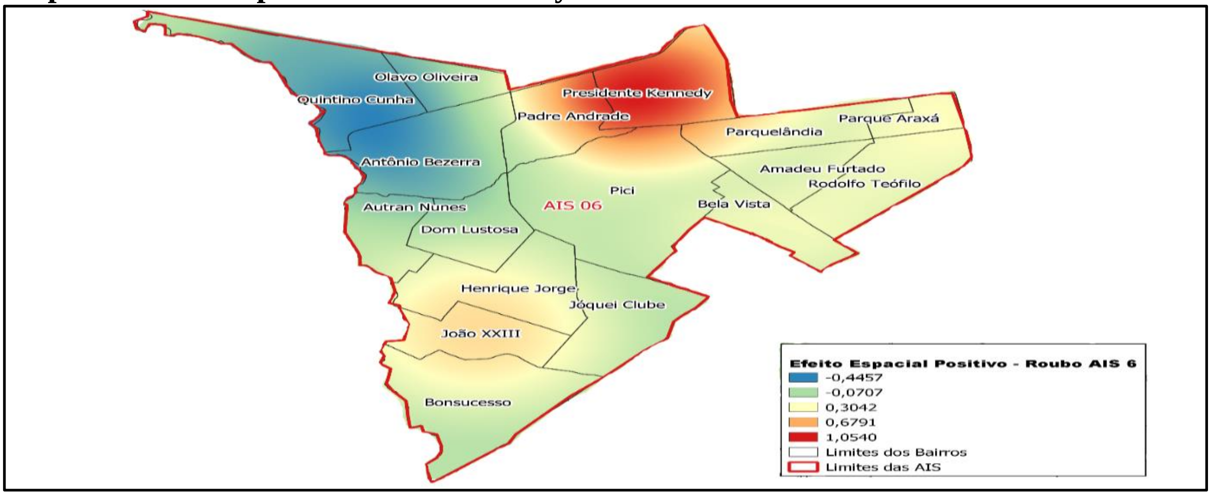
In AIS 10, the spillover with the highest magnitude is in the eastern region of this area, affecting the Manuel Dias Branco neighborhood and overflowing into the Praia do Futuro I and II, De Lourdes, Cidade 2000, and Cocó neighborhoods. The spillover of lower magnitude is in the western region, affecting the Engenheiro Luciano Cavalcante and Guararapes neighborhoods, and overflowing into the Salinas, Tauape, Dionísio Torres, and Joaquim Távora neighborhoods. The other neighborhoods have no spillover effect for theft.

Map 18: Positive Spatial Effect - Robbery Rate - AIS 3



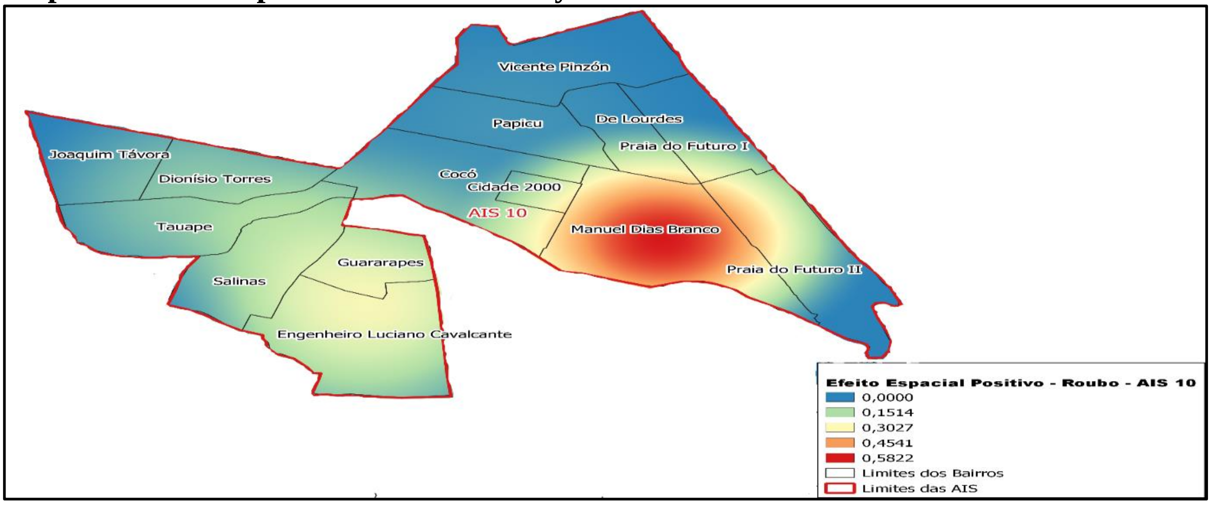
Source: prepared by the authors.

Map 19: Positive Spatial Effect - Robbery Rate - AIS 6



Source: prepared by the authors.

Map 20: Positive Spatial Effect - Robbery Rate - AIS 10



Source: prepared by the authors.

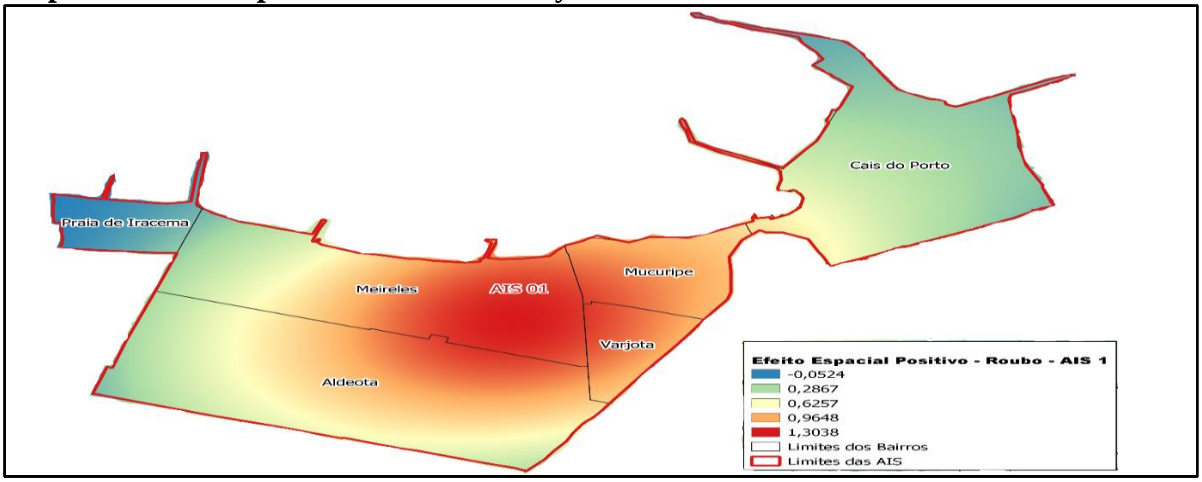
In AIS 1, 5, 7, and 9, the spillover effect has a significant influence on most neighborhoods, indicating a high degree of crime interaction among neighbors in these areas. In SIA 1, the spillover effect affects each other between the Meireles, Aldeota, Varjota, and Mucuripe neighborhoods and overflows through the Cais do Porto neighborhood. The Praia de Iracema neighborhood presents a reverse effect, indicating a concentration of robbery crimes.

In AIS 5, spillover occurs in Montese and overflows to a large extent in the Bom Futuro, Parreão, Damas, Jardim América, Couto Fernandes, Demócrito Rocha, Itaoca, Vila União, and Aeroporto neighborhoods. It also influences neighborhoods in the extreme north of this area such as Fatima, Benfica, and José Bonifácio. The neighborhoods located in the extreme south of this region do not present spillover effects.

The spillover present in AIS 7 is one of the most extensive ones, although in terms of magnitude it is smaller. The incidence happens in the Parque Manibura neighborhood and overflows in both extremes of this area, influencing the Sabiaguaba neighborhood in the east and the Parque Dois Irmãos in the west. Among the most affected neighborhoods are Sapiranga, Parque Iracema, Cambeba, and Cidade dos Funcionários. The neighborhoods Aerolândia, Alto da Balança, Dias Macêdo, and Jardim das Oliveiras present a reverse effect.

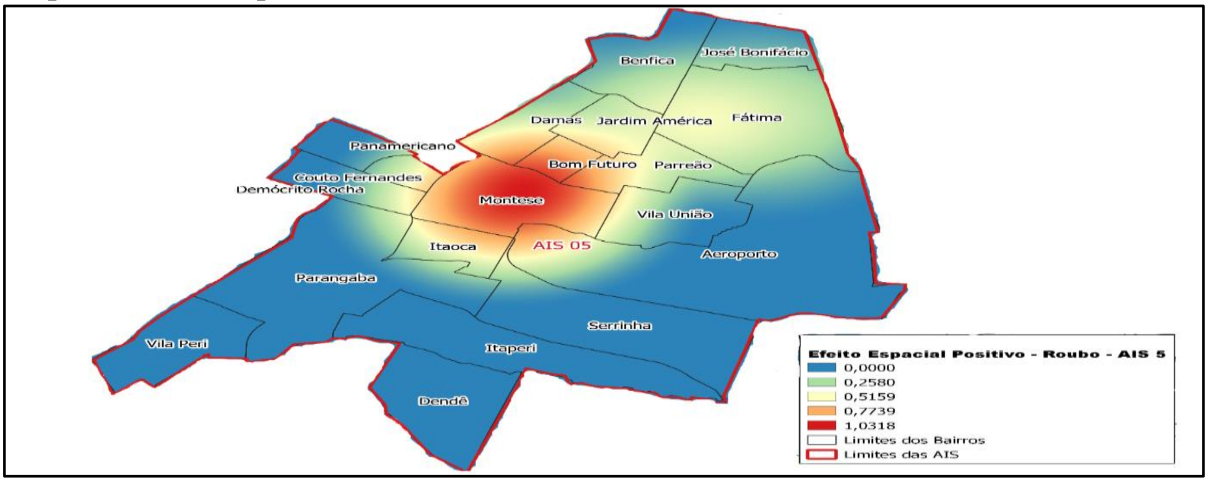
Similarly, AIS 9 presents an extensive spillover that influences several neighborhoods in this area. The incidence occurs between the Parque São José, Manoel Sátiro, and Novo Mondubim neighborhoods, and overflows through neighborhoods like Jardim Cearense, Maraponga, Mondubim, Conjunto Esperança, and Parque Santa Rosa. In neighborhoods located in the far east, no overflow effect is observed, for example, in the José Walter neighborhood.

Map 21: Positive Spatial Effect - Robbery Rate - AIS 1



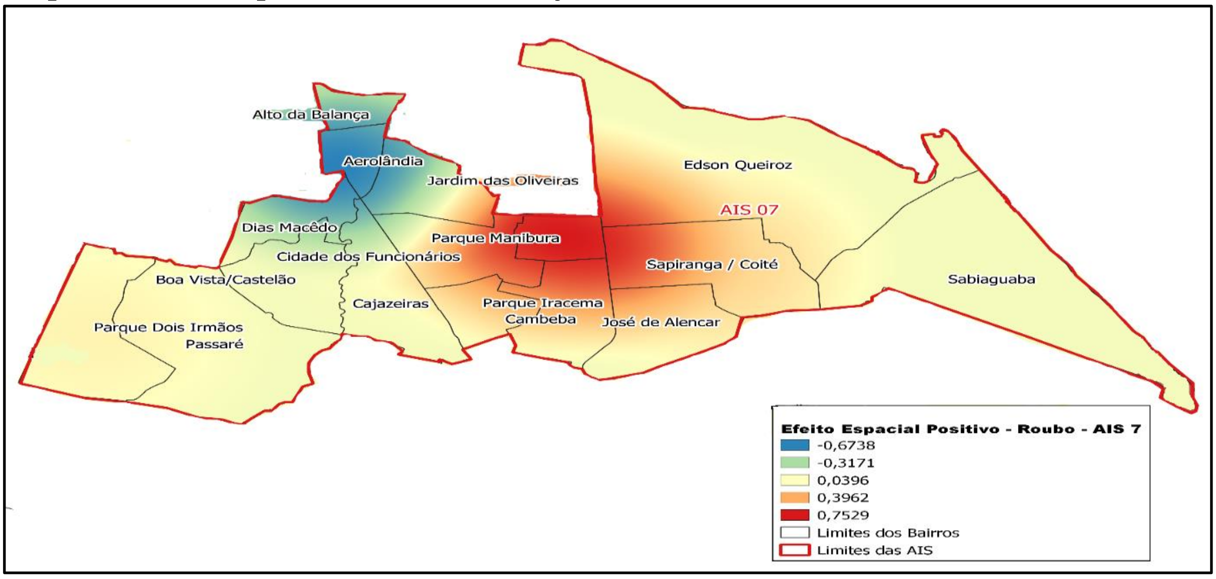
Source: prepared by the authors.

Map 22: Positive Spatial Effect - Theft Rate - AIS 5



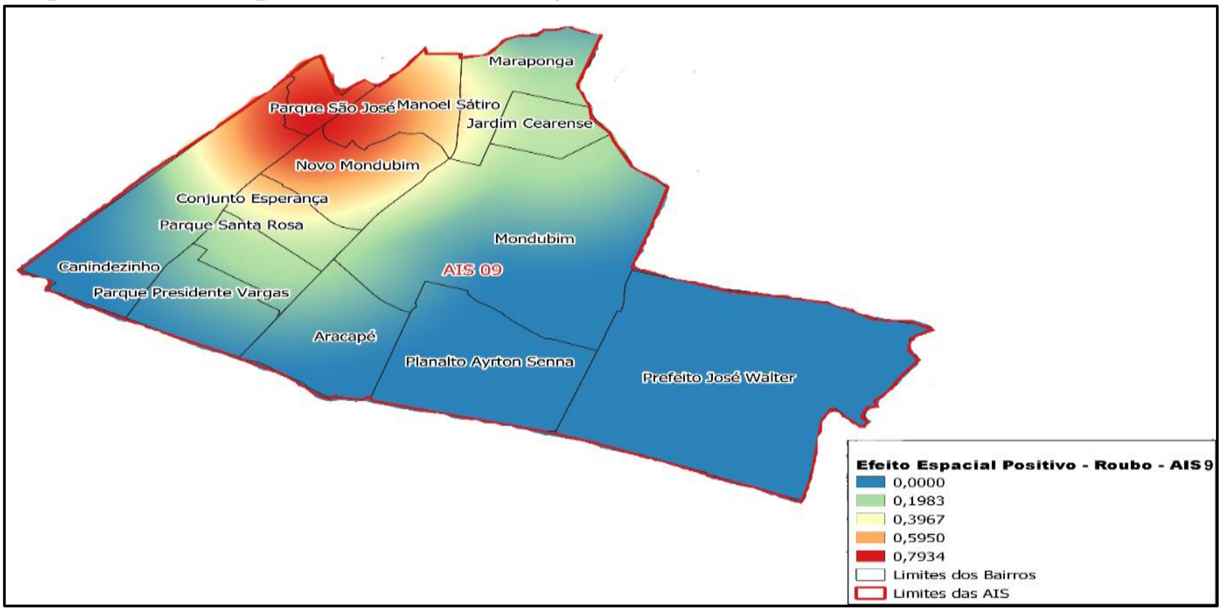
Source: prepared by the authors.

Map 23: Positive Spatial Effect - Robbery Rate - AIS 7



Source: prepared by the authors.

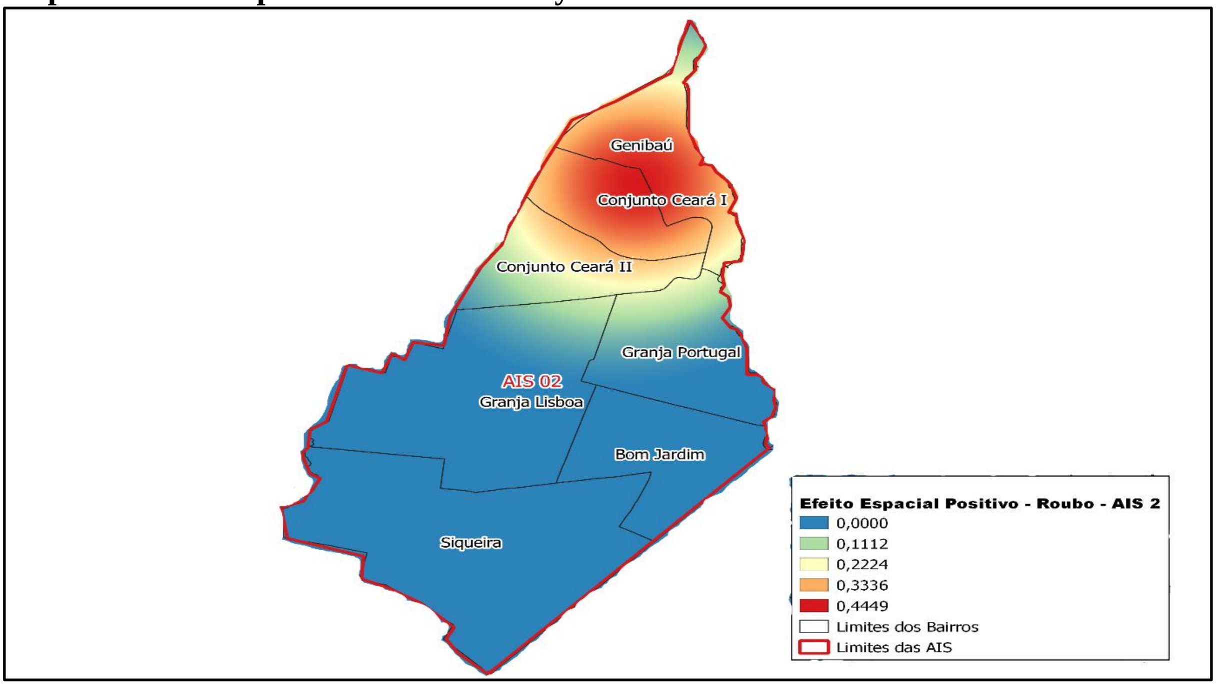
Map 24: Positive Spatial Effect - Robbery Rate - AIS 9



Source: prepared by the authors.

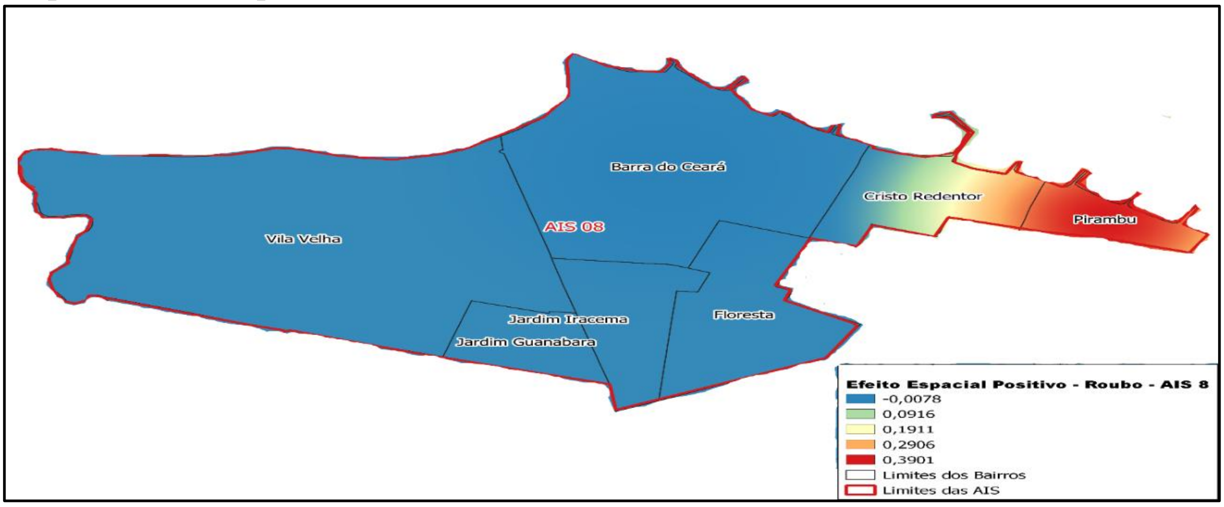
In AIS 2 and 8, the extent of spillover is smaller. In the former, the incidence is in the North region, between the neighborhoods of Conjunto Ceará I and Genibaú, which spills over into the neighborhoods of Conjunto Ceará II and Granja Portugal. However, for the neighborhoods in the South region, there is no spillover effect. In AIS 8, the spillover effect occurs in the Pirambu neighborhood and overflows only into the Cristo Redentor neighborhood. For the other neighborhoods, there is a low-magnitude reverse effect.

Map 25: Positive Spatial Effect - Robbery Rate - AIS 2



Source: prepared by the authors.

Map 26: Positive Spatial Effect - Theft Rate - AIS 8



Source: prepared by the authors.

Regarding negative spatial effects, AIS 2, 3, 4, 6, 7, 9 and 10 exhibit more than one cluster, with neighborhoods in these areas having the highest concentrations of robbery crime in Fortaleza. In AIS 2, the cluster with the highest magnitude is centered on the Granja Lisboa neighborhood and influences the Siqueira, Bom Jardim, Granja Portugal and Conjunto Ceará II neighborhoods. The second cluster, of much lower magnitude, is located between the Genibaú and Conjunto Ceará I neighborhoods. It can be observed that all neighborhoods in this area have a high concentration of robberies.

In AIS 3, the cluster with the highest intensity occurs between the Conjunto Palmeiras and Jangurussu neighborhoods, influencing the Parque Santa Maria, Messejana and Barroso neighborhoods. The cluster of lesser magnitude is centered on the Coaçu neighborhood and influences the Guajeru, Paupina, Lagoa Redonda and São Bento neighborhoods. In the other neighborhoods in this area do not exhibit negative spatial effect.

AIS 4 has clusters with the highest intensity among all areas. The first cluster, with the greatest magnitude, covers the entire Centro neighborhood and influences Farias Brito neighborhood. The second cluster, with the greatest extension, includes the Monte Castelo, Carlito Pamplona and Jacarecanga neighborhood, and influences the São Gerardo, Ellery and Alvaro Weyne neighborhood. Meanwhile, the Moura Brasil neighborhood shows a reverse effect, indicating that it overflows the crime of robbery to its neighbors.

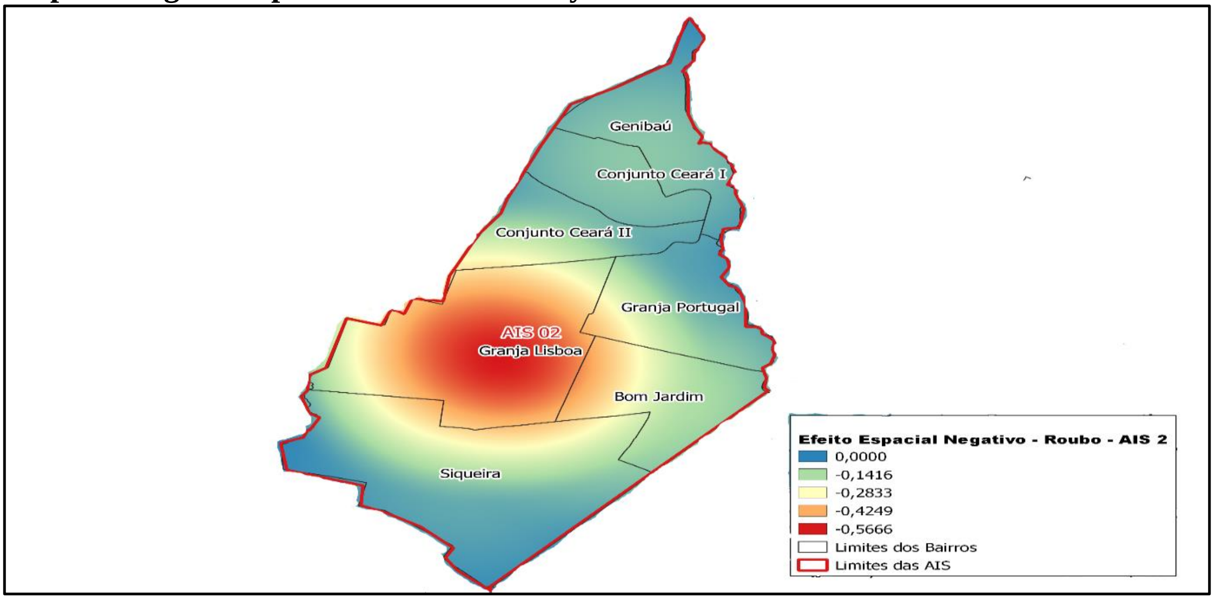
In AIS 6, the cluster of greater magnitude focuses on the Quintino Cunha, Olavo Oliveira and Antônio Bezerra neighborhoods and influences the Padre Andrade, Autran Nunes, Dom Lustosa, Pici, Henrique Jorge, João XXIII and Jóquei Clube neighborhoods. The second cluster, of lesser magnitude, falls between the Parquelândia, Amadeu Furtado and Parque Araxá neighborhoods, and influences the Rodolfo Teófilo, Bela Vista, Presidente Kennedy and Pici neighborhoods.

In AIS 7, the clusters are concentrated in the Western region of the area. The cluster of greatest magnitude is centered on the Parque Dois Irmãos, Passaré and Castelão neighborhoods. The second cluster focuses on the Cidade dos Funcionários and Parque Manibura neighborhoods and influences the Jardim das Oliveiras, Parque Iracema, Cambeba, Cajazeiras, Aerolândia and Alto da Balança neighborhoods. The third cluster of lower intensity is located focuses in the José de Alencar neighborhood and influences the Sapiranga and Cambeba neighborhoods.

In AIS 9, the clusters are concentrated towards the East of this area. The cluster of greater magnitude focuses on the neighborhoods Jardim Cearense, Maraponga and Mondubim and influences the neighborhoods Manoel Sátiro, Novo Mondubim and Planalto Ayrton Senna. The second cluster of lesser magnitude focuses entirely on the neighborhood José Walter.

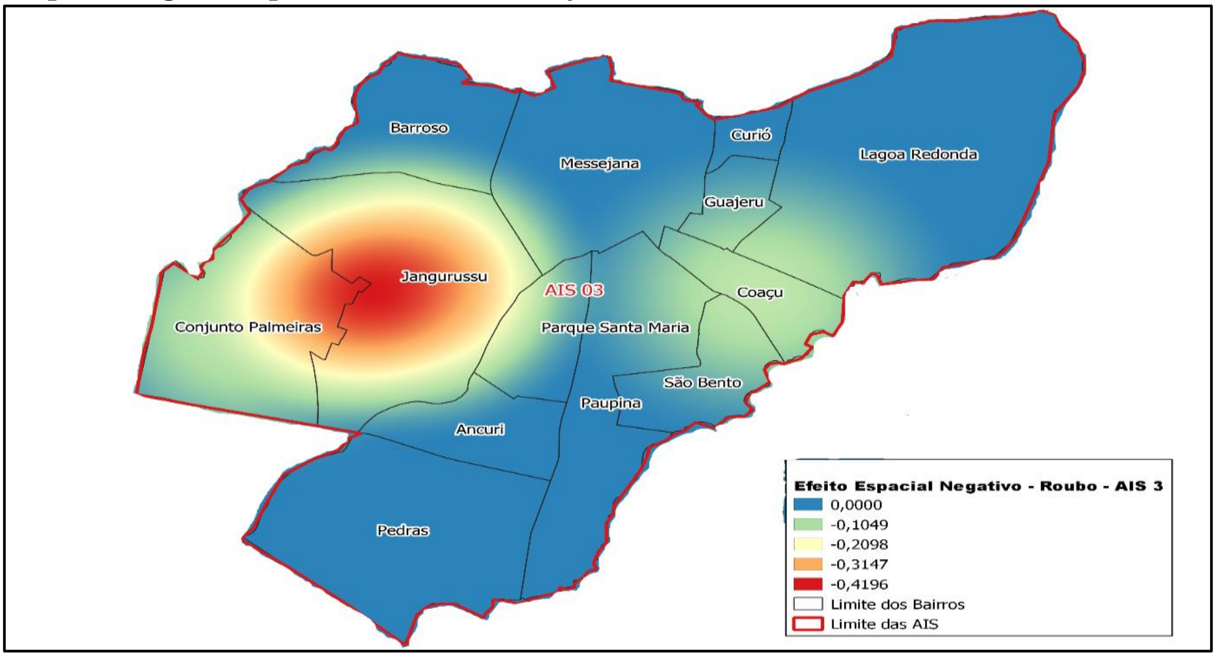
In AIS 10, the clusters are distributed on both sides of this area. The cluster of greater magnitude is concentrated on the east side, focusing on the neighborhoods Manoel Dias Branco and Praia do Futuro II and eventually influencing the neighborhoods Praia do Futuro I, De Lourdes, Cidade 2000, Papicu, Cocó and Vicente Pizón. The cluster of smaller magnitude is in the West region, affecting the neighborhoods Dionisio Torres, Tauape, Guararapes Joaquim Távora, Engenheiro Luciano Cavalcante and Salinas.

Map 27: Negative Spatial Effect - Robbery Rate - AIS 2



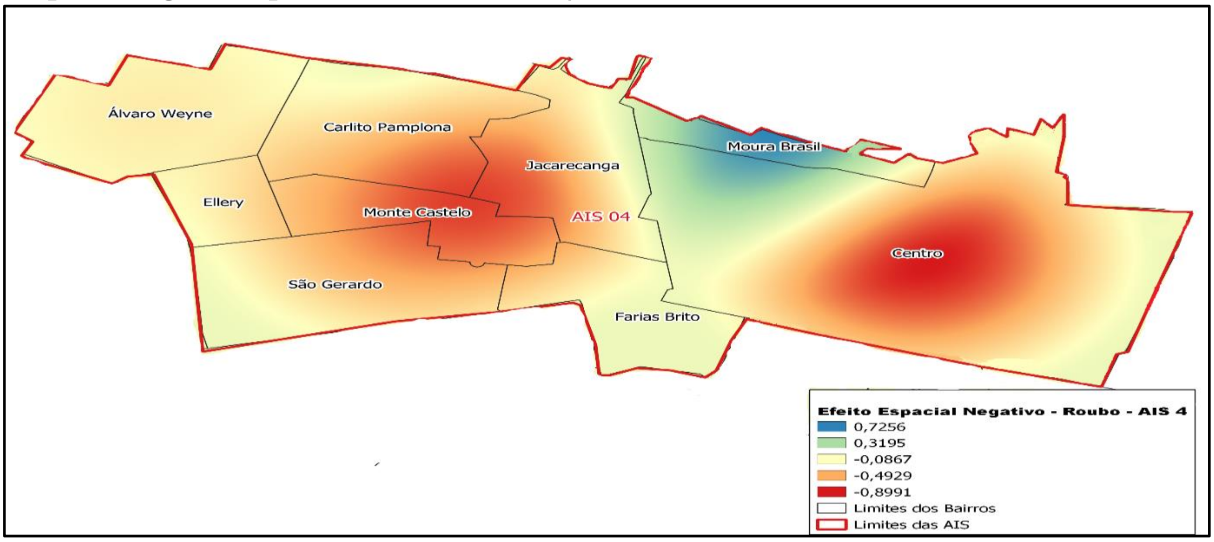
Source: prepared by the authors.

Map 28: Negative Spatial Effect - Robbery Rate - AIS 3



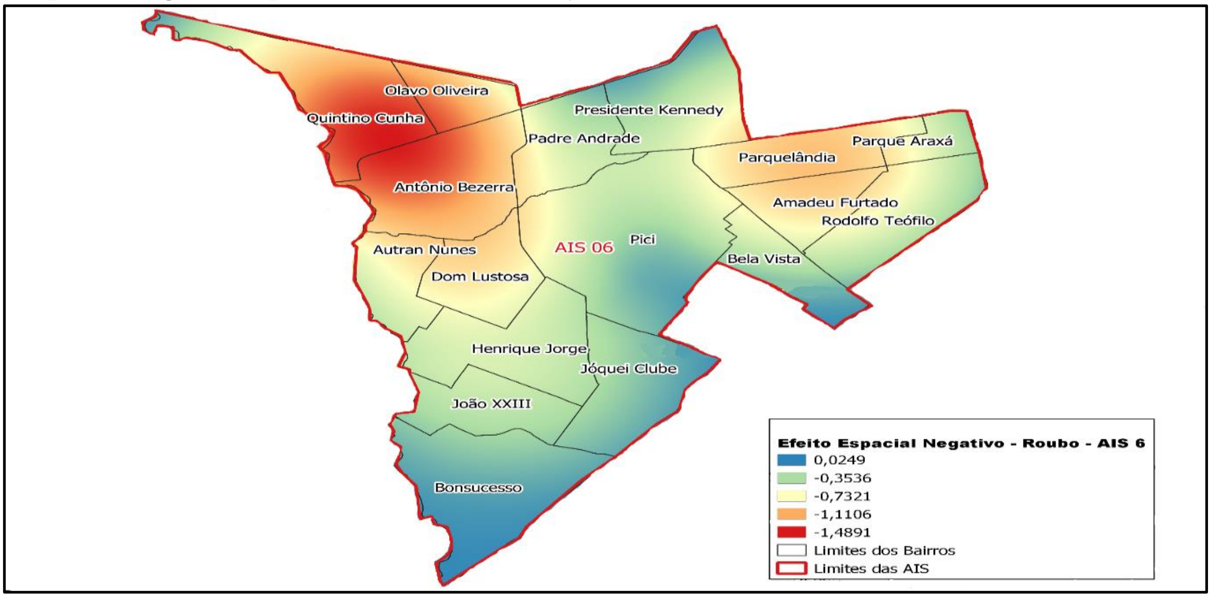
Source: prepared by the authors.

Map 29: Negative Spatial Effect - Robbery Rate - AIS 4



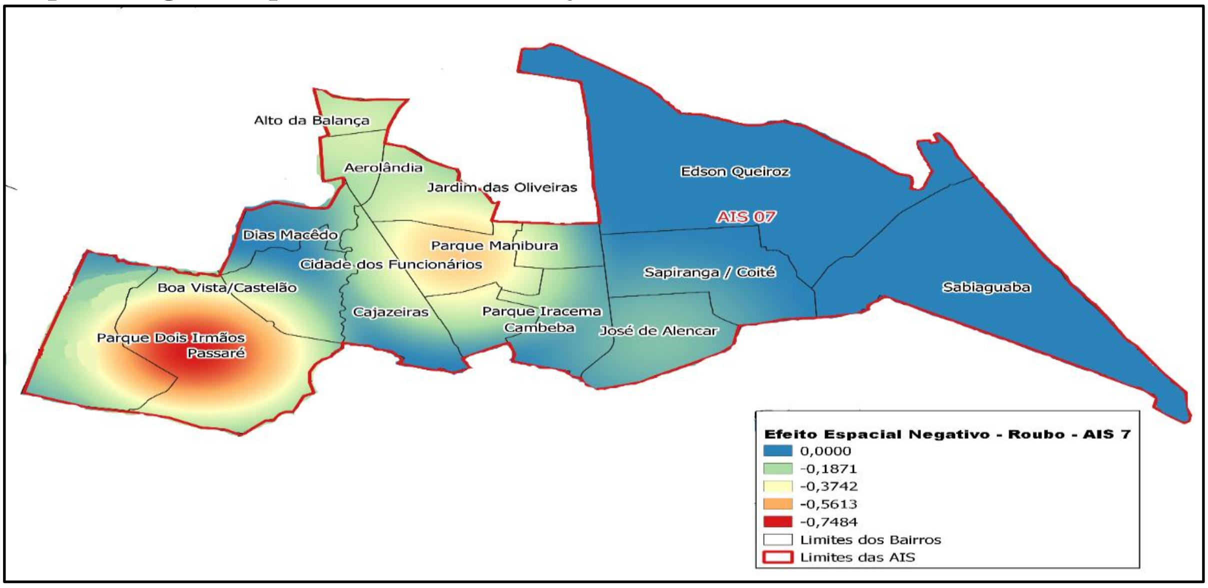
Source: prepared by the authors.

Map 30: Negative Spatial Effect - Robbery Rate - AIS 6



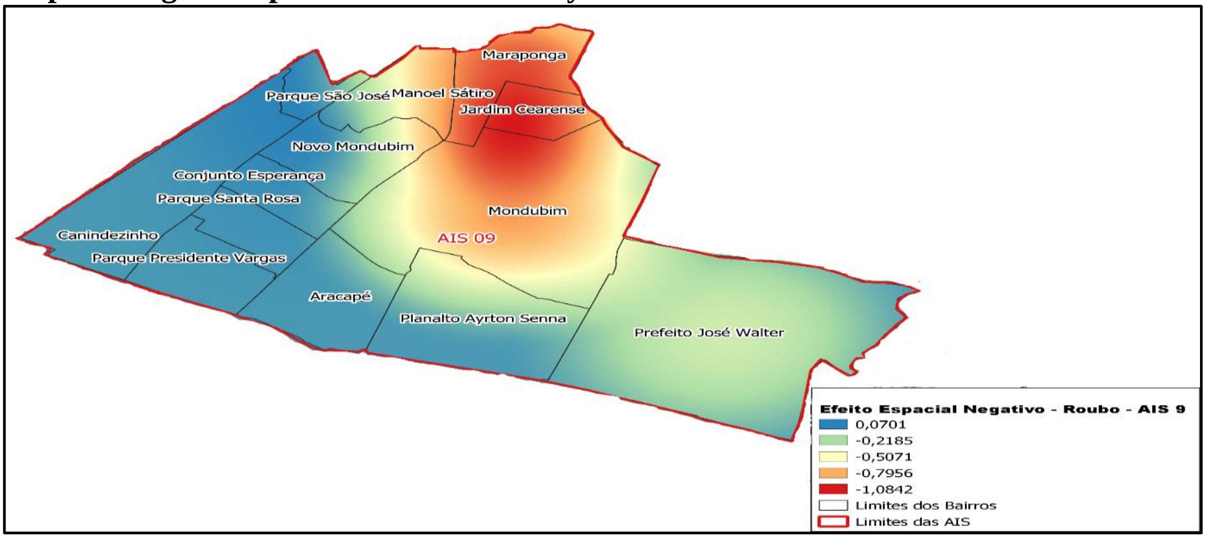
Source: prepared by the authors.

Map 31: Negative Spatial Effect - Robbery Rate - AIS 7



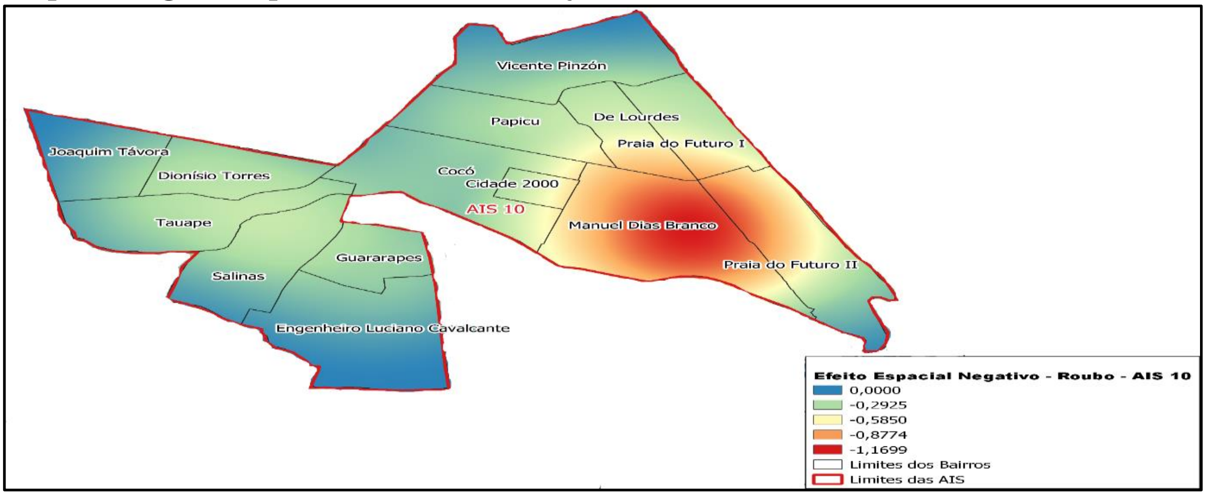
Source: prepared by the authors.

Map 32: Negative Spatial Effect - Robbery Rate - AIS 9



Source: prepared by the authors.

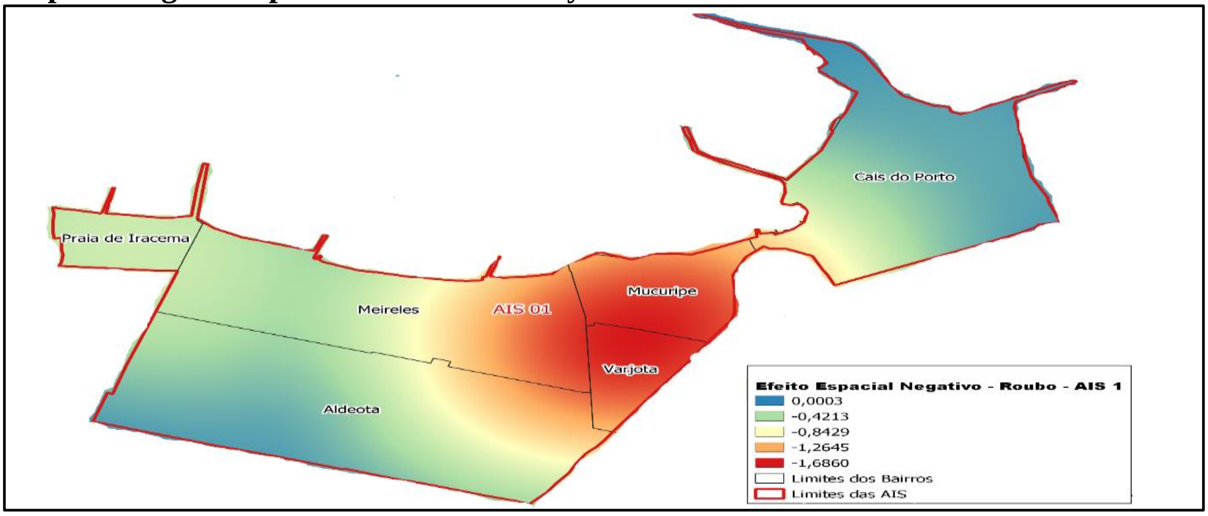
Map 33: Negative Spatial Effect - Robbery Rate - AIS 10



Source: prepared by the authors.

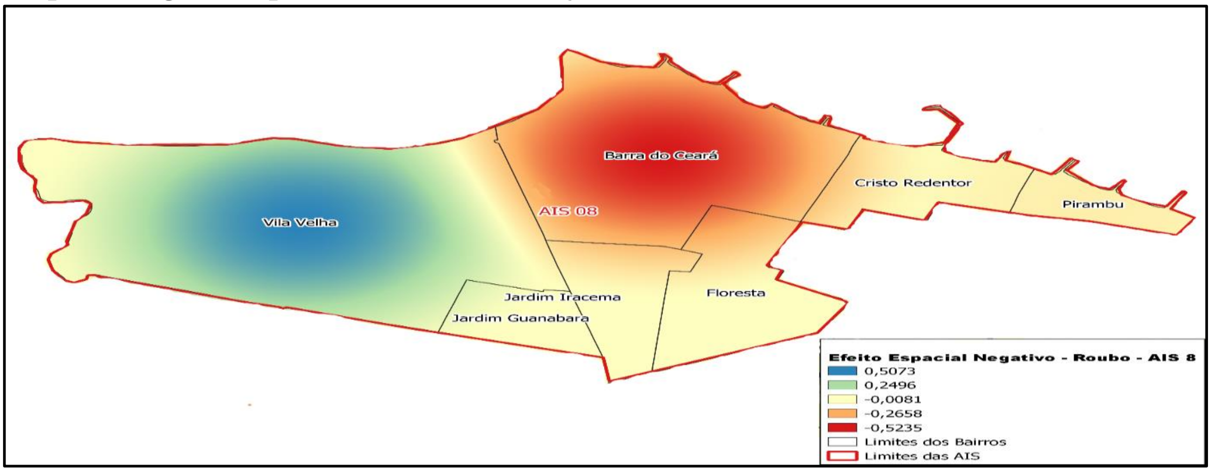
In AIS 1 and 8, the clusters assume a large extension along these areas. In AIS 1, the cluster mainly affects the neighborhoods of Mucuripe and Varjota, but also has an influence on all other neighborhoods in the area. In AIS 8, the cluster is centered on the Barra do Ceará neighborhood and has an impact on all the neighborhoods located in the Eastern region of this area. Meanwhile, the Vila Velha neighborhood shows the opposite effect, indicating an overflow of crime.

Map 34: Negative Spatial Effect - Robbery Rate - AIS 1



Source: prepared by the authors.

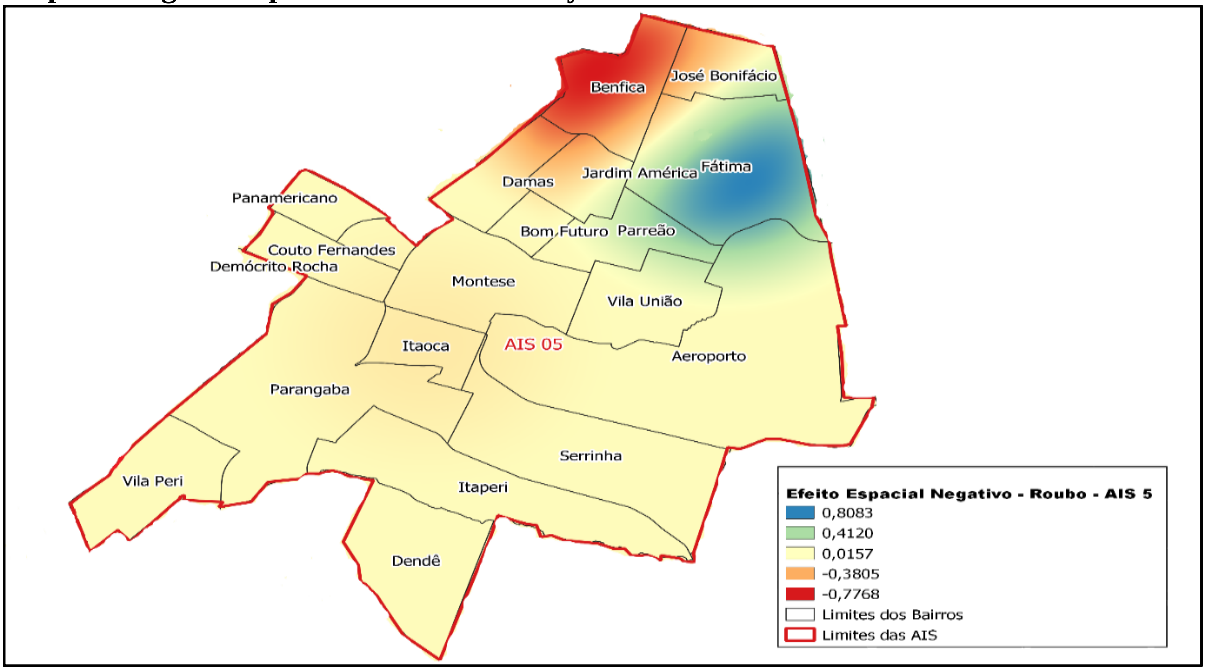
Map 35: Negative Spatial Effect - Robbery Rate - AIS 8



Source: prepared by the authors.

AIS 5 presents a cluster of small extension, affecting only the Benfica neighborhood and influencing the neighborhoods areas of José Bonifácio, Damas and Jardim América. However, the other neighborhoods show the opposite effect, indicating overflow, with the neighborhood of Fátima experiencing the highest level of overflow.

Map 36: Negative Spatial Effect - Robbery Rate - AIS 5



Source: prepared by the authors.