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Sumário

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Abstract

Vehicle theft are a recurring problem in São Paulo, affecting both public safety and the perception of risk in the city. This type of crime does not happen randomly but follows specific patterns that can be analyzed to understand its distribution and spread. Many studies use hotspot maps and statistical models to identify the most affected areas, but these approaches do not always capture the connections between crimes and how they propagate over time and space. To fill this gap, this study adopts a complex network-based approach, allowing for a broader analysis of crime dynamics. For this purpose, vehicle robberies that occurred between 2017 and 2021 were analyzed using data from the São Paulo Public Security Department. Each crime was represented as a tide in a network, and the connections between them were established based on geographical and temporal proximity. The network efficiency metric was applied to measure crime connectivity and identify structural patterns. In addition to that, statistical tests such as ANOVA, Kruskal-Wallis, and Dunn were used to verify significant differences between the administrative regions of the city. The results indicate that some regions act as crime hubs, consistently concentrating vehicle robberies over the years. A decline in criminal network connectivity was also observed in 2019, followed by a reorganization of patterns in 2021, possibly influenced by external factors, such as changes in policing strategies and mobility restrictions caused by the COVID-19 pandemic. Furthermore, a spatial diffusion effect was identified, where districts neighboring highly affected areas also exhibit high robbery rates, suggesting that crime spreads between adjacent regions. This study highlights the potential of complex networks as a powerful tool for understanding urban crime more deeply. Rather than treating robberies as isolated events, this approach recognizes them as part of an interconnected system, where certain city areas play a central role in the spread of criminal activities.

Keywords: Complex networks. Urban crime. Criminal informatics. Urban planning.

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Resumo

Roubos de veículos são um problema recorrente em São Paulo, afetando tanto a segurança pública quanto a percepção de risco na cidade. Esse tipo de crime não ocorre aleatoriamente, mas segue padrões específicos que podem ser analisados para compreender sua distribuição e propagação. Muitos estudos utilizam mapas de hotspots e modelos estatísticos para identificar as áreas mais afetadas, mas essas abordagens nem sempre capturam as conexões entre os crimes e como eles se propagam no tempo e no espaço. Para preencher essa lacuna, este estudo adota uma abordagem baseada em redes complexas, permitindo uma análise mais ampla da dinâmica criminal. Para tanto, foram analisados roubos de veículos ocorridos entre 2017 e 2021, utilizando dados da Secretaria de Segurança Pública de São Paulo. Cada crime foi representado como um nó em uma rede, e as conexões entre eles foram estabelecidas com base na proximidade geográfica e temporal. A métrica de eficiência de rede foi aplicada para medir a conectividade do crime e identificar padrões estruturais. Além disso, testes estatísticos como ANOVA, Kruskal-Wallis e Dunn foram utilizados para verificar diferenças significativas entre as regiões administrativas da cidade. Os resultados indicam que algumas regiões atuam como centros de crime (crime hubs), concentrando consistentemente roubos de veículos ao longo dos anos. Uma diminuição na conectividade da rede criminal também foi observada em 2019, seguida por uma reorganização dos padrões em 2021, possivelmente influenciada por fatores externos, como mudanças nas estratégias policiais e restrições de mobilidade causadas pela pandemia de COVID-19. Além disso, foi identificado um efeito de difusão espacial, onde distritos vizinhos a áreas altamente afetadas também exibem altas taxas de roubo, sugerindo que o crime se espalha entre regiões adjacentes. Este estudo destaca o potencial das redes complexas como uma ferramenta poderosa para aprofundar a compreensão do crime urbano. Em vez de tratar os roubos como eventos isolados, essa abordagem os reconhece como parte de um sistema interconectado, onde certas áreas da cidade desempenham um papel central na disseminação das atividades criminosas.

Palavras-chave: Redes complexas. Crime urbano. Informática criminal. Planejamento urbano.

1 Introdução

With a population of close to 12 million inhabitants and a territorial extension of 1,521.202 km², the city of São Paulo has the highest population density in Brazil. In addition to that, the city has an average vehicle fleet of 8.5 million. Based on these figures, it is estimated that two out of three inhabitants own a motor vehicle. These high numbers trigger a series of factors, among which is the criminal act of vehicle robbery. Consequently, between 2017 and 2019, São Paulo recorded an average of 26,841 vehicle robberies per year. Given the territorial and population context, considering the municipal vehicle fleet and the average vehicle robbery rate, there arises a need to identify how this criminal dynamic is distributed across the different administrative regions of São Paulo city.

Such as a context of territorial crime analysis, the literature shows that crime does not occur randomly in time and space. Just the opposite ou conversely, there are concentration points of offenses, recurring victims, and repeat offenders. Therefore, the analysis and interpretation of crime should be guided by models that reveal the non-uniformity of the phenomenon, allowing for a more precise understanding of criminal patterns and facilitating the development of more targeted and effective public security strategies[1].

Researches of crime dynamics has advanced by incorporating modern techniques to better understand and anticipate criminal patterns. The results highlight the importance of considering spatiotemporal va-

[1] BRANTINGHAM, Paul J; BRANTINGHAM, Patricia L. The geometry of crime and crime pattern theory. In: ENVIRONMENTAL criminology and crime analysis. [S.l.]: Routledge, 2016. P. 117–135.

riables in the analysis of criminal dynamics in urban contexts[2]. Among these approaches, models utilizing algorithms inspired by ant colonies stand out for identifying critical areas and optimizing patrol[3]. Big data analysis tools and deep learning techniques are also applied, enabling the processing of large volumes of information to uncover trends and support decision-making. Research report the challenges of analyzing vast amounts of criminal data, which are heterogeneous, originate from multiple sources, and are dynamic. They argue that many approaches fail to process and extract useful information from these data, emphasizing the need to filter incident types[4]. Another essential resource is the use of Geographic Information Systems (GIS), which allow for mapping incidents and identifying areas with higher crime concentrations, aiding in the development of preventive policies. Furthermore, predictive models based on machine learning have shown great potential in understanding crime dynamics, offering new perspectives for public security management[5] [6].

Geographic Information Systems (GIS) and spatial statistical techniques, such as spatial cluster analysis, have been applied to analyze police data and news reports on environmental crimes in Sweden from 2000 to 2017. The study identified that local changes after 2006 led to an increase in cases recorded by the police and newspaper articles about environmental crimes, eventually stabilizing over time. The research revealed persistent spatial patterns of environmental crimes, primarily in rural and remote areas, where the most severe offenses were concentrated[7]. Spatiotemporal analysis has also been employed through Kernel density estimation to identify hotspots of gender-based violence. It was concluded that GIS and spatial analysis provide critical materials that can help allocate resources more effectively in combating these crimes[8] [9].

To understand these crime events, it is essential to consider the specific characteristics of each region, as criminal patterns change and reflect the unique attributes of each environment, whether urban or rural. Factors such as population density, socioeconomic conditions, land use, and accessibility directly influence how crimes are distributed and concentrated. Therefore, analyzing crime at different scales, from large administrative areas to specific streets, is crucial for understanding how these local elements shape criminal dynamics and the spread of illicit activities[10].

Researches of crime in the city of São Paulo city can encompass diverse perspectives. One study analyzed homicide variables in the municipality to identify the districts with the highest crime incidence and their motivating causes. The analysis combined criminal data from the INFOCRIM system (1999-2003), information from the Forensic Medical Institute (IML), and socioeconomic indicators from IBGE and DATASUS, applying statistical modeling, spatial regression, and GIS to identify homicide patterns and test hypotheses regarding the influence of structural and situational factors on lethal crime variation. The results demonstrated a spatial variation in homicides in São Paulo, showing that these events are associated with socioecono-

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mic, situational, and criminal factors. The findings highlight areas marked by poverty and inequality, as well as regions with high population flow[11].

Population flow is a determining factor in crime patterns in the city. In this context, considering that public transportation is essential for urban mobility, it was necessary to study victimization conditions in the subway to identify station characteristics and their surroundings that directly impact violent crimes. Using data from the Public Security Department, violent incidents were mapped, and land use data were employed to characterize the areas surrounding the stations. A negative binomial regression model was applied to test the relationship between crime incidence and variables such as passenger flow, staff presence, station infrastructure, and the socioeconomic characteristics of the surrounding area. Additionally, GIS was used to map and identify victimization patterns. The results indicate that women's victimization occurs predominantly during peak hours and at night, reflecting their greater exposure during commutes for work and study, while men are more frequently victimized on weekends and at night, usually in situations involving physical confrontations or robbery[12].

These tools provide a broader and more detailed perspective on the influence of spatial and temporal factors on criminal behavior, highlighting the importance of considering multiple perspectives when assessing changes in the urban environment[13]. Moreover interventions in specific areas could reduce crime rates in the city if strategically implemented[14]. The application of GIS in crime analysis has made significant contributions and advancements in the field. In addition to enhancing crime mapping and visualization, this technology enables deeper investigations into the spatial dynamics of criminality and assists in defining strategies for law enforcement[15].

Basedon this, focusing on crime analysis techniques for territorial management, complex networks emerge as a potential approach to studying crime by revealing the interactions between several factors that shape its occurrence and propagation. Unlike traditional analyses, complex networks allow crime to be modeled as a dynamic system, where each element—whether a region, a street, or a critical point—acts as a node connected to others through spatial and temporal relationships. The efficiency metric provides tools to identify underlying patterns, highlight priority areas for intervention, and understand how crime is organized and spreads.

1.1 Complex systems

To fully understand complex networks, it is necessary to use different metrics. These types of networks have multiple dimensions, involving connection patterns, flow, resilience, and modular organization. Therefore, relying on a single metric, such as degree or shortest path, is not sufficient to capture the full complexity of their structure. The diversity of metrics allows for a complementary perspective, enabling an understanding of both local details and the overall network structure[16].

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There is a diversification in the use of complex networks, as they can be applied to various systems with different metrics[17]. One of the main characteristics of complex systems is their structure, which consists of discrete parts that interact through self-organization, evolution, and adaptation. A fundamental element of these systems is the application of Power Laws, which help identify the intensity of connections between two or more points. This allows for the use of interconnected samples, reflecting the behavior of the entire system rather than individual units, based on the organization and adaptation of its elements[18].

Based on this, studies on complex networks have increasingly intersected with research on criminal networks. Researchers collected real data from official sources in the province of Nineveh, Iraq, and constructed two main networks: the crime network, where each node represented a type of crime, with connections based on correlations between different crimes, and the criminal regions network, where each node represented a geographic region, connected to others based on shared criminal occurrences. They applied centrality metrics, such as degree and closeness, to identify the most influential nodes and the most central regions within the networks. This approach revealed crime types and regions that function as criminal influence hubs, making them priorities for intervention strategies[19].

With the aim of applying complex network techniques to geographical spatial analyses, this research seeks to compare the spatial dynamics of vehicle robberies in the city of São Paulo. To achieve this, the following hypotheses are proposed: a) Vehicle robberies do not occur randomly but follow a clustering pattern in specific districts, where this crime is more recurrent; b) Districts with high vehicle robbery rates in a given year tend to maintain elevated rates in subsequent years, indicating a persistent pattern in crime distribution; c) The proximity between districts influences criminal activity, such that districts adjacent to high-incidence areas of vehicle robberies exhibit higher rates, suggesting a diffusion effect of crime.

Environmental criminology examines criminal actions through three main dimensions: routine activity, rational choice, and crime geometry[20]. In this research focuses on crime geometry, a theory that suggests individuals tend to concentrate their criminal activities in locations with which they are familiar[21].

In this context, Newton and Felson investigated the need for an integrated approach to the spatiotemporal analysis of crime. Their research was based on a literature review and the synthesis of empirical studies conducted in different cities, which employed methods such as geospatial hotspot analysis, statistical modeling of crime patterns, and the application of routine activity and crime pattern theories. The results indicated that crime does not occur randomly but follows predictable patterns in time and space, influenced by factors such as land use, population movement, and urban dynamics. The study highlighted that in specific locations, such as schools, subway stations, and recreational areas, exhibit significant variations in crime rates depending on the time of day and day of the week, reinforcing the importance of simultaneously analyzing time and space to develop effective prevention and policing strategies[22].

Using criminal records between 2000 to 2004, Garcia-Zanabria et al. developed a visual analysis tool to identify crime patterns in São Paulo, considering the spatial distribution and temporal variation of crimes. The authors applied Non-Negative Matrix Factorization to detect hotspots. The results showed that crimes

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vary between neighboring districts, influenced by urban factors, and exhibit seasonal patterns, such as an increase in commercial thefts during winter and the concentration of cargo robberies on specific highways[23].

Another method used to study the spatial aspect of crime is Group-Based Trajectory Analysis. Using criminal records from Brooklyn Park, Minnesota, between 2000 and 2014, Gill, Wooditch, and Weisburd detected that 2% of street segments accounted for 50% of crimes, while 0.4% were responsible for 25%, highlighting a pronounced and stable concentration of crime in urban areas[24]. Additionally, Weisburd analyzed the law of crime concentration, investigating whether crimes are predictably distributed across urban micro-geographies. The author compared the distribution of criminal incidents across street segments, applying standardized metrics to assess concentration and its stability over time. The results indicated that 50% of crimes occur in just 4% to 6% of street segments, while 25% are concentrated in less than 1.6%, confirming a consistent pattern of crime concentration. Moreover, the study demonstrated that this distribution remains stable over the years, even with fluctuations in overall crime rates[25]. It is worth noting that variations occur due to external factors, such as the increase in crimes during festivals and holidays[26].

Finally, the systematic review presented by Butt et al. highlights techniques for identifying high-crime areas. The researchers discuss that traditional methods, such as Kernel Density Estimation and Getis-Ord G*i, have been widely applied, while clustering algorithms like DBSCAN, K-Means, and Fuzzy C-Means have demonstrated greater accuracy in segmenting crime-prone areas. Additionally, machine learning approaches, including Random Forest, XGBoost, LightGBM, Naïve Bayes, and Support Vector Machines, have shown a higher capacity to adapt to multiple contextual factors. More advanced methods based on neural networks, such as Artificial Neural Networks, Convolutional Neural Networks, and Recurrent Neural Networks, have emerged as promising tools for spatiotemporal modeling. However, they still face challenges due to the scarcity of structured data. The authors conclude that integrating different techniques—particularly combining deep learning with statistical and geospatial methods—can significantly enhance the accuracy of crime analysis and prediction[27].

The representation of networks in real-world systems is referred to as a graph. Graph theory traces its origins to the solution of the Königsberg bridge problem in 1736. A graph is a mathematical structure composed of vertices connected by edges, where the connections represent relationships between elements. Complex networks emerge in real systems when connections follow irregular patterns, forming scale-free structures, small-world effects, and communities. Small-world networks are known for their high local connectivity[28 29], . Unlike random graphs, they reflect the organization and interaction of systems such as social networks and urban infrastructure. Their study, based on graph theory, helps to understand emerging dynamics across various fields[30]. Real networks follow a scale-free structure, where a few highly connected nodes support the network. As a result, new nodes tend to preferentially connect to the more connected nodes. This type of organization makes networks resilient to random failures[31]. Most individuals in a network have

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few connections; however, a small number of individuals possess a high number of connections. These individuals, known as hubs, serve as central points and are essential for the dissemination of information within the network[32 33].

The Barabási-Albert model is one of the main paradigms for understanding scale-free networks. This model captures the heterogeneity of connections. Scale-free networks emerge due to two fundamental principles: network growth, where new nodes are added over time, and preferential attachment, where new nodes are more likely to connect to highly connected nodes. This mechanism generates a power-law degree distribution, meaning that complex systems tend to have a larger number of nodes with few connections than highly connected nodes[34 35]. In other words, complex networks follow distinct organizational patterns compared to classical random models, being governed by specific structural principles. Scale-free networks emerge through mechanisms of growth and preferential attachment[36]. Both scale-free networks and small--world networks exhibit the small-world effect, where the distance between any two nodes is significantly smaller than the total number of nodes. This occurs due to the randomness in the creation of connections between nodes[37 38].

Given the discussion on studies of criminal spatiality and the presentation of how complex networks function, it is evident that most research on crime and urban space relies on statistical models, hotspot analysis, and geospatial tools to map crime patterns. While these methods are effective in identifying high--crime areas, they treat robberies as isolated events, without considering the connections between them or how crime spreads within the city.

This study aims to bridge this gap by exploring the use of complex networks to understand the dynamics of vehicle robberies in São Paulo. Unlike traditional analyses, this methodology allows crime to be viewed as an interconnected system, where each robbery is related to other events occurring nearby in time and space. This approach makes it possible to uncover hidden patterns, understand the organization of crimes, and map how they spread across different regions. Instead of treating robberies merely as scattered data points on a map, this study reveals how they are connected and organized within the city. Rather than analyzing the city in a generalized manner, the article compares vehicle robberies across administrative regions, providing more detailed insights to enhance public security strategies.

In this study, an analysis of vehicle robberies in the city of São Paulo between 2017 and 2021 will be presented, using complex networks to identify the spatial and temporal patterns of this crime. Initially, the methodological procedures will be detailed, from data collection from the Public Security Department to modeling in GeoDataFrames. The criminal network will be structured by considering each robbery as a node, connected based on geographical and temporal proximity, with thresholds ranging from 100 to 2000 meters. To validate the analyses, statistical tests such as One-Way ANOVA, Kruskal-Wallis, and Dunn's test will be applied to identify significant differences between the city's regions. The results will then be presented, revealing the existence of structured patterns in criminal activity. Subsequently, these findings will be discussed in light of the literature, demonstrating how complex networks provide a deeper understanding of crime dynamics. Unlike traditional methods, this approach allows for a visualization of how crimes are

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interconnected and spread across different areas of the city. Finally, in the conclusion, the importance of complex networks in criminological analysis will be reinforced, showing that vehicle robberies do not occur randomly but follow an interconnected pattern.

This study shows limitations that should be considered when interpreting the results. The use of records from the Public Security Department may be subject to crime underreporting, which could impact the accurate representation of criminal activity. Additionally, the absence of a more granular temporal analysis restricts the understanding of daily, weekly, and seasonal variations in crimes, limiting the identification of seasonal patterns or behavioral changes over time. Another relevant factor is the exclusion of external variables, such as public security policies, legislative changes, and mobility restrictions caused by the COVID-19 pandemic, which may have influenced the dynamics of vehicle robberies, altering their spatial and temporal distribution.

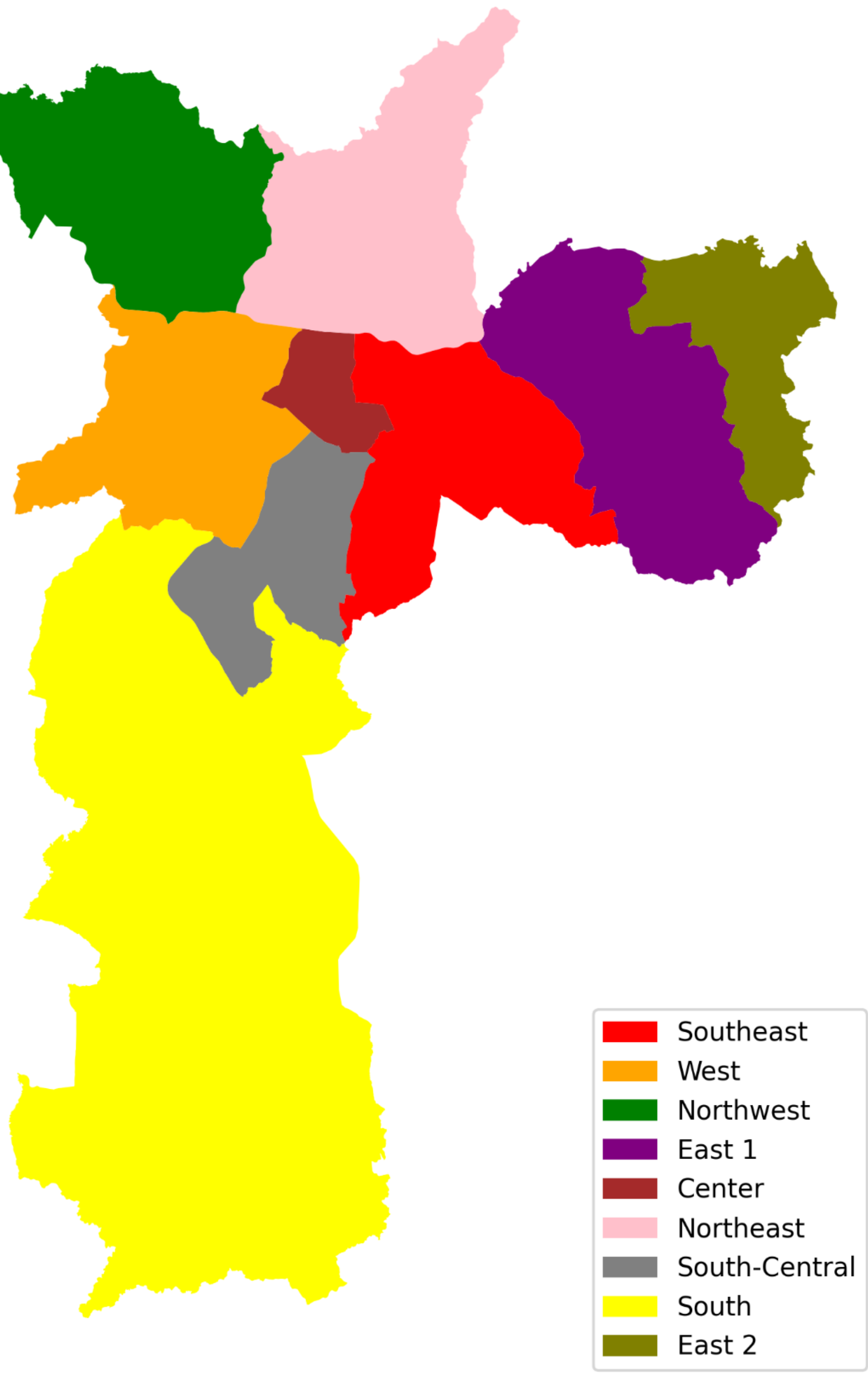
2 Methods

Vehicle theft data in the city of São Paulo were analyzed for 2017 to 2021. These data were obtained from the Public Security Department. The geographical coordinates of vehicle robberies were initially loaded into a GeoDataFrame using the "geopandas" library, a format that enables geospatial operations similar to a pandas DataFrame. The coordinate reference system (CRS) was defined, setting the source system as WGS84 and the target system as SIRGAS 2000 (UTM projection). The UTM zone code was selected based on the data location (e.g., zone 23S for São Paulo).

The division of vehicle robbery data was based on the administrative regions of the city of São Paulo, which include the Center, Northeast, Northwest, West, South-Central, South, Southeast, East 1, and East 2 areas, as illustrated in Figure 1.

Each vehicle theft incident was represented as a node in the network, while edges were established based on geographic and temporal proximity criteria. Robberies that occurred in nearby locations within a predefined time window were connected, forming the links between nodes. This approach allowed for the identification of spatial and temporal clustering patterns of vehicle robberies across the different analyzed regions.

Figura 1 - Administrative Regions of the City of São Paulo – Brazil.



Source: Authors (2025).

For network analysis, the efficiency metric was applied. This metric quantifies how closely connected the nodes are by considering the network distance, meaning the number of nodes that must be traversed to move from node A to node B. The higher the efficiency, the fewer nodes are required to reach a point from another, indicating a more compact network. In this study, efficiency is used to understand the connectivity of the vehicle robbery network, providing insights into how the spread of information or criminal behaviors occurs quickly and efficiently within the network, and how this affects the spatial and temporal dynamics of crime[39]. For the network analysis, the following Equation 1 was used:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}}. \tag{1}$$

Network efficiency refers to the ability with which information or behaviors are transmitted quickly and effectively between nodes. In complex networks, this metric is used to assess the communication capability between different parts of the network, considering the distances separating them[40].

The metric analysis were conducted using the average of the applied thresholds: 100, 250, 500, 1000, and 2000 meters. The threshold concept refers to a critical limit that guides the formation of connections in a network, determining the point at which two nodes should be considered connected[41]. In criminal network analysis, such as vehicle robbery networks, the threshold is used to establish precise distance and time parameters, defining when two events are close enough to be considered related. This allows for a more sensitive network adjustment, enabling an analysis that more accurately reflects spatial and temporal dynamics. The threshold calculation is presented in Equation 2.

$$\text{Connection}_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq D_{\text{threshold}} \text{ e } t_{ij} \in T \\ 0, & \text{Otherwise} \end{cases}. \tag{2}$$

Adjust network sensitivity in relation to the threshold means defining how two vehicle robbery events should be connected, considering variables such as distance and time. To effectively refine this adjustment, the following steps were considered: i) Definition of initial thresholds; ii) Gradual variation of the limits, increasing or decreasing both distance and time, and observing how this impacts the connections between robbery events in the network. To illustrate the network dynamics, Fig 2 presents the formation of networks using 100, 500, and 2000 meters.

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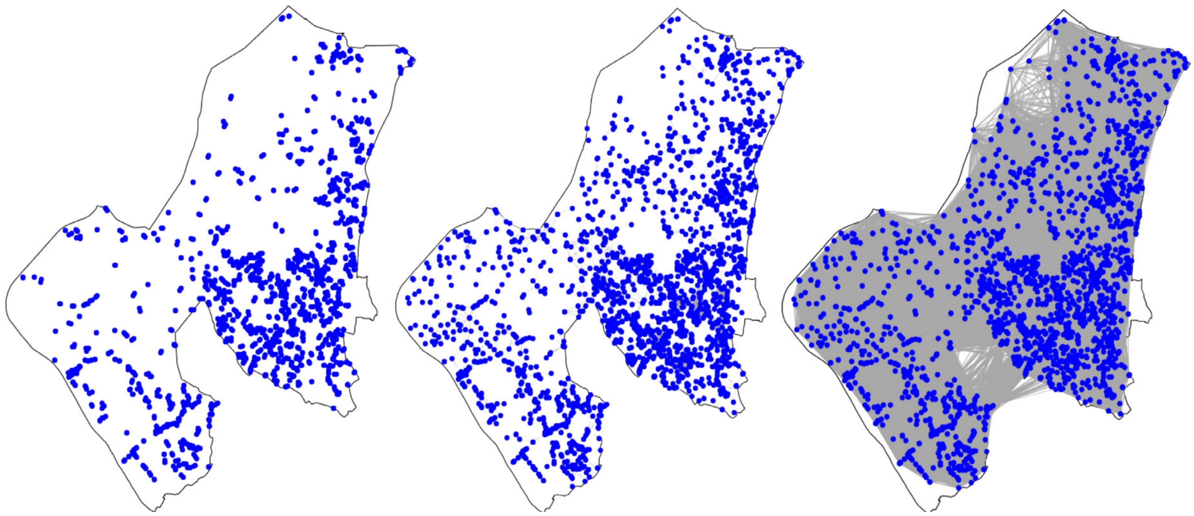
41 BARABASI, Albert-László. Network science. ´ Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, The Royal Society Publishing, v. 371, n. 1987, p. 20120375, 2013.

Figura 2 - This is a widefig. Spatial representation of vehicle thefts in the South-Central administrative region, with distances of 100, 500, and 2,000 meters. Illustrative representation for visualizing the dynamics of network formation.



Source: Authors (2025).

To better understand the differences in the characteristics of complex networks based on network efficiency across the nine regions of São Paulo, a one-way ANOVA test was applied. Before conducting the ANOVA test, essential checks were performed to ensure the validity of the results: a) Independence: Measurements from different regions were kept independent, in accordance with the study design; b) Normality: Assessed using the Shapiro-Wilk test for each data group, ensuring that the distribution meets the test requirements; c) Homogeneity of variances: Verified using Levene's test, ensuring that variances among groups are equivalente, an essential condition for the applicability of one-way ANOVA.

To complement the ANOVA results, the Kruskal-Wallis test Equation 3 was conducted. This non-parametric approach assesses differences between the analyzed groups and was applied to confirm the robustness of the observed variations, particularly in cases where the normality and homogeneity assumptions might not be fully met.

$$H = \frac{12}{N(N-1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1). \tag{3}$$

In cases where the Kruskal-Wallis test did not confirm the statistically significant differences observed in the ANOVA, the Dunn's test Equation 4 was applied to perform pairwise comparisons between groups.

$$\frac{R_i - R_j}{\sqrt{\frac{N(N+1)}{12}\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}}. \tag{4}$$

As a non-parametric approach, Dunn's test allows for the evaluation of which pairs of groups exhibit significant differences, even in situations where the normality and homogeneity of variance assumptions are not met.

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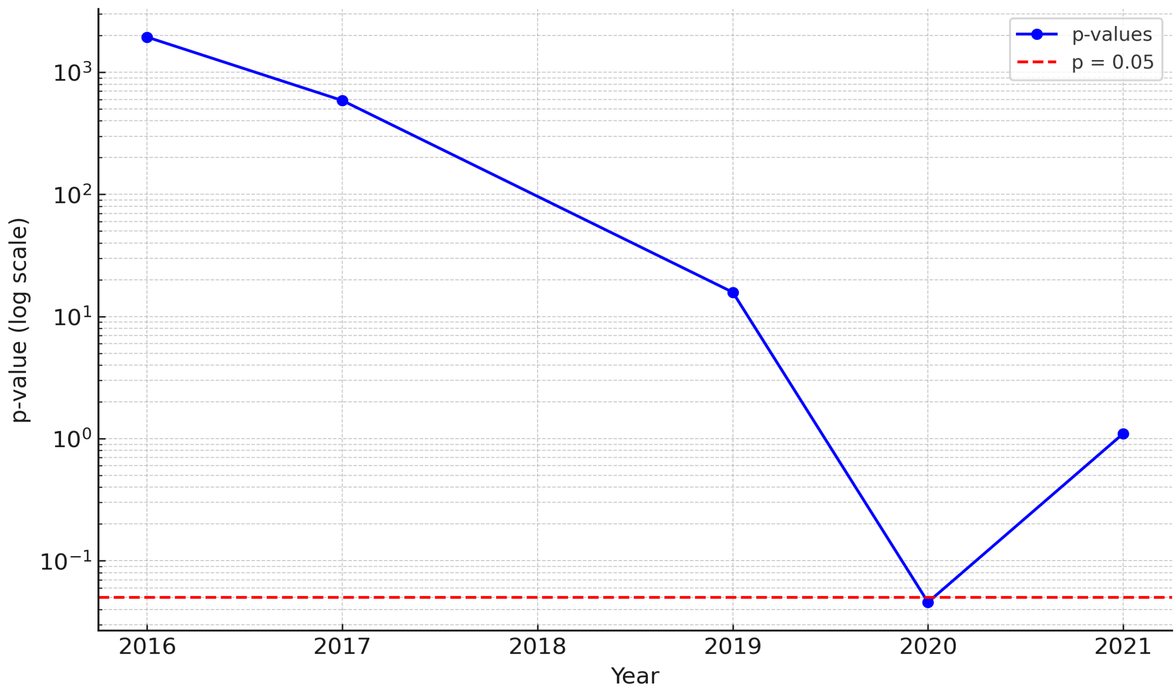
3 Results

Figure 3 presents a graphical representation of the Shapiro-Wilk normality test results applied to the efficiency metric across the administrative regions of São Paulo, considering the years 2016 to 2021.

Figura 3 - Shapiro-Wilk Normality Test Results – The blue line represents p-values over the years, plotted on a logarithmic scale. The red dashed line (p=0.05) marks the significance threshold; values below it indicate deviation from normality.

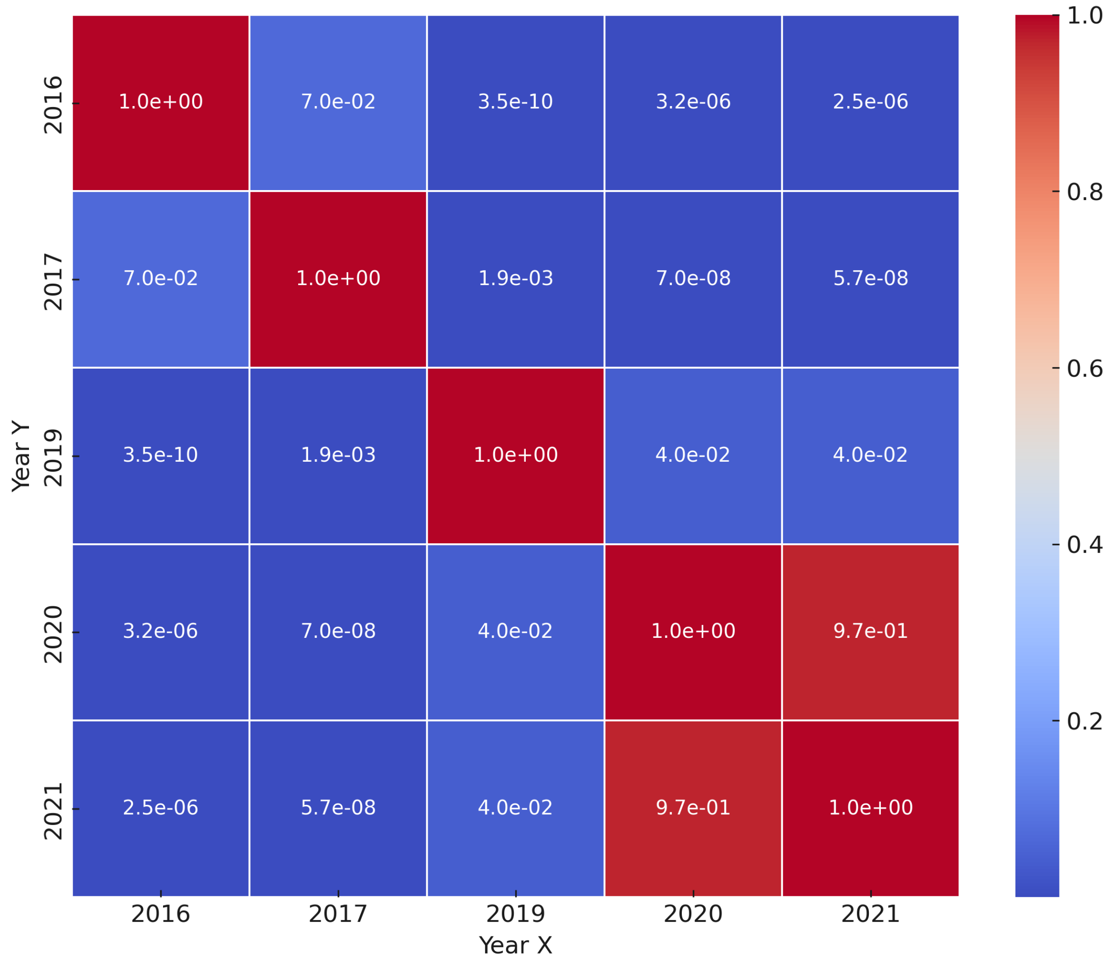


Source: Authors (2025).

The values represented fit to the obtained for each year, indicating the probability that the data follow a normal distribution. The reference line at p = 0.05 marks the conventional threshold for rejecting the null hypothesis of normality. It is observed that in the year 2020, the -value is very close to this threshold, suggesting a tendency toward normality, albeit with a reduced level of significance. Since the analysis assumes sample normality, confirming this criterion allows for the application of parametric statistical tests to compare the means of different administrative regions over the years.

Additionally, Figure 4 presents a heatmap displaying the from Levene's test, which assesses whether the variance of the efficiency metric is homogeneous across different years analyzed.

Figura 4 - Levene's Test p-values: The heatmap displays p-values comparing variance homogeneity between years.



Source: Authors (2025).

The cells in reddish tones represent comparisons where are high (0.05), suggesting variance homogeneity and, therefore, compliance with the equal variance assumption required for parametric tests such as ANOVA. On the other hand, cells in bluish tones indicate low (0.05), signaling variance heterogeneity, which suggests statistically significant differences in variance between the compared years.

The analysis indicates that, in some comparisons, variances cannot be considered homogeneous. In such cases, as a complement to ANOVA, the non-parametric Kruskal-Wallis test was applied.

The one-way ANOVA analysis revealed significant differences in the distribution of vehicle robberies among the administrative zones of São Paulo for the period 2016 to 2021, as shown in Table 1 The results demonstrate that, in all years analyzed, there are significant variations in the incidence of these crimes across different administrative regions.

Table 1 - ANOVA results for the distribution of vehicle robberies across administrative zones.

Year	*F Value*	*P Value*
2016	39.357	0.000206
2017	30.435	0.002733
2018	28.358	0.004913
2019	36.316	0.000502
2020	26.190	0.008980
2021	24.072	0.016011

Source: Original research results.

The changed over the years, indicating that the intensity of differences between the administrative zones changed from one year to another. The , all below 0.05, confirm that these differences are statistically significant, demonstrating that vehicle robberies are not uniformly distributed across the zones of São Paulo during the analyzed period.

After conducting the one-way ANOVA analysis, the Kruskal-Wallis test was applied to further investigate and confirm whether the observed differences between the administrative zones remain significant under a non-parametric approach, as shown in Table 2.

Table 2 - ANOVA and Kruskal-Wallis test results.

Year	*F - value*	PR *(>F)*	*Kruskal-Wallis Statistic*	Kruskal-Wallis *p - value*
2016	0.8963	0.5201	56.881	0.6821
2017	14.875	0.1618	48.006	0.7787
2018	28.104	0.0053	109.931	0.2021
2019	42.295	0.0001	147.490	0.0642
2020	43.402	0.0001	144.620	0.0705
2021	0.7862	0.6152	28.772	0.9418

Source: Original research results.

In the years 2016 and 2021, the -values (0.896 and 0.786, respectively) and the high -values (0.520 and 0.615) indicate that there were no statistically significant differences between the administrative zone clusters. In 2017, although the -values increased to 1.487, the -value of 0.162 still does not indicate statistical significance. On the other hand, between 2018 and 2020, the -values increased considerably, with -values below 0.05, indicating significant differences in these years. Notably, 2019 and 2020 had -values of 4.23 (= 0.000087) and 4.34 (= 0.000062), respectively, confirming that the discrepancies among clusters were more pronounced during this period.

In 2018, the ANOVA results indicated statistically significant differences among the clusters of administrative zones, with an F-value of 2.81 and a p-value of 0.0053. This suggests that the distribution of vehicle robberies among the zones was not homogeneous that year. However, when applying the Kruskal-Wallis test, which is less sensitive to parametric assumptions, the p-value obtained was 0.2021, indicating that the observed differences may not be robust when the analysis does not assume data normality. Thus, specifically for the year 2018, Dunn's test was applied to conduct pairwise comparisons between the regions, with the results presented in Table 3.

Table 3 - Region similarity matrix.

Regions	Southeast	West	Northwest	East 1	Center	Northeast	South- -Central	South	East 2
Southeast	1	1	1	1	1	1	1	1	1
West	1	1	1	1	1	1	1	1	1
Northwest	1	1	1	1	1	1	1	1	1
East 1	1	1	1	1	1	1	1	1	1
Center	1	1	1	1	1	1	1	0.268	1
Northeast	1	1	1	1	1	1	1	0.352	1
South- -Central	1	1	1	1	1	1	1	1	1
South	1	1	1	1	0.268	0.352	1	1	1
East 2	1	1	1	1	1	1	1	1	1

Source: Original research results.

Although the Dunn's test results for the year 2018 did not identify statistically significant differences between the administrative regions, pairwise comparisons were conducted to explore potential trends in the data. The comparisons between Center and South (= 0.268) and Northeast and South (= 0.352) yielded the lowest p-values, suggesting that there may be subtle variations in the distribution of vehicle robberies between these regions. Despite not reaching statistical significance (> 0.05), these comparisons provide preliminary insights that could be further investigated in future analyses using more robust datasets or complementary methods.

Table 4 presents the ANOVA one-way results, compared to the Kruskal-Wallis test, conducted to assess efficiency across the different analyzed groups.

The analysis conducted between 2016 and 2021, using ANOVA and Kruskal-Wallis tests, confirmed significant differences in efficiency among the groups in all years. In 2016, the results indicated = 3.82, = 0.000285 (ANOVA) and statistic = 31.39, = 0.00012 (Kruskal-Wallis), highlighting important variations. In 2017, values of = 4.12, = 0.00012, along with statistic = 32.82, = 0.000066, reinforced these differences. In 2018, the tests showed = 3.77, = 0.000339, and statistic = 30.48, = 0.00017, demonstrating consistent results. In 2019, the differences were even more pronounced, with = 5.68, = 0.000001, and statistic = 37.56, = 0.000009. In 2020, the values = 3.83, = 0.00028, and statistic = 25.72, = 0.00117, continued to indicate significant variations. Finally, in 2021, the results = 4.63, = 0.000026, and statistic = 33.45, = 0.000051, confirmed these differences. These findings reveal a consistent pattern of significant variations in efficiency among the analyzed groups over the years.

Table 4 - ANOVA and Kruskal-Wallis test results.

Year	*F Value*	PR(>*F*)	Kruskal-Wallis *Statistic*	Kruskal-Wallis *p-value*
2016	38.248	0.000285	313.894	0.0001198
2017	41.186	0.000120	328.187	0.0000664
2018	37.662	0.000339	304.761	0.0001741
2019	56.782	0.000001	375.617	0.0000091
2020	38.317	0.000280	257.190	0.0011731
2021	46.332	0.000026	334.536	0.0000510

Source: Original research results.

The analysis of the vehicle robbery network across different regions of São Paulo from 2016 to 2021 revealed significant variations in the efficiency with which criminal events propagated.

During the first three years, the network connectivity patterns remained stable, indicating consistent behavior among the events. However, in 2019, there was a sharp decline in network efficiency, followed by adjustments in 2021, which highlighted the formation of new connectivity patterns among different regional pairs. To further discuss the fluctuation in vehicle robbery incidence, it is essential to examine Table 5.

A consistent connectivity pattern was observed between several regions from 2016 to 2018, with high-efficiency values in multiple regional combinations, such as Center – South-Central, Center – East 2, and Northeast – Center. This stability suggests a highly connected network, facilitating the spread of information and criminal events across these areas.

However, in 2019, there was a generalized decline in network efficiency, reflected by a reduction in connections across almost all analyzed regions. Only a few combinations, such as Southeast–Northwest and Northeast–South, maintained some level of connectivity, indicating a partial restructuring of criminal patterns. In 2020, the network remained mostly disconnected, reflecting low efficiency in regional interactions.

Table 5 - Regional connectivity over the years.

Region 1	Region 2	2016	2017	2018	2019	2020	2021
Center	Center-South	1	1	1	0	0	0
Center	East 2	1	1	1	0	0	0
Center	Northeast	1	1	1	0	0	0
Center	South	1	1	1	0	0	0
Center-South	East 2	0	0	0	0	0	1
East 1	Center	1	1	1	0	0	0
East 1	Center-South	0	0	1	0	0	1
East 1	Northeast	0	1	0	1	0	1
Northeast	East 2	0	0	0	0	0	1
Northeast	South	0	0	0	1	0	0
Northwest	Center	1	1	1	0	0	0
Northwest	Center-South	1	0	0	0	0	0
Northwest	East 1	1	1	0	0	0	0
West	Center	1	1	1	0	0	0
West	East 1	0	0	0	1	0	1
Southeast	Center	1	1	1	0	0	0
Southeast	Center-South	0	0	1	1	0	1
Southeast	Northeast	0	1	0	1	1	1
Southeast	Northwest	1	1	0	1	0	0
Southeast	West	0	0	0	1	0	0

Source: Original research results.

In 2021, a resurgence of connections was observed in certain regions, such as South-Central – East 2 and Northeast – East 2, suggesting an adjustment in network structure and a possible adaptation of robbery patterns to new geographic and operational dynamics.

This fluctuation in efficiency highlights the importance of understanding how contextual and inter-regional factors influence network connectivity and the spread of criminal events. These oscillations underscore the need for continuous monitoring and an adaptive approach in analyzing crime propagation, allowing for a deeper understanding of the factors that shape network efficiency and providing valuable insights for the development of more effective public policies in crime prevention and control.

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Consequently, when analyzing efficiency, we are evaluating the capacity for information transmission within the network, highlighting high-connectivity points that facilitate the dissemination of crimes[42].

Between 2016 and 2021, statistically significant differences were observed in the dynamics of vehicle robberies across the analyzed regions, highlighting the existence of a consistent pattern in this phenomenon. However, in 2019, there was a break in efficiency, with a decrease in connections, which may have been caused by external factors or changes in criminal behavior, among other influences. From early 2020 onward, this pattern underwent substantial changes, suggesting shifts in the factors influencing the occurrence of these events throughout the studied period. This scenario coincides with the onset of the COVID-19 pandemic, which led to mobility restrictions, reduced vehicle circulation, and changes in urban dynamics—factors that may have directly impacted crime rates during this period. In 2021, some connections were reestablished, indicating a regional adaptation to new crime dynamics.

4 Discussion

The results of this research indicate that vehicle robberies in São Paulo do not occur randomly but follow well-defined spatial patterns. This finding reinforces the importance of analyses that consider the geography of crime. The uneven distribution of crimes across the administrative regions highlights that certain areas concentrate the majority of incidents, confirming the existence of crime hotspots, areas where offenses tend to recur frequently over time, as previously identified in other studies[43 44].

The statistical analysis revealed significant differences in the distribution of vehicle robberies across the city's regions, indicating that crime follows structured patterns. This result reinforces the idea that crime does not spread randomly but rather responds to specific territorial factors. Studies using GIS and statistical methods have already identified certain areas with higher crime concentrations due to urban and social characteristics[45 46 47], demonstrating that criminal dynamics can be analyzed through territorial structure and urban space connectivity. The comparison between regions further highlights the importance of crime's spatial organization, as certain areas consistently maintain high crime rates over the years[48].

The application of complex networks demonstrates that crime does not occur in isolation but follows an interconnected pattern. This behavior aligns with research using network models to understand crime organization in different cities, showing that certain locations serve as strategic points for crime propagation[49]. The results revealed that districts with high vehicle robbery rates in one year tend to maintain this

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43 BRANTINGHAM, Paul J; BRANTINGHAM, Patricia L. The geometry of crime and crime pattern theory. In: ENVIRONMENTAL criminology and crime analysis. [S.l.]: Routledge, 2016. P. 117–135.

44 CHEN, Xiliang et al. Using street view images to examine the impact of built environment on street property crimes in the old district of CA City, China. Discrete Dynamics in Nature and Society, Wiley Online Library, v. 2023, n. 1, p. 1470452, 2023.

45 STASSEN, Richard; CECCATO, Vania. Environmental and Wildlife Crime in Sweden from 2000 to 2017. Journal of Contemporary Criminal Justice, SAGE Publications Sage CA: Los Angeles, CA, v. 36, n. 3, p. 403–427, 2020.

46 STASSEN, Richard; CECCATO, Vania. Environmental and Wildlife Crime in Sweden from 2000 to 2017. Journal of Contemporary Criminal Justice, SAGE Publications Sage CA: Los Angeles, CA, v. 36, n. 3, p. 403–427, 2020.

47 KOO, Hyeongmo et al. Space-time cluster detection with cross-space-time relative risk functions. Cartography and Geographic Information Science, Taylor & Francis, v. 47, n. 1, p. 67–78, 2020.

48 CECCATO, Vania; HAINING, Robert; KAHN, Tulio. The geography of homicide in S˜ao Paulo, Brazil. Environment and Planning A, SAGE Publications Sage UK: London, England, v. 39, n. 7, p. 1632–1653, 2007.

49 SULTAN, Husam B; MAHMOOD, Basim Mohammed. Analyzing Crime Networks: A Complex Network-Based Approach. AL-Rafidain Journal of Computer Sciences and Mathematics, University of Mosul, v. 15, n. 1, p. 57–73, 2021.

characteristic in subsequent years, suggesting a persistent pattern in crime distribution, similar to the behavior observed in previously analyzed urban crime networks[50 51].

The efficiency metric used in this study demonstrated variations among criminal networks across the analyzed years, indicating changes in connectivity between districts over time. This behavior is consistent with studies on complex networks applied to crime, where interactions between different urban spaces influence how crimes are distributed[52 53].

The comparative analysis between districts revealed that proximity between regions can influence crime propagation, supporting previous studies suggesting that areas near high-crime locations tend to exhibit higher crime rates[54]. This similarity among neighboring districts indicates that crime may follow a spatial diffusion effect, reinforcing the need for security planning approaches that consider area connectivity in public safety strategies.

The results presented reinforce the relevance of complex systems in the analysis of criminal networks, highlighting the ability of networks to capture the structural dynamics of complex systems[55]. Additionally, significant variations between administrative regions were identified and confirmed through ANOVA and Kruskal-Wallis tests, empirically validating spatial heterogeneities. This approach aligns with the principles of environmental criminology, where crime geometry helps explain how spatial factors influence criminality in specific areas[56].

This study shows that complex networks are a powerful tool for complementing traditional crime analysis methods, enabling the identification of structural crime patterns and providing new insights for policing strategies. By viewing crime as an interconnected network rather than isolated events, it becomes possible to better understand its organization within urban space.

5 Conclusion

The use of complex networks for criminal data analysis provides a powerful and detailed approach to understanding event dynamics and the interactions between different regions. This type of analysis enables the observation of not only crime incidence patterns but also the connections and propagation of events over time, capturing the complexity of spatial and temporal interactions in an urban environment.

The analysis of vehicle robberies in São Paulo using complex networks demonstrated that crime does not occur randomly but follows a structured and interconnected pattern. The application of the efficiency metric helped identify the criminal pattern of each district, revealing that some regions function as crime hubs, playing a central role in the spread of criminal activity over the years.

50 GILL, Charlotte; WOODITCH, Alese; WEISBURD, David. Testing the "law of crime concentration at place" in a suburban setting: Implications for research and practice. Journal of quantitative criminology, Springer, v. 33, p. 519–545, 2017.

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55 COSTA, Luciano da Fontoura et al. Analyzing and modeling real-world phenomena with complex networks: a survey of applications. Advances in Physics, Taylor & Francis, v. 60, n. 3, p. 329–412, 2011.

56 WORTLEY, Richard; TOWNSLEY, Michael. Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In: ENVIRONMENTAL criminology and crime analysis. [S.l.]: Routledge, 2016. P. 20–45.

The statistical analysis revealed significant differences among the administrative regions, demonstrating that crime is not uniformly distributed throughout the city. Tests such as One-Way ANOVA, Kruskal-Wallis, and Dunn reinforce the importance of analyzing crime within its spatial context. The results indicate that certain areas consistently exhibit high vehicle robbery rates over the years, suggesting the need for more adaptable and targeted security policies in these regions.

Additionally, criminal network efficiency varied over time, with a sharp decline in 2019 followed by a reconfiguration of patterns in 2021. These shifts may be linked to external factors, such as new policing strategies or even mobility restrictions imposed by the COVID-19 pandemic. This reinforces the idea that crime is not static—it responds to different influences, requiring constant monitoring and adaptive security approaches.

This study demonstrates how complex networks can enhance the understanding of the relationship between crime and urban structure. Instead of viewing vehicle robberies as isolated cases, this approach reveals how they spread and connect within the urban framework. Certain areas of the city exhibit higher crime concentrations, which may be linked to factors such as pedestrian flow, land use, and accessibility. With this broader perspective, it becomes possible to design security strategies that align with urban planning, contributing to the development of safer and more functional spaces for the population.

Future researches could further explore vehicle theft patterns by integrating additional data sources, such as policing strategies, socioeconomic conditions, and urban mobility patterns. Additionally, analyzing crime at finer temporal scales, such as daily and seasonal variations, would help identify critical periods and provide a deeper understanding of crime dynamics over time. Another promising approach involves combining complex networks with machine learning, creating models capable of predicting crime evolution and supporting more efficient policing strategies. Finally, replicating this study in other cities would help determine whether the patterns observed in São Paulo city are consistent across different urban contexts, contributing to more adaptable and effective security policies.

Declarations

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