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Research article

Urban Violent Crime Dynamics in Kuala Lumpur and Putrajaya: Utilizing Spatial Temporal Techniques

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Abstract

This paper investigates the patterns of violent crime in Kuala Lumpur and Putrajaya between 2015 and 2020 using advanced spatial analysis techniques, including Spatial Autocorrelation, Standard Deviational Ellipse (SDE), and Mean Centre (MC). The study analyzes the spatial distribution and temporal dynamics of violent crimes, tracks shift in crime hotspots and examines the influence of socio-economic factors on these patterns. Findings reveal that violent crimes predominantly occur in the late afternoon and night, with peak incidents at 3:00 PM (1,830 cases, 8.28%). The study highlights notable shifts in crime hotspots, initially concentrated in commercial districts and gradually expanding to transportation networks and emerging urban areas. The Moran Index values indicate a transition from a near-random pattern in 2015 (-0.002668) to a mild clustering in 2018 (0.032962). Additionally, socio-economic factors, including population density, economic conditions, and the COVID-19 pandemic, significantly impacted crime patterns, leading to changes in crime rates and hotspot locations. These findings are crucial for law enforcement and urban planning, emphasizing the need for adaptive crime prevention strategies that respond to evolving urban challenges, and demonstrating the importance of integrating socio-economic data into spatial crime analysis for comprehensive crime mitigation.

Keywords: Mean Centre (MC); Spatial Analysis; Spatial Autocorrelation; Standard Deviational Ellipse (SDE); Urban Crime Patterns; Violent Crime.

1. Introduction

Violent crime is a persistent issue in urban environments, significantly affecting the quality of life and socioeconomic development (Abubakar Ghani, 2017). In Malaysia, urban centers such as Kuala Lumpur and Putrajaya have experienced varying levels of violent crime, necessitating a deeper understanding of spatial and temporal patterns to develop effective crime prevention strategies (Figure 1). The study of urban crime has been approached through various methodologies, ranging from descriptive statistical analyses to more advanced spatial-temporal techniques. Traditional studies often rely on aggregate statistics to describe crime trends and hotspots, focusing on counts and rates within predefined administrative boundaries (Che Soh, 2012).

However, this approach frequently neglects the underlying spatial relationships and temporal shifts in crime distribution, limiting its explanatory power (Johnson, 2010). Geographic Information Systems (GIS) offer powerful tools for analyzing and visualizing crime data, enabling researchers and policy-makers to identify trends, hot spots, and the movement of criminal activities over time. Moreover, hotspot mapping, while widely employed, often provides static views of crime concentrations, failing to capture dynamic changes over time and their relation to socio-environmental factors (Dağlar & Argun, 2016; Mission, 2024).

These methods are widely recognized for their application in crime studies. SDE provides insights into the directional dispersion and spread of incidents, while MC pinpoints the central location of crime activities and tracks spatial shifts over time. Their utilization offers a robust framework for understanding crime dynamics and supports the development of data-driven intervention strategies. The SDE method provides a summary of the spatial distribution of crime incidents by capturing the directional distribution, dispersion, and overall spatial trend. Recent advancements in Geographic Information Systems (GIS) and spatial analysis have revolutionized urban crime research, enabling a more nuanced understanding of crime patterns. Techniques such as Kernel Density Estimation (KDE), Spatial Autocorrelation (e.g., Moran's I), and hot spot detection have allowed researchers to visualize crime distribution and identify statistically significant clusters (Ahmad *et al.*, 2024a; Masron *et al.*, 2024). For example, KDE helps generate continuous surfaces that highlight crime intensity across geographic spaces, making it easier to identify high-risk areas than traditional choropleth maps.

Despite these developments, a gap persists in studies applying dynamic and directional spatial techniques, such as the Standard Deviational Ellipse (SDE) and Mean Centre (MC). These methods offer unique insights by examining the directional trends and shifts in crime hotspots over time. For instance, SDE captures the extent and orientation of crime distribution, highlighting patterns that may be influenced by urban growth, changes in land use, or transportation infrastructure development (Zhao *et al.*, 2024). On the other hand, MC analysis identifies shifts in the geographic center of crime incidents, enabling researchers to track changes in the spatial focus of criminal activity (ESRI, 2022b).

This research seeks to bridge the methodological gap by integrating SDE and MC analyses with socio-economic data, providing a holistic framework for understanding urban crime dynamics. By exploring the interplay between spatial distribution, temporal trends, and socio-environmental transformations, this study not only enhances our understanding of urban violent crime but also offers actionable insights for urban planning and law enforcement strategies. Urban violent crime research in places like Kuala Lumpur and Putrajaya re-quires the use of ArcGIS software because of its powerful spatial analysis, data management, and visualization features (Ahmad *et al.*, 2024b; Jamru *et al.*, 2024; Jubit *et al.*, 2024; Marzuki *et al.*, 2024; Masron *et al.*, 2024). This technique is valuable in identifying the general orientation and spread of crime occurrences. On the other hand, the MC technique identifies the central point of crime incidents, offering insights into the geographical center of crime activities and how this center shifts over time (ESRI, 2022a). Understanding how these transformations correlate with crime hotspots provides a framework for designing effective interventions.

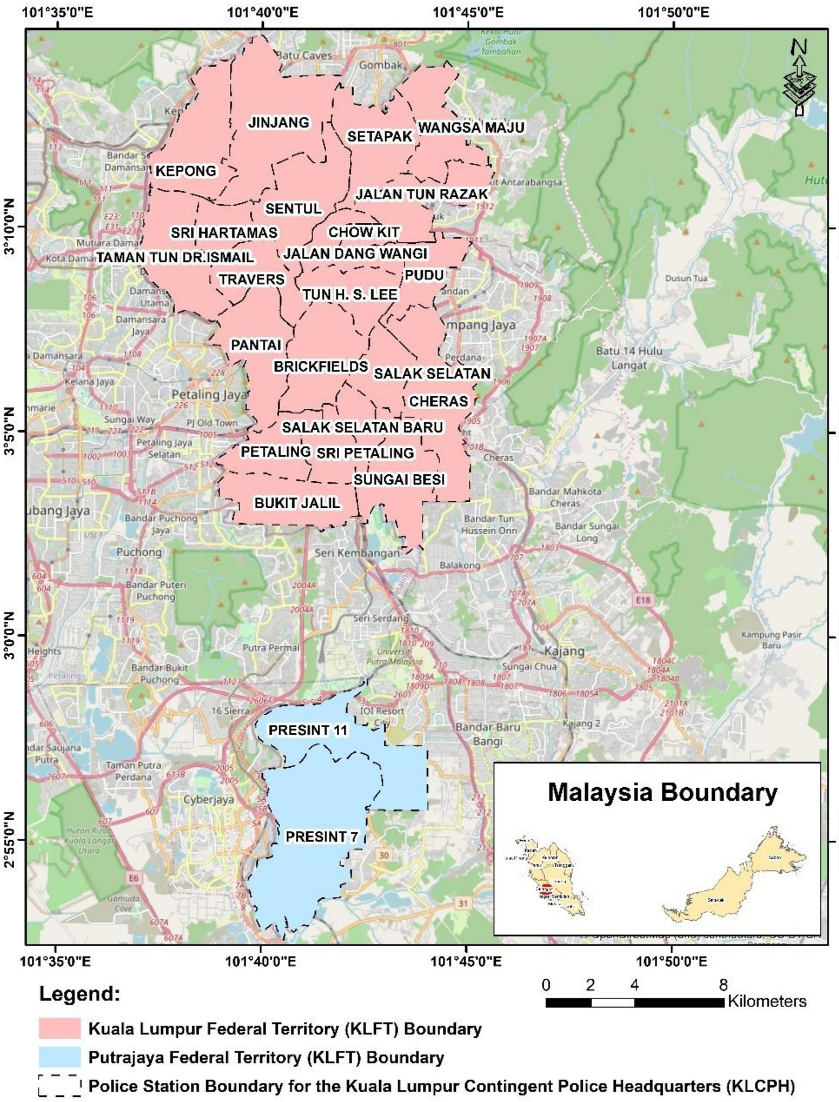

Figure 1. Police Station Boundaries for the Kuala Lumpur Contingent Police Headquarters (KLCPH).

This study highlights the significance of analyzing violent crime through advanced spatial and temporal techniques, but a stronger connection to the socio-spatial transformation of Kuala Lumpur and Putrajaya is essential. Urban development, including expanding transportation networks and shifting land use patterns, is critical in influencing crime distribution (Ahmad *et al.*, 2024a). Understanding how these transformations correlate with crime hotspots provides a framework for designing effective interventions. This research bridges a crucial gap by integrating spatial dynamics with socio-economic variables, offering a holistic perspective on urban crime patterns (Zakaria & Abdul Rahman, 2015). The issue of the study is that urban centers in Malaysia, particularly Kuala Lumpur and Putrajaya, have experienced fluctuating levels of violent crime, which not only affects residents' sense of security but also has broader implications for social stability and economic development (Jubit *et al.*, 2022; Mohd Hakim *et al.*, 2019).

Despite various crime prevention strategies implemented by law enforcement agencies, the persistent nature of violent crime underscores the need for a more comprehensive understanding of its spatial and temporal dynamics (Haberman *et al.*, 2016). The existing literature on violent crime in urban Malaysia has primarily focused on descriptive statistics and hotspot analysis, often neglecting the deeper spatial and temporal patterns that could be revealed through advanced GIS techniques. This gap in the analysis limits the ability of policymakers and law enforcement agencies to develop effective, data-driven strategies to combat violent crime. Moreover, while some studies have utilized GIS tools, there is a lack of comprehensive research employing the SDE and MC techniques to analyze violent crime movements (Cummings *et al.*, 2019).

The rationale for this study lies in the underutilization of advanced GIS techniques like SDE and MC in the study of violent crime in urban Malaysia (Ahmad *et al.*, 2024a). These methods can provide more nuanced insights into the spatial dispersion and central tendency of crime incidents, which are crucial for understanding crime dynamics. It is also due to the lack of research examining how the MC of violent crime incidents shifts over time (Mordwa, 2015). Understanding these temporal shifts can help predict future crime hot spots and trends, allowing for proactive crime prevention measures (Zakaria *et al.*, 2025). The SDE technique can reveal important directional trends and the extent of dispersion, which are vital for strategic planning and resource allocation in crime prevention (He *et al.*, 2017; Mansor *et al.*, 2019). Few studies have connected the findings from spatial analysis techniques directly to policy development. Bridging this gap is essential for translating research insights into actionable strategies that can effectively reduce violent crime rates (Ahmad *et al.*, 2024a). Understanding the spatial dynamics of violent crime through these GIS techniques can provide valuable insights into the factors driving crime in urban areas and support the formulation of targeted interventions.

According to Elfadaly *et al.* (2024), land use influences crime patterns. Commercial zones attract property crimes, residential areas face burglaries with low surveillance, and abandoned lands see violent crimes. GIS mapping and urban planning strategies like CPTED improve safety by addressing crime hotspots through better lighting, visibility, and zoning (Yue *et al.*, 2017). The findings of this research will contribute to the broader literature on crime analysis and urban safety, highlighting the importance of spatial analysis in addressing urban crime challenges in Malaysia. Despite various crime prevention strategies, many studies on violent crime have relied on descriptive statistics and basic hotspot analysis, often overlooking advanced GIS methods such as SDE and MC (Ahmad *et al.*, 2024a). This methodological gap limits the understanding of deeper spatial and temporal dynamics, crucial for data-driven policy interventions. By employing these advanced spatial methods, this study aims to bridge this gap and provide actionable insights into the shifting patterns of urban crime in Kuala Lumpur and Putrajaya. The spatial distribution of violent crimes in Kuala Lumpur and Putrajaya reflects the interplay between socioeconomic disparities and urban environmental factors. High-crime areas often correspond with densely populated zones, commercial districts, and transportation hubs, where anonymity and accessibility facilitate criminal activities. Additionally, urban land-use patterns, such as poorly lit public spaces and areas with limited surveillance, further exacerbate crime risks (Brunsdon & Corcoran, 2022). These findings underscore the importance of integrating socioeconomic data with spatial analysis to develop targeted urban planning and law enforcement strategies that address both the root causes and enabling conditions of crime.

2. Research Methods

This study employs advanced spatial analysis techniques, including Spatial Autocorrelation, SDE, and MC, to uncover nuanced patterns in the spatial and temporal distribution of violent crime. These methods address a significant gap in existing research, which often relies on basic descriptive approaches, by integrating socio-economic data for a more comprehensive understanding of crime dynamics.

2.1. Sampling

The flowchart (Figure 2) visually represents the sequential stages in this research methodology, illustrating the step-by-step approach required to achieve the objectives of violent crime analysis. The research follows a systematic sequence of stages to ensure the accurate collection, processing, analysis, and interpretation of violent crime data across the targeted study areas, specifically Kuala Lumpur (Figure 2). The methodology is divided into the following phases:

2.1.1. Data Collection

In the initial phase, the focus is on acquiring comprehensive violent crime data from reliable sources:

- Violent crime records are obtained from Bukit Aman Police Headquarters for the Selangor and Kuala Lumpur Contingent Police Headquarters covering the period from 2015 to 2020.
- The collected data includes key crime attributes such as the location of the crime, date of occurrence, and temporal components necessary for further analysis.

2.1.2. Updating Data Collection

This stage involves refining and enhancing the collected dataset to ensure completeness and accuracy for spatial and temporal analysis. The following key activities are undertaken:

- Updating and Identifying Police Station Boundaries: Accurate boundary data for police jurisdictions within Selangor and Kuala Lumpur are updated to align with the current spatial administrative divisions.
- Identifying and Verifying Crime Locations and Addresses: Crime incidents are meticulously reviewed to confirm the specific locations (including street addresses) where the crimes occurred.
- Incorporating Temporal Details: Key crime-related time data is updated to ensure precision. This includes:
    - The date when the investigation paper was filed.
    - The date and time the crime incident started and ended.
    - Any relevant timelines that provide insight into the duration of the crime.
    - This step ensures that both spatial and temporal data attributes are reliable and ready for further geospatial analysis.

2.1.3. Geocode Data Collection

Geocoding is a critical process that converts descriptive addresses into precise geographic coordinates, enabling spatial representation and analysis. Two approaches are adopted for geocoding:

- Manual Geocoding: Crime locations are geocoded manually where automated tools are less effective, ensuring accuracy for complex or ambiguous addresses.
- Automated Geocoding: Tools such as Google Sheets combined with geocoding plug-ins like Awesome Table and Smart Monkey are utilized to geocode large datasets efficiently.

By leveraging manual and automated geocoding techniques, the research ensures that all crime location data is spatially mapped accurately.

2.1.4. Develop Geodatabase

A Crime Geodatabase is developed to serve as the central repository for storing, managing, and analyzing spatial and non-spatial data related to violent crimes. Key steps include:

- Structuring and organizing the crime database to integrate spatial coordinates, temporal details, and crime attributes.
- Ensuring compatibility with Geographic Information System (GIS) platforms for advanced spatial analysis.

The geodatabase facilitates seamless spatial queries, visualization, and analysis of crime patterns within the study areas.

2.1.5. Analyze Data Collection

This phase involves the comprehensive analysis of crime data to identify significant spatial patterns and trends. The following analytical techniques are employed:

- Crime Data Analysis: Statistical and spatial analyses are performed to explore relationships between crime incidents, land use, and other variables.
- Spatial Autocorrelation, Standard Deviational Ellipses (SDE) and Movement Pattern Analysis (Mean Centre): This geospatial technique is used to identify and visualize high-intensity crime clusters and low-intensity areas.
    - The point dataset of crime incidents is analyzed to determine the spatial distribution of violent crime.
    - Results from the hot spot analysis are overlaid with Land Use data, enabling the identification of crime concentrations within specific land use categories (e.g., residential, commercial, industrial).
    - Crime intensity is further examined by aggregating results to polygon sizes, allowing for a detailed understanding of spatial crime patterns.

The analytical outcomes provide critical insights into how violent crime incidents are distributed geographically and temporally within the targeted jurisdictions.

2.1.6. Pattern Identification, Visualization, Results, and Discussion

The final stage synthesizes the analytical findings to present comprehensive conclusions. Key activities include:

- Pattern Identification: Identifying recurring crime trends, spatial clusters, and correlations with land use variables.
- Visualization: Generating maps, charts, and visual outputs to effectively communicate crime patterns, hot spots, and temporal trends.
- Results and Discussion: Interpreting the findings to explain the spatial and temporal behavior of violent crimes in relation to land use characteristics.
- Conclusion: Summarize the key findings, address the research objectives, and provide recommendations for crime prevention strategies based on the spatial analysis outcomes.

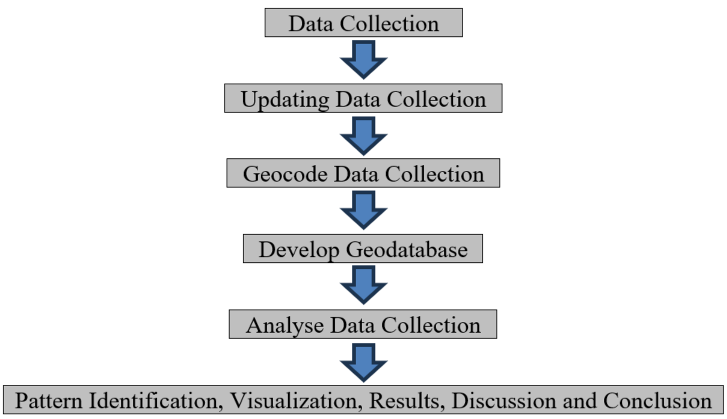

Figure 2. Methodology Flowchart. (Source: Ahmad *et al.*, 2024a).

2.2. Data Limitations

While this study utilizes police-reported crime data to analyze violent crime patterns in Kuala Lumpur and Putrajaya, it is important to acknowledge inherent limitations in the data. Police records, while comprehensive, may be subject to underreporting or selective reporting biases (Heap, 2008). Certain crimes, particularly those considered minor, culturally sensitive, or involving marginalized communities, may not be reported or adequately documented. These gaps can result in an incomplete representation of the true crime landscape, potentially skewing the spatial and temporal patterns identified in this study (Boivin & Ouellet, 2014). Furthermore, variations in data recording practices across police jurisdictions could introduce inconsistencies, affecting the comparability of data over time and across locations (Fagerlund *et al.*, 2018).

To address these limitations, future research could incorporate supplementary data sources, such as victimization surveys, community feedback, or social media analytics, to provide a more nuanced and representative understanding of crime dynamics (Breen *et al.*, 2022). Additionally, integrating qualitative data from stakeholders, such as law enforcement officers and community leaders, could help contextualize the findings and account for potential blind spots in the data (Verma *et al.*, 2024). Acknowledging these limitations ensures a balanced interpretation of the study's findings and highlights the need for cautious application of the results in policymaking and urban planning (Chen, 2023).

2.3. Spatial Autocorrelation

This autocorrelation analysis is carried out using the Moran's Index method. This Moran's index can determine the level of strength of the relationship of each object or polygon with others around the room and has a correlation coefficient or Moran's index which is the value I = -1 to +1 (Bassam *et al.*, 2018; Chen, 2023). To assess Moran's I Global relevance, this analysis calculates its value along with Z-Score, p-value and other metrics. A P-value constrained by a statistical test, is a numerical estimate of the area under the curve given a known distribution. The Moran's I index, which ranges from -1 to +1, measures spatial autocorrelation. Values near +1 indicate clustering of similar values, while values near -1 indicate a dispersed pattern (Andresen & Hodgkinson, 2023). A value of 0 suggests a random spatial distribution. This study uses Moran's I to determine the degree of spatial clustering of violent crime incidents across the study region (Huang et al., 2024). Calculation in terms of column autocorrelation according to Moran's I statistic as Equation 1 below.

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \quad (1)$$

Where Z_i is the attribute deviation for feature i from the mean (xi-X), W_{ij} is the spatial weight between features i and j, n is equal to the total number of features and S_0 is the aggregate of all spatial weights, in Equation 2.

$$\bar{S}_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j} \quad (2)$$

The z score for the statistic was calculated as Equation 3.

$$z_I = \frac{I - E[I]}{\sqrt{V[I]}} \quad (3)$$

Where Equation 4 and 5.

$$E[I] = -1/(n-1) \quad (4)$$

$$V[I] = E[I^2] - E[I]^2 \quad (5)$$

where:

s2 is the sample variance

i and j are column index units

y is a variable value for each specific location

yi and yy are overall means

Wij is the weighted location index of the associated i

$\bar{y}$i is the mean of y

n is the sum or number of points or polygons

2.4. Standard Deviational Ellipses (SDE)

The distribution of criminal episodes is shown using the Standard Deviational Ellipses (SDE) technique is to identify spatial variation and create an ellipse that represents it, statistical metrics are needed (Zhao *et al.*, 2024). The ellipse's size and shape, which capture spatial variance and offer comprehensive knowledge of crime distribution, suggest places with greater crime rates. Longer ellipses indicate that directions have higher crime incidence frequencies (Cummings *et al.*, 2019). SDE is also capable of identifying temporal differences in the spatial distribution of crime across regions or time periods. The MC and SDE approach were used to analyze movement (Ahmad *et al.*, 2024a).

The average x- and y-coordinates of all the features in the research region are represented by the MC. Based on reported data, the SDE determines the direction and target areas of criminal offenses by measuring the difference between the average distance and the distance from specific characteristics to the Mean Centre. Equation 6 is used to acquire measurements.

$$SD = \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{n} + \frac{\sum_i (x_i - \bar{x})^2}{n}} \tag{6}$$

Knowing each crime's geographic center, distribution, orientation, and direction is crucial to comprehending how each crime shifts over time in terms of day categories. In light of this, the Standard Deviational Ellipse (SDE) is a logical extension of the standard distance circle that can capture the directional bias in the point distribution (Ahmad *et al.*, 2024a; Furfey, 1927; Wong & Lee, 2005). SDE is expressed as Equations 7, 8, 9, and 10.

$$C = \begin{pmatrix} var(x) & cov(x, y) \\ cov(y, x) & var(y) \end{pmatrix} = \frac{1}{n} \begin{pmatrix} \sum_{i=1}^{n} \tilde{x}_i^2 & \sum_{i=1}^{n} \tilde{x}_1 \tilde{y}_i \\ \sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i & \sum_{i=1}^{n} \tilde{y}_i^2 \end{pmatrix} \tag{7}$$

$$var(x) = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 = \frac{1}{n} \sum_{i=1}^{n} \tilde{x}_i^2 \tag{8}$$

$$cov(x, y) = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) = \frac{1}{n} \sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i \tag{9}$$

$$var(y) = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 = \frac{1}{n} \sum_{i=1}^{n} \tilde{y}_i^2 \tag{10}$$

where n is the number of features, {x\} denotes the feature's mean center, and x and y are the coordinates for feature I. After factoring the sample covariate matrix into standard form, a matrix with its eigenvalues and eigenvectors is produced. The x- and y-axis' standard deviations are as Equation 11.

$$\sigma 1{,}2 = \left(\frac{\left(\sum_{i=1}^{n} \tilde{x}_i^2 + \sum_{i=1}^{n} \tilde{y}_i^2\right) \pm \sqrt{\left(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i\right)^2}}{2n} \right)^{\frac{1}{2}} \tag{11}$$

Three-dimensional data can be solved using an extension of this equation. The required proportion of data points is represented by an ellipse or ellipsoid that is created by scaling the variance using an adjustment factor. The table below (ESRI, 2022a) provides these correction factors. Integrating socioeconomic and environmental data with SDE analysis provides a more nuanced understanding of crime patterns. By overlaying spatial crime data with variables such as population density, unemployment rates, and land-use types, researchers can identify systemic factors driving criminal activities.

For instance, SDE could reveal directional shifts in crime hotspots that correlate with changes in urban zoning, public infrastructure, or socioeconomic conditions. This integration not only enhances the explanatory power of spatial techniques but also informs targeted urban planning and policy interventions aimed at addressing the root causes of crime.

2.5. Movement Pattern Analysis (Mean Centre)

The MC can be used to compare points of various characteristic kinds or to monitor changes in the distribution of points. The average of the x-, y-, and z-coordinates for each feature in the research region is the MC (Ahmad *et al.*, 2024a; ESRI, 2022b) in Equation 12.

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{12}$$

Where n is the total number of features, and xi and yi are the coordinates of feature I. The following is covered by MC weighting in Equation 13.

$$\bar{X}_w = \frac{\sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} w_i}, \bar{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{13}$$

Where on feature I is the weight? If the z attribute is present for every feature, the tool further determines the center for the third dimension, Equation 14.

$$\bar{Z} = \frac{\sum_{i=1}^{n} Z_i}{n}, \bar{Z}_w = \frac{\sum_{i=1}^{n} w_i Z_i}{\sum_{i=1}^{n} w_i} \quad (14)$$

One of the GIS methods for examining the geographic distribution of crime is MC analysis, which is used to examine crime data. This analysis can be used to identify areas with the highest density of criminal incidents (Verma *et al.*, 2024). The information gathered might be helpful to law enforcement and urban planners. The average center, which yields a single point that represents the center of the crime occurrence, is calculated by averaging the x and y coordinates of all criminal incidents that occur inside a specific area. The MC can then be contrasted with other geographic variables, including land use patterns or demographic data, to look for any possible relationships between crime and other factors (Kent & Leitner, 2008). One drawback of MC analysis is that it relies on the assumption of a uniform distribution of crime episodes, which isn't always the case. In heavily populated locations, the MC may not accurately depict the center of gravity for crime occurrences. It is recommended that MC analysis be applied in conjunction with other analytical techniques and considered within the broader framework of social, economic, and political issues that impact crime trends. The MC can be used to compare points of various characteristic kinds or to monitor changes in the distribution of points. The average of the x-, y-, and z-coordinates for each feature in the research region is the mean canter (ESRI, 2022b; Muhamad Ludin *et al.*, 2013) in Equation 15.

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad (15)$$

Where n is the total number of features, and xi and yi are the coordinates of feature I. The following is covered by mean canter weighting Equation 16.

$$\bar{X}_w = \frac{\sum_{i=1}^{n} Z_i}{\sum_{i=1}^{n} w_i}, \bar{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \quad (16)$$

Where on feature I is the weight? If the z attribute is present for every feature, the tool further determines the centre for the third dimension in Equation 17.

$$\bar{Z} = \frac{\sum_{i=1}^{n} Z_i}{n}, \bar{Z}_w = \frac{\sum_{i=1}^{n} w_i Z_i}{\sum_{i=1}^{n} w_i} \quad (17)$$

2.6. Study Area

Peninsular Malaysia, notably the federal territories of Kuala Lumpur (KLFT) and Putrajaya (PFT), both located in Selangor Darul Ehsan, is the subject of this study. It is essential to comprehend the sociocultural, administrative, and economic relationships between KLFT and PFT. Key financial institutions including Bank Negara Malaysia and the Kuala Lumpur Stock Exchange are housed at KLFT, which is Malaysia's economic powerhouse (Mohd Shariff, 2019; Tan et al., 2018). PFT The Prime Minister's office, several ministries, and government agencies are housed in PFT, which was intended to serve as the federal administrative center.

This arrangement promotes effective governance (Nagulendran et al., 2016). Six District Police Headquarters (DPH)-Brickfields, Cheras, Dang Wangi, Putrajaya, Sentul, and Wangsa Maju-combine to form the Kuala Lumpur Contingent Police Headquarters (KLCPH), which oversees 24 police stations (Ahmad et al., 2024c). Multiple police stations are located within each DPH, allowing for more efficient coordination and communication (Ahmad et al., 2024d). The limits of these police stations inside KLCPH are shown graphically in Figure 1. For example, DPH Brickfields consists of the following stations: Taman Tun Dr. Ismail, Brickfields, Pantai, Petaling, Sri Hartamas, and Travers. In a similar vein, DPH Cheras has stations such as Sungai Besi, Bukit Jalil, Cheras, Salak Selatan, and Salak Selatan Baru.

Land use in the study area consists of water bodies, forests, industry, infrastructure & utilities, institutions & community facilities, open spaces & recreational facilities, residential & housing, mixed development, transport & roads, trade & commercial, agriculture and vacant land (Figure 3). The objectives of this study are: (i) to determine the spatial distribution and directional trends of violent crime in Kuala Lumpur and Putrajaya using SDE, (ii) to identify the central tendency of violent crime incidents and analyze shifts in the MC over time, and (iii) to evaluate the implications of these spatial patterns for crime prevention and urban policy development.

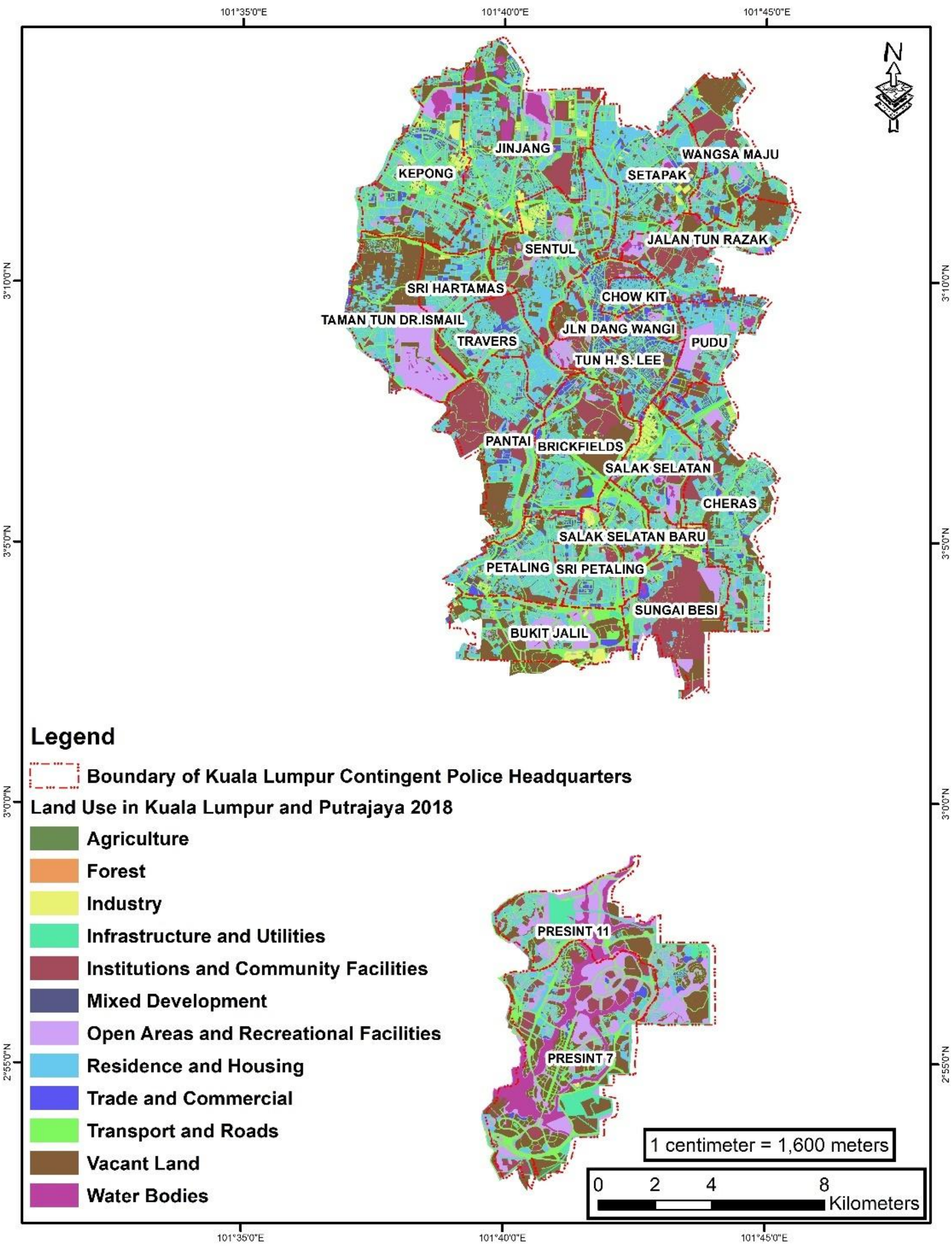

Figure 3. Land Use Data for Kuala Lumpur Federal Territory (KLFT) and Putrajaya Federal Territory (PFT) Areas for 2018. (Data Source: MyGDI Program (Malaysian Geospatial Data Infrastructure).

3. Results and Discussion

3.1. Temporal Considerations-Violent Crime by Time (Hours)

Figure 4 provides a comprehensive overview of violent crime incidents by hour over the six-year period from 2015 to 2020. This time analysis offers valuable insight into violent crime patterns and fluctuations in the jurisdictions studied. The data reveals interesting variations in violent crime incidents across different hours of the day. Notably, violent crime rates fluctuate throughout the 24-hour cycle, with certain hours showing higher incidents than others.

In the early morning, from 12:00 AM (689 cases-3.12%), 1:00 AM (481 cases-2.18%), 2:00 AM (386 cases-1.75%), 3:00 AM (404 cases- 1.83%), 4:00 AM (369 cases-1.67%), 5:00 AM (353 cases-1.60%), 6:00 AM (355 cases-1.61%) to 7:00 AM (279 cases-1.26%)) violent crime rates are relatively low, gradually increasing as the days pass. However, the most significant spike in violent crime incidents occurred in the late afternoon and night, peaking between 2:00 PM (1,440 cases-6.52%), 3:00 PM (1,830 cases-8.28%), 4:00 PM (1,564 cases-7.08%), 5:00 PM (1,373 cases-6.22%), 6:00 PM (1,326 cases-6.00%), 7:00 PM (1,303 cases-5.90%), 8:00 PM (1,471 cases- 6.66%) until 9:00 PM (1,373 cases-6.22%). The peak number of cases is at 3:00 PM, indicating a sustained period of higher criminal activity during these hours.

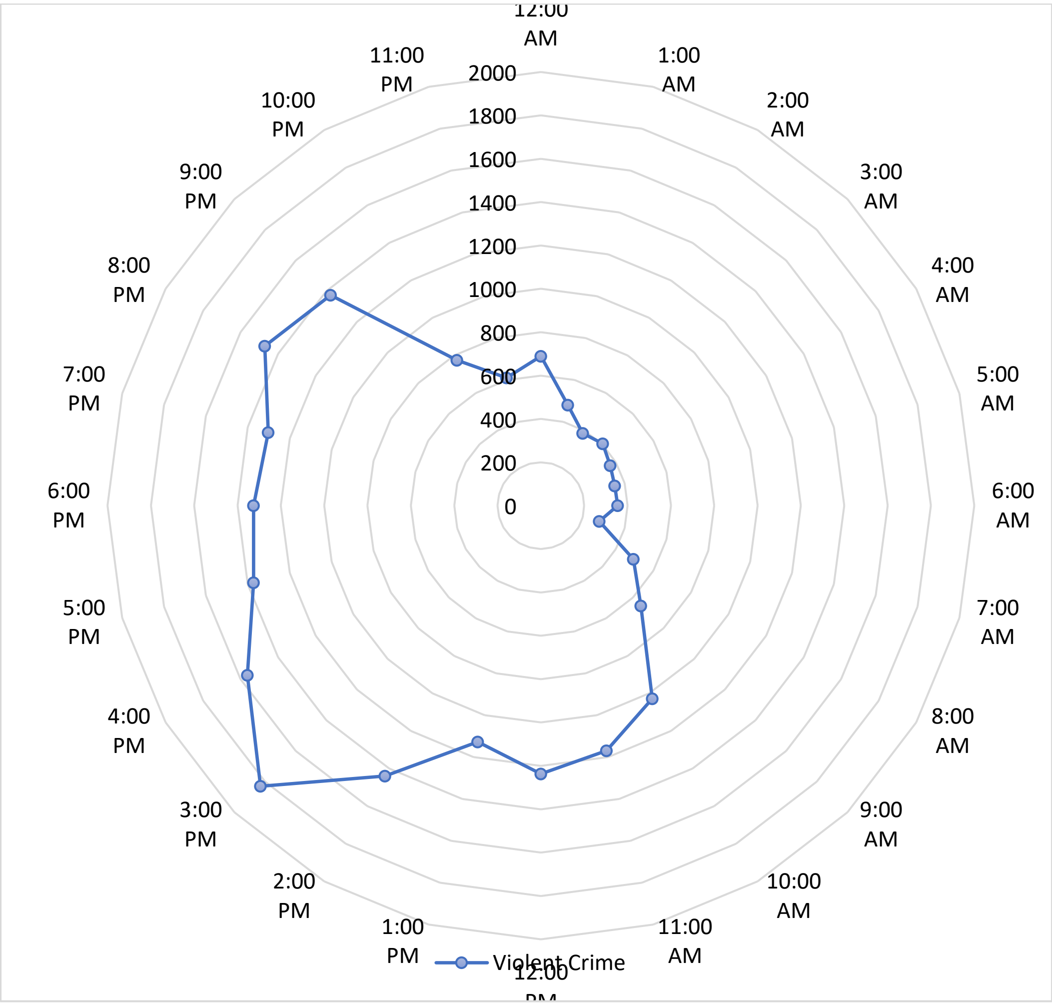

Figure 4. Violent Crime by hour (2015-2020). (Source: Criminal Investigation Department (D4), Bukit Aman, 2021).

3.2. Violent Crime Distribution Pattern in KLCPH in 2015 to 2020 using Spatial Autocorrelation (Global Moran Index)

The study meticulously analyzed the spatial distribution of violent crimes in the KLCPH region from 2015 to 2020 using the Global Moran's Index, a statistical measure used to identify spatial autocorrelation (Table 1 and Figure 5). This index helps in understanding whether the observed distribution of a variable—in this case, violent crime—across a given area is random, clustered, or dispersed. The results indicated a range of Moran Index values across the years, from a slightly negative value of -0.002668 in 2015, which suggests a near-random pattern with minimal negative autocorrelation, to a positive value of 0.032962 in 2018, which indicates a mild but statistically significant degree of clustering.

Table 1. Global Summary of the Moran Index Violent Crime Rate in KLCPH From 2015 to 2020.

No.	Year	Moran Index	Expectations Index	Variance	Z-Score	P-Value	Distance Threshold (m)	Pattern
1.	2015	-0.002668	-0.001585	0.001412	-0.028814	0.977013	3135.3989	Random
2.	2016	0.016231	-0.001019	0.000392	0.871353	0.383561	2513.3539	Random
3.	2017	0.020762	-0.000422	0.000168	1.632045	0.102670	1554.2280	Random
4.	2018	0.032962	-0.001089	0.000268	2.079341	0.037586	1596.4248	Clustered
5.	2019	0.023992	-0.001443	0.000672	0.981303	0.326443	4659.9978	Random
6.	2020	0.025751	-0.001546	0.001116	0.817222	0.413801	1803.6435	Random

The Z-scores, which provide insight into the statistical significance of the spatial patterns, were particularly revealing. A Z-score near zero typically indicates a random distribution, while a Z-score far from zero suggests either clustering or dispersion. In 2018, the Z-score of 2.079341, coupled with a p-value of 0.037586, indicates that the clustering pattern observed that year was statistically significant, with less than a 5% probability that this pattern occurred by chance. This suggests that violent crimes were not randomly distributed in 2018 but were instead concentrated in specific locations, forming noticeable clusters. Conversely, in the other years (2015, 2016, 2017, 2019, and 2020), the Z-scores did not deviate significantly from zero, and the p-values were not below the common threshold for statistical significance (0.05), indicating that violent crime was distributed in a random pattern across the KLCPH region during those years.

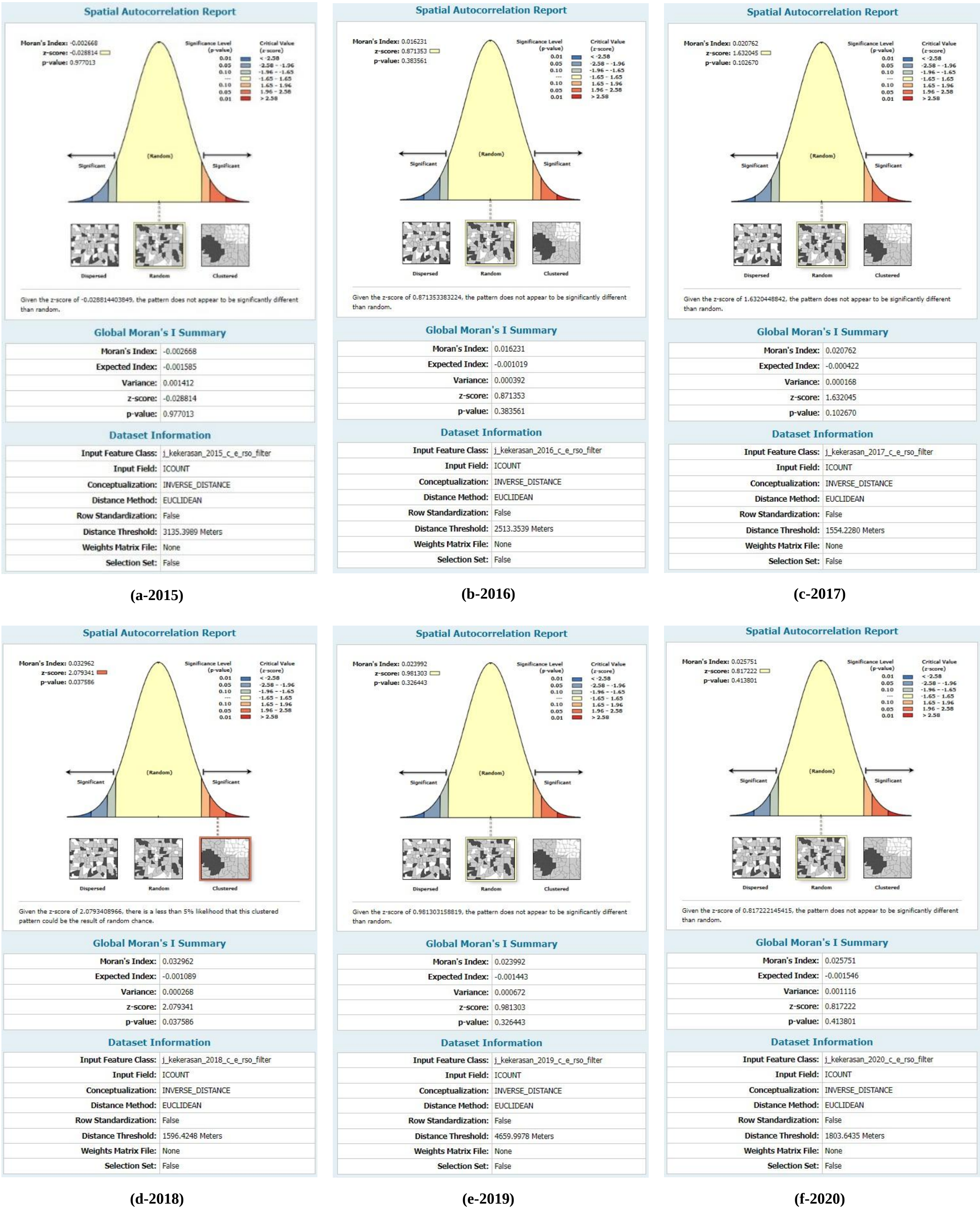

Figure 5. Global Summary of the Moran Index Violent Crime Rate in KLCPH From 2015 to 2020.

3.3. Mean Centre (MC) and Standard Deviational Ellipse (SDE) Violent Crime

Table 2 and Figure 6 show the MC and SDE for violent crime incidents from 2015 to 2020. These spatial parameters offer important information about the geographic distribution and spread pattern of violent crime in the study area. The MC represents the average location of violent crime incidents, while the Standard Deviation Ellipse SDE outlines the spatial extent and orientation of crime clusters.

Analyzing these parameters over time provides valuable information on the dynamics of crime patterns and their spatial evolution. In 2015, violent crime incidents occurred around Jalan Tuanku Abdul Rahman, especially in trade and commercial areas. The following years saw a shift in crime hot spots, with Jalan Tunku Abdul Rahman emerging as a focal point in the transport and road network in 2016. By 2017, violent crime gangs were expanding towards the City Centre, indicating a dynamic change in land use and urban development. However, in 2018, there was a shift to institutions and community facilities with Jalan Langgak Tunku, Federal Territory, becoming locations known for violent crime incidents. In 2019, violent crime incidents were again concentrated around Jalan Tuanku Abdul Rahman, suggesting potential changes in socioeconomic factors influencing crime patterns. Finally, in 2020, Jalan Dato Onn emerged as an important location for violent crime incidents in transport and road networks.

MC and SDE analyses for violent crime have several implications for law enforcement and urban planning strategies. By identifying and understanding the spatial distribution of violent crime incidents, law enforcement agencies can more effectively allocate resources and implement targeted interventions to address crime hot spots. Furthermore, urban planners and policy makers can use this information to inform land use planning and urban development initiatives aimed at creating a safer and more secure environment. Interventions such as lighting, enhanced surveillance and community engagement programs can be implemented in areas identified as high-risk hot spots to deter criminal activity and improve public safety. Regular monitoring of spatial crime patterns and ongoing analysis of the MC and SDE for violent crime can provide early warning indicators of shifting crime trends, enabling timely intervention and allocation of resources.

Collaborative efforts between law enforcement agencies, local communities and other stakeholders are essential to addressing the root causes of violent crime and fostering safer and more resilient neighborhoods. In conclusion, understanding the spatial dynamics of violent crime patterns offers valuable insights into developing evidence-based strategies to prevent and reduce crime, improve urban livability and promote community well-being.

Table 2. Movement of MC and SDE for Violent Crime in 2015 to 2020.

No.	Year	Location Name	Land Use Type	Police Stations Involved	XStdDist	YStdDist	Rotation	Area (km^2)
1	2015	Jalan Tuanku Abdul Rahman	Trade and Commercial	Jalan Dang Wangi	4552.453424	7616.59411	176.338237	108.924213
2	2016	Jalan Tuanku Abdul Rahman	Transport and Roads	Jalan Dang Wangi	4363.001557	7579.920353	175.254922	103.888309
3	2017	Masjid India, Pusat Bandar	Transport and Roads	Jalan Dang Wangi	4140.565137	7522.677221	173.129892	97.846797
4	2018	Jalan Langgak Tunku, Wilayah Persekutuan	Community Institutions and Facilities	Jalan Dang Wangi	4273.848434	7806.467378	174.785916	104.806439
5	2019	Jalan Tuanku Abdul Rahman	Trade and Commercial	Jalan Dang Wangi	3835.009599	6362.834787	164.22181	76.654155
6	2020	Jalan Dato Onn	Transport and Roads	Jalan Dang Wangi	4077.722132	6900.333583	164.662923	88.390484

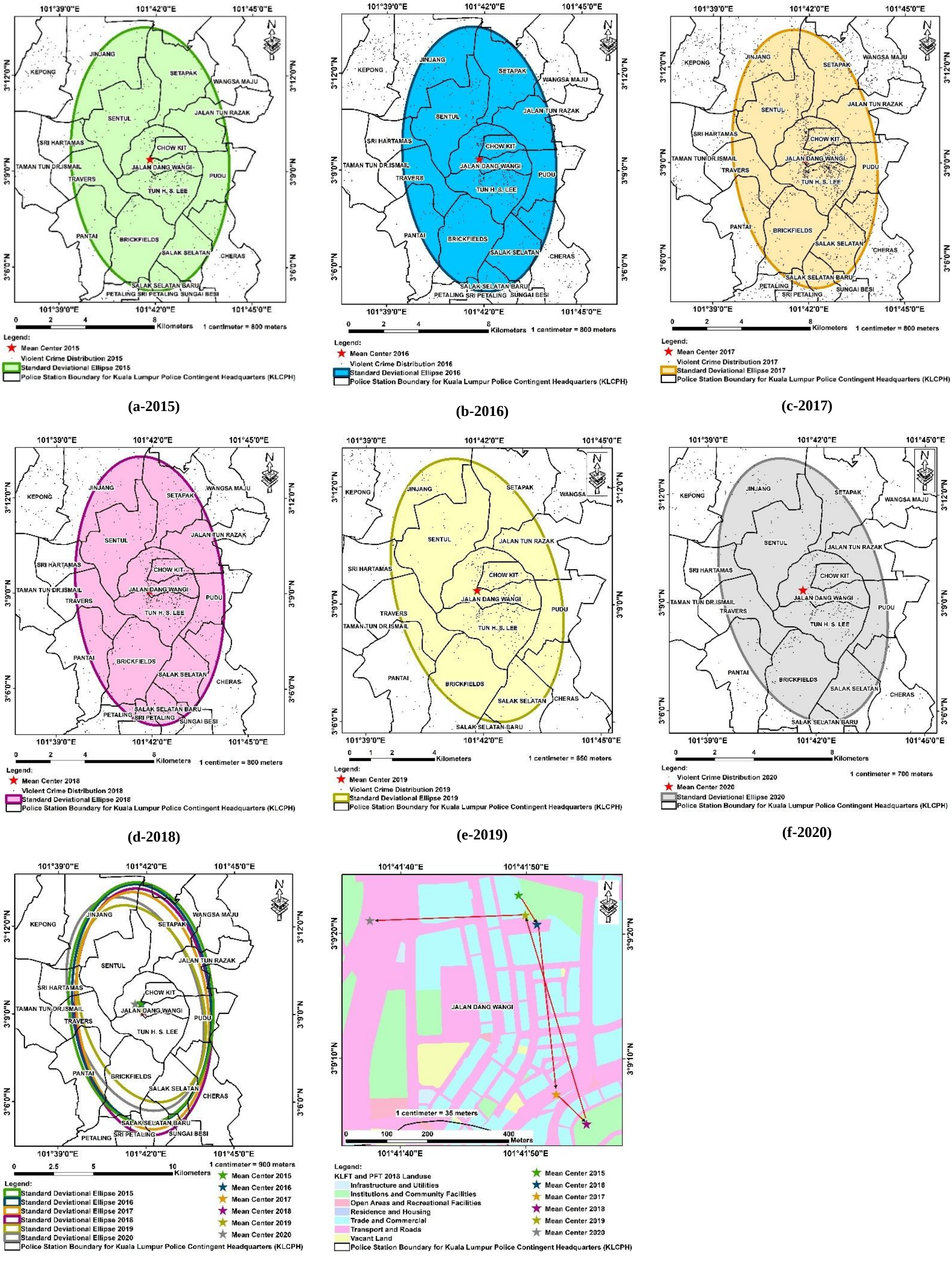

Figure 6. MC and SDE of Violent Crime Movement Based on Year 2015 to 2020 with Land Use 2018.

4. Discussion

The COVID-19 pandemic introduced unprecedented disruptions to socioeconomic structures and urban activity patterns, which, in turn, significantly influenced violent crime dynamics. Changes in routine activities, such as restricted movement during lockdowns and economic distress due to job losses, likely contributed to the redistribution of crime hotspots and shifts in temporal patterns. This period underscores the importance of integrating public health crises into the analysis of urban crime to better understand their multifaceted impacts on criminal behavior.

4.1. Temporal Violent Crime

The temporal analysis of violent crimes provides crucial insights into the daily rhythms and behavioral patterns that contribute to criminal activity. The lower crime rates observed in the early morning hours can be attributed to several interrelated factors. During these hours, there is generally lower human activity, with most people either at home or in places where they are less exposed to potential threats. The reduced opportunity for crime, coupled with the higher likelihood of detection due to fewer people being present, acts as a deterrent to criminal behavior. Furthermore, the early morning hours often coincide with heightened law enforcement vigilance, further reducing the likelihood of violent incidents (D'Orsogna & Perc, 2015; Felson & Poulsen, 2003).

The significant rise in violent crimes in the late afternoon and evening hours, particularly the peak at 3:00 PM, can be understood through the lens of socio-economic and environmental factors. The end of the school day at around 3:00 PM often leads to increased gatherings of youths, who may be more prone to engaging in altercations due to social dynamics. Additionally, this time of day marks the beginning of high-traffic periods, where a larger number of people are present in public spaces, thereby increasing the probability of encounters that could escalate into violence. The sustained high crime rates from 2:00 PM to 9:00 PM suggest that this period is marked by activities or behaviors that are conducive to violent crime. For example, the early evening hours are often associated with the consumption of alcohol and the subsequent loosening of social inhibitions, which can lead to an increase in aggressive behavior. The fact that violent crimes remain relatively high even into the evening suggests that certain social environments, such as bars, public transportation hubs, and densely populated areas, may become hotspots for criminal activity as the day progresses.

The identification of these temporal patterns in violent crime is of paramount importance for law enforcement agencies, urban planners, and policymakers. By understanding the specific hours during which violent crimes are most likely to occur, law enforcement can strategically deploy resources to ensure a more effective and timely response. For instance, increasing police presence in high-risk areas during peak hours, such as between 2:00 PM and 9:00 PM, could act as a deterrent to potential offenders and provide quicker intervention when incidents do occur. Urban planners can use this data to design public spaces and transportation systems that reduce the likelihood of violent interactions during peak crime hours. This could involve implementing measures such as increased lighting, the presence of security personnel, and the strategic placement of surveillance cameras in areas identified as having higher crime rates during specific times of the day.

For policymakers, these findings underscore the need for targeted interventions during the late afternoon and evening hours. Potential strategies could include community-based programs aimed at reducing violence, particularly those that engage at-risk youth in constructive activities during these critical hours. Additionally, stricter regulation of alcohol sales and consumption during these times might be an effective strategy to curb violent behavior. In conclusion, the temporal analysis of violent crime incidents provides a nuanced understanding of when these crimes are most likely to occur, which is crucial for developing effective prevention and intervention strategies. The marked increase in violent crimes during the late afternoon and evening hours highlights the need for focused efforts during these times to mitigate the risks of such incidents. By aligning law enforcement, urban planning, and policy initiatives with the identified temporal patterns of violent crime, it is possible to create safer communities and significantly reduce the overall incidence of violent crime. These insights not only enhance our understanding of crime dynamics but also pave the way for more informed decision-making aimed at promoting public safety and well-being (Butt *et al.*, 2020; Towers *et al.*, 2018).

4.2. Spatial Pattern Variation of Violent Crime

The variation in spatial patterns observed across different years suggests that the distribution of violent crime in the KLCPH region is influenced by a complex interplay of factors that vary over time. The significant clustering observed in 2018 could be attributed to a combination of localized socio-economic conditions, shifts in demographic patterns, or changes in law enforcement practices that may have created or exacerbated hot spots of criminal activity. For instance, areas with high levels of poverty, unemployment, or social disorganization might have experienced an increase in violent crime, leading to the observed clustering. Additionally, any changes in policing strategies, such as the concentration of law enforcement resources in certain areas or changes in community policing efforts, could also have contributed to this pattern. The randomness observed in the other years suggests that violent crime was more diffusely spread across the region, without specific areas experiencing unusually high or low rates of crime. This could indicate that the drivers of violent crime in these years were more generalized and not confined to specific neighborhoods or zones. Factors such as overall economic conditions, broad social policies, or generalized law enforcement efforts may have played a role in maintaining this random distribution.

The study's findings highlight the importance of examining both temporal and spatial variations in crime patterns. The presence of significant clustering in one year but not in others suggests that violent crime in the KLCPH region is dynamic and can be influenced by a range of factors that vary over time. This underscores the need for flexible and adaptive crime prevention strategies that can respond to changing conditions. The implications of these findings are profound for law enforcement agencies, policymakers, and community leaders in the KLCPH region. The identification of a clustered pattern of violent crime in 2018 indicates that certain areas experienced a higher concentration of violent incidents, suggesting the presence of hot spots that could benefit from targeted interventions. Law enforcement agencies could focus their efforts on these areas by increasing patrols, enhancing surveillance, or implementing community policing strategies that foster stronger relationships between police officers and residents. This approach could help in deterring crime and addressing the underlying issues contributing to the clustering of violent crime (Andresen & Malleson, 2013; Johnson *et al.*, 2008).

Moreover, the presence of a random pattern in the other years suggests that violent crime prevention efforts should not be confined to specific areas but rather should be applied more broadly across the region. This could involve implementing community-wide initiatives aimed at addressing the root causes of crime, such as poverty, unemployment, and lack of educational opportunities. Programs designed to improve economic conditions, provide job training, and enhance social cohesion could be effective in reducing violent crime across the board. For policymakers, the study underscores the importance of using spatial analysis tools like the Global Moran's Index to monitor and evaluate crime patterns over time. By doing so, they can identify emerging trends and adapt their strategies accordingly. The dynamic nature of crime patterns in the KLCPH region suggests that a one-size-fits-all approach to crime prevention may not be effective. Instead, a combination of targeted interventions in high-risk areas and broader community-wide initiatives may be necessary to effectively reduce violent crime (Carcach, 2015; Nelson *et al.*, 2001).

In conclusion, the spatial analysis of violent crime in the KLCPH region from 2015 to 2020 reveals a nuanced and dynamic picture of crime distribution. The results demonstrate that while violent crime generally exhibited a random pattern across most of the study period, 2018 was an outlier with a statistically significant clustered pattern. This suggests that violent crime in KLCPH is influenced by a range of factors that vary over time and space, requiring a flexible and adaptive approach to crime prevention. The findings highlight the importance of understanding both the spatial and temporal dimensions of crime, as well as the need for a combination of targeted and broad-based strategies to effectively address violent crime. By focusing on the specific factors contributing to the clustering observed in 2018 and maintaining a region-wide approach in other years, law enforcement agencies and policymakers can work towards creating safer communities and reducing the overall incidence of violent crime in the KLCPH region. Future research could build on these findings by exploring the specific socio-economic, demographic, and law enforcement factors that contributed to the observed patterns, providing a deeper understanding of the dynamics of violent crime in urban areas (Masron *et al.*, 2025; Mohd Ali *et al.*, 2025).

4.3. Movement Pattern of Violent Crime

The critical error analysis is essential to achieving convincing results regarding crime movement. However, in this study, there is no error in the analysis because we use actual location data from the Royal Malaysian Police. The analysis of the MC and SDE for violent crime from 2015 to 2020 provides crucial insights into the spatial dynamics and evolving patterns of crime in the study area. These spatial parameters not only highlight the average location of crime incidents but also reveal the spread and orientation of crime clusters, offering a comprehensive breakdown of how crime hot spots change over time. Table 1 and Figure 5 reflect the significant shift in crime focus areas from 2015 to 2020. In 2015, violent crime incidents were primarily concentrated around Jalan Tuanku Abdul Rahman, particularly in trade and commercial zones. This initial focus indicates high crime rates in busy commercial areas with significant foot traffic and economic activity. By 2016, crime hot spots had shifted to Jalan Tunku Abdul Rahman, suggesting a possible relocation of criminal activity due to increased police presence or urban redevelopment in previously affected areas. The trend continued in 2017, with violent crimes expanding towards the City Centre, indicating dynamic changes in land use and urban development. In 2018, the focus shifted to institutions and community facilities, with Jalan Langgak Tunku, Federal Territory, emerging as notable locations for violent crime incidents. This shift may reflect changes in community dynamics or the impact of socioeconomic factors. The re-concentration of violent crime around Jalan Tuanku Abdul Rahman in 2019 suggests a return to previously established crime patterns, possibly due to changes in socioeconomic conditions or the diminishing effectiveness of prior interventions. Finally, in 2020, hot spots moved to Jalan Dato Onn, indicating a new focus on transport and road networks. This shift may be due to various factors, including changes in urban mobility patterns or the socioeconomic impact of the pandemic.

The MC and SDE analyses for violent crime have several implications for law enforcement and urban planning strategies. By identifying and understanding the spatial distribution of violent crime incidents, law enforcement agencies can more effectively allocate resources and implement targeted interventions to address crime hot spots. Moreover, urban planners and policymakers can use this information to inform land use planning and urban development initiatives aimed at creating a safer and more secure environment. Interventions such as enhanced lighting, increased surveillance, and community engagement programs can be implemented in high-risk hot spots to deter criminal activity and improve public safety. Regular monitoring of spatial crime patterns and ongoing analysis of the MC and SDE for violent crime can provide early warning indicators of shifting crime trends, enabling timely intervention and resource allocation. Collaborative efforts between law enforcement agencies, local communities, and other stakeholders are essential for addressing the root causes of violent crime and fostering safer and more resilient neighborhoods. In conclusion, understanding the spatial dynamics of violent crime patterns offers valuable insights for developing evidence-based strategies to prevent and reduce crime, improve urban livability, and promote community well-being. It is important to note that the data used in this analysis is based on actual locations provided by the Royal Malaysian Police, ensuring high accuracy and reliability of the findings (Army & Vellani, 2021; Elfadaly et al., 2024; Oliveira & Menezes, 2019; Thomas & Mohan, 2023). While the study effectively identifies spatial clusters and temporal shifts in violent crime, the analysis does not establish direct causal relationships between observed crime patterns and the socio-economic or urban development factors highlighted. This limits the ability to pinpoint why specific trends, such as peak crime hours or hotspot shifts, occur.

4.4. Future Research and Policy Recommendations

The study presented uses advanced spatial analysis techniques such as Moran's Index and SDE effectively to examine violent crime patterns. However, the methodology section could expand further on how these tools were tailored to the specific urban dynamics of Kuala Lumpur and Putrajaya (Wang et al., 2019). This article could benefit from elaborating on how these variables were integrated into the analysis. Providing a transparent framework for this integration would strengthen the conclusions and align the findings with broader urban planning and policy implications. The spatial and temporal patterns identified in this study have profound implications for urban planning and law enforcement (Butt, 2020). For urban planners, insights into crime hotspot shifts can inform decisions about public space design, such as improving lighting, enhancing visibility, and adjusting zoning policies to reduce crime-prone areas. Law enforcement agencies can use these findings to allocate resources more effectively, focusing on high-risk zones during identified peak hours (Nadian et al., 2018). Additionally, the integration of socio-economic data underscores the need for community-based interventions addressing root causes, such as unemployment or inadequate public services, to mitigate crime rates.

The findings of this research suggest several actionable recommendations for policymakers:

1. Deploy adaptive policing strategies that prioritize emerging crime hotspots identified through spatial analysis.

2. Develop targeted urban planning initiatives that address socio-economic triggers of crime, such as providing recreational facilities for youth in high-crime areas.

3. Enhance public safety infrastructure by integrating advanced surveillance systems and community engagement programs in high-risk locations.

Future studies should consider integrating qualitative socio-economic data with spatial analysis to explore causative mechanisms behind crime patterns. For example, examining how economic disruptions or urban migration directly influence the emergence or dissipation of crime hotspots could provide deeper insights. By adopting these strategies, policymakers can better translate research findings into practical, long-term crime prevention measures, fostering safer urban environments.

5. Conclusions and Future Research

The analysis of violent crime in Kuala Lumpur and Putrajaya using SDE and MC techniques has revealed significant shifts in crime hotspots from commercial areas to transportation routes and developing zones, emphasizing the dynamic nature of urban crime. Socio-economic factors, notably the disruptions from the COVID-19 pandemic, have profoundly influenced these changes, affecting crime rates and hotspot distribution. These insights stress the importance of continuous spatial analysis and socio-economic contextual understanding in developing effective crime prevention strategies that enhance community safety and urban livability. Future research should focus on deepening the understanding of the causal relationships between socio-economic changes and crime dynamics, employing longitudinal studies that could offer predictive insights into crime trends. Additionally, exploring the application of newer spatial analytical techniques and integrating real-time data could refine the responsiveness of crime prevention measures, ensuring they remain effective in the face of rapidly evolving urban environments.

This study provides a foundation for understanding the dynamic interplay between socio-economic factors and violent crime patterns in urban areas. The integration of spatial techniques, such as the Standard Deviational Ellipse and Mean Centre analysis, demonstrates the potential for data-driven urban safety strategies. Future research could expand on these findings by exploring predictive models that integrate real-time spatial data and longitudinal studies that examine the impact of socio-economic transformations on crime dynamics. Such advancements will ensure that crime prevention measures remain adaptive and effective in rapidly evolving urban contexts.

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Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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