Journal of Sustainability Science and Management
Volume 20 Number 12, December 2025: 2573-2595
eISSN: 2672-7226

ANALYSING PROPERTY CRIME MOVEMENTS IN URBAN MALAYSIA: THE ROLE OF STANDARD DEVIATIONAL ELLIPSE (SDE) AND MEAN CENTRE (MC) TECHNIQUES

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http://doi.org/10.46754/jssm.2025.12.003
Submitted: 2 December 2024 Revised: 21 May 2025 Accepted: 28 May 2025 Published: 15 December 2025

Abstract: Property crime poses a significant threat to urban safety, socioeconomic stability, and sustainable development in Malaysia's rapidly urbanising cities. However, the lack of advanced spatial analyses has limited the understanding of crime pattern evolution. This study investigates the spatial and temporal dynamics of 58,130 property crime incidents in Kuala Lumpur and Putrajaya from 2015 to 2020, employing Standard Deviational Ellipse (SDE) and Mean Centre (MC) techniques to map directional trends and identify crime hotspots. The analysis reveals strong diurnal patterns, with peak incidents at 8:00 p.m. (8.12%) and the lowest at 4:00 a.m. (0.61%), consistent with routine activity theory. Spatially, crime shifted from commercial areas (e.g., Jalan Tuanku Abdul Rahman) to transportation corridors (e.g., Jalan Raja Laut) and re-converged in urban commercial hubs (e.g., Pertama Complex) by 2020. The SDE area varied from 100.82 km² to 117.01 km², with increased dispersion and rotation in 2020, reflecting socioeconomic disruptions, notably from the COVID-19 pandemic. Although comprehensive statistical modelling of socioeconomic variables was limited, observable shifts suggest economic vulnerability and urban development as key drivers. The findings highlight the utility of spatial analytics for predictive policing and evidence-based urban planning, enabling more effective crime prevention and resilient city design.

Keywords: Mean Centre (MC), property crime, spatial analysis, Standard Deviational Ellipse (SDE), urban crime patterns.

Introduction

Globally, urban areas are facing escalating crime rates, adversely affecting community safety and socioeconomic stability (Vanderschueren, 1996; Mohamad Ali *et al*., 2020; Cesario, 2023). Rapid urbanisation has intensified this issue, bringing urban crime to the forefront of social and policy concerns. The phenomenon of urban crime has often been attributed to social disorganisation—characterised by broken families and fragmented communities—leading to various urban problems (Witte, 1996; Glaeser & Sacerdote, 1999; Sheykhi, 2016). High population density, socioeconomic disparities, and limited access to resources are prominent factors linked to the rise in different types of crime in urban environments (Alanezi, 2010; da Silva, 2014; Hew *et al*., 2019; Z. Zhang *et al*., 2023). As a consequence, urban areas tend to exhibit higher rates of property crime, violent crime, and drug-related offences compared to rural regions (Tacoli *et al*., 2014; Ray, 2016; Mburu & Mutua, 2023). Research has consistently shown that areas with insufficient social services and economic opportunities are more prone to higher crime rates (Marzuki, 2016; Elfversson & Höglund, 2023). Besides posing threats to community wellbeing, urban crime also imposes substantial financial burdens on cities through costs associated with law enforcement, legal proceedings, and incarceration (Aos *et al*., 2001; Mansourihanis *et al*., 2024). In this regard, the increase in urban crime rates can be viewed as a multidimensional issue that requires a holistic approach to be effectively mitigated.

Property crime remains a significant issue in urban environments, necessitating continual analysis to understand its spatial and temporal dynamics. This study examines property crime patterns and movements in Kuala Lumpur and Putrajaya from 2015 to 2020, utilising Standard Deviational Ellipse (SDE) and Mean Centre (MC) techniques (Abdullah *et al*., 2018; Pooja *et al*., 2024). These advanced spatial analysis methods provide comprehensive insights into areas of high crime concentration and their shifts over time (Tabangin *et al*., 2008; X. Zhang & Chen, 2023).

The SDE technique elucidates the dispersion and directional trends of crime while the MC technique identifies the central point representing the average location of crime incidents (Ahmad *et al*., 2024a). This dual approach facilitates a detailed understanding of the evolution of crime hotspots, the influenced by various socio-economic and environmental factors. Kuala Lumpur, as the economic hub and Putrajaya, as the administrative centre offer unique urban landscapes that contribute to the complexity of crime patterns (Masron *et al*., 2025). This study aims to map the spatial distribution of property crimes, identifying critical areas for targeted law enforcement and urban planning interventions.

The research objectives are threefold: (i) to analyse the spatial distribution and movement of property crime in Kuala Lumpur and Putrajaya using the SDE technique; (ii) to identify and map changes in the central location of property crime incidents using the MC technique, highlighting shifts in crime hotspots over time; and (iii) to provide insights and recommendations for law enforcement and urban planners based on the findings, supporting evidence-based policy-making and strategic urban crime prevention. Previous studies on property crime in Kuala Lumpur and Putrajaya have mainly relied on descriptive statistics and traditional mapping techniques, lacking the spatial precision offered by advanced geospatial analysis methods (Masron *et al*., 2025).

There is a notable gap in the literature regarding the application of SDE and MC techniques to comprehensively understand the directional trends and central tendencies of property crime over time. This study seeks to fill this gap by providing a detailed spatial analysis of crime movements, identifying key factors contributing to these changes, and offering a robust foundation for evidence-based policy-making and strategic planning in urban crime prevention (Bhati, 2005; Melo *et al*., 2017; Chemin *et al*., 2024). The integration of SDE and MC techniques offers a novel approach to understanding the spatial dynamics of property crime, enabling the identification of directional trends, shifts in central locations, and the influence of urban development and socio-economic factors (Zhou *et al*., 2023).

The majority of the research on crime patterns and trends that has been done so far has been on using conventional spatial analysis methods such spatial autocorrelation and kernel density estimation (Johnson, 2010; Melo *et al*., 2017; He *et al*., 2023). The literature still lacks a thorough grasp of the directional patterns and central tendencies of property crime over time, despite the fact that these methodologies have yielded insightful results (Balocchi & Jensen, 2019; Oliveira & Menezes, 2019; Nader *et al*., 2023).

The purpose of this study is to close this gap by using MC and Standard SDE techniques to provide a solid spatial analysis of crime movements, pinpoint important factors influencing these changes, and provide a framework for evidence-based strategic planning and policy-making in urban crime prevention (He *et al*., 2020; Alazawi *et al*., 2022). Developing successful crime prevention methods requires analysing spatial patterns and trends in property crime (Alazawi *et al*., 2022; J. M. MacDonald *et al*., 2024). Prior research has demonstrated the striking patterns in the time dynamics and spatial distribution of criminal occurrences, with crimes frequently concentrating in particular areas (Oliveira & Menezes, 2019; Wen *et al*., 2024). The multifaceted structure of crime dynamics, including the directionality and central tendencies of crime movements across time is however difficult to capture by the current analytical approaches (Oliveira & Menezes, 2019; Drozdowski *et al*., 2023).

Methodology

Standard Deviational Ellipses (SDE)

ArcGIS software is extensively used in GIS for its robust capabilities in spatial analysis, data management, and visualisation, making it essential for studying property crime in regions like Kuala Lumpur and Putrajaya (Jamru *et al*., 2024). The SDE technique is utilised to display the distribution of crime incidents, requiring statistical metrics to determine spatial variation and generate an ellipse that represents this variation. The size and shape of the ellipse indicate areas with higher crime rates, capturing spatial variation and providing comprehensive insights into crime distribution. Extended ellipses suggest more frequent crime incidents in certain directions. SDE can also distinguish the spatial distribution of crime across regions or time periods, detecting variations over time. Movement analysis was conducted using the MC and SDE technique (Ahmad *et al*., 2024a). The MC represents the average x- and y-coordinates of all features in the study area. The SDE measures the difference between the average distance and the distance from certain features to the MC, identifying the direction and target areas of criminal offences based on reported data. Measurements are obtained using equation (1).

$$SD = \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{n} + \frac{\sum_i (x_i - \bar{x})^2}{n}} \tag{1}$$

To understand how each crime changes over time in terms of day categories, it is crucial to know the geographic centre, distribution, orientation, and direction associated with each crime. Therefore, a logical extension of the standard distance circle that can capture the directional bias in point distribution is the SDE (Furfey, 1927; Wong & Lee, 2005). SDE is defined as:

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

$$var(x) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n}\sum_{i=1}^{n} \tilde{x}_i^2 \tag{3}$$

$$cov(x, y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) = \frac{1}{n}\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i \tag{4}$$

$$var(y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n}\sum_{i=1}^{n} \tilde{y}_i^2 \tag{5}$$

where x and y are the coordinates for feature i and $\{x\hat{y}\}$ represents the MC for the feature, with n is equal to the number of features. The sample covariate matrix is factored into standard form, resulting in a matrix represented by its eigenvalues and eigenvectors. The standard deviation of the x-axis and y-axis is:

$$\sigma 1,2 = \left(\frac{(\sum_{i=1}^{n} \tilde{x}_i^2 + \sum_{i=1}^{n} \tilde{y}_i^2) \pm \sqrt{(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2)^2 + 4(\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i)^2}}{2n} \right)^{\frac{1}{2}} \tag{6}$$

This equation can be extended to solve for three-dimensional data. The variance is scaled by an adjustment factor to produce an ellipse or ellipsoid containing the desired percentage of data points. These adjustment factors are provided in the table below (ESRI, 2022a).

Movement Pattern Analysis (Mean Centre)

MC is useful for tracking changes in the distribution of points or for comparing points of different characteristic types. For all features in the study area, the MC is the average of the x-, y-, and z-coordinates (ESRI, 2022b).

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad (7)$$

where x_i and y_i are the coordinates of feature i and n is equal to the total number of features. MC weighting covers the following:

$$\bar{X}_w = \frac{\sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} w_i}, \bar{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \quad (8)$$

where w_i is the weight on feature i. The tool also calculates the centre for the 3rd dimension if the z attribute exists for each feature:

$$\bar{Z} = \frac{\sum_{i=1}^{n} z_i}{n}, \bar{Z}_w = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i} \quad (9)$$

MC analysis computes the geographic "centre of gravity" of point-pattern data—such as crime incidents—by averaging the x- and y-coordinates of all events within the study area to yield a single representative point. This central point succinctly encapsulates the spatial tendency of crime, enabling researchers, law enforcement, and urban planners to identify shifts in crime concentration over time or to compare hotspot locations across different crime types. By overlaying the mean centre on layers of socio-demographic or land-use data, analysts can explore potential correlates—such as population density, zoning classifications, or transportation networks—that may drive spatial patterns in offending (Ahmad *et al*., 2024a; Masron *et al*., 2024).

Despite its utility, MC analysis rests on the simplifying assumption of uniform incident distribution around the centre, which may obscure multiple clusters or skew towards areas of extreme density. In highly heterogeneous urban landscapes, the MC can be pulled towards outliers, misrepresenting the "true" focal area of criminal activity. To mitigate this, it is recommended to pair mean centre calculations with complementary techniques—such as kernel density estimation, optimised hotspot analysis, or spatial autocorrelation measures—and to interpret results within broader socio-economic and political contexts. Integrating multiple GIS methods ensures a more nuanced, robust understanding of crime geography for both academic research and practical crime-prevention strategies (Muhamad Ludin *et al*., 2013; ESRI, 2022b).

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad (10)$$

where x_i and y_i are the coordinates of feature i and n is equal to the total number of features. MC weighting covers the following:

$$\bar{X}_w = \frac{\sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} w_i}, \bar{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \quad (11)$$

where w_i is the weight on feature i. The tool also calculates the centre for the 3rd dimension if the z attribute exists for each feature:

$$\bar{Z} = \frac{\sum_{i=1}^{n} z_i}{n}, \bar{Z}_w = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i} \quad (12)$$

Study Area

The study area for this research is Peninsular Malaysia, specifically the Kuala Lumpur Federal Territory (KLFT) and the Putrajaya Federal Territory (PFT), located in Selangor Darul Ehsan (Ahmad *et al*., 2024a; Masron *et al*., 2024). Understanding the economic, administrative, and socio-cultural dynamics between KLFT and PFT is crucial. KLFT serves as Malaysia's economic powerhouse, housing key financial institutions such as Bank Negara Malaysia and the Kuala Lumpur Stock Exchange (Tan *et al*., 2018; Mohd Shariff, 2022). PFT, designed as the federal administrative centre, accommodates the Prime Minister's office, various ministries, and government agencies, ensuring efficient governance (Nagulendran *et al*., 2016; Manaf *et al*., 2023).

The Kuala Lumpur Police Contingent Headquarters (KLPCH) consists of six District Police Headquarters (DPH): Brickfields, Cheras, Dang Wangi, Putrajaya, Sentul, and Wangsa Maju, encompassing 24 police stations (Table 1). Each DPH includes multiple police stations, facilitating streamlined communication and coordination.

Figure 1 shows a map of Kuala Lumpur (KL) and Putrajaya, illustrating police jurisdiction boundaries. The District Police Headquarters (DPHs) within the Kuala Lumpur Police Contingent Headquarters (KLPCH) are outlined, each labelled by district. DPH Brickfields includes stations such as Brickfields, Pantai, Petaling, Sri Hartamas, Sri Petaling, Taman Tun Dr. Ismail, and Travers. Similarly, DPH Cheras comprises stations like Bukit Jalil, Cheras, Salak Selatan, Salak Selatan Baru, and Sungai Besi. This map provides spatial context for the study area, illustrating how the city's policing districts cover different urban zones.

Meanwhile, Figure 2 shows land-use classification in Kuala Lumpur and Putrajaya (2018). This map (source: MyGDI) highlights major land-use categories (e.g., commercial, residential, transportation) in the study area. It helps interpret crime patterns by showing where business districts and transportation corridors lie relative to crime hotspots. Figures 1 and 2 provide contextual maps of the study area, illustrating where crime occurs in relation to police coverage and urban land uses.

Property Crime Index in Malaysia

The Property Crime Index in Malaysia, as outlined by the Criminal Investigation Department (D4) of Bukit Aman in 2021, provides a comprehensive framework for categorising non-violent criminal offences that involve the unlawful taking of property (Masron

Table 1: Dataset summary for property crime analysis (2015-2020) in Kuala Lumpur and Putrajaya

Variable	Description	Data Source	Spatial Unit	Temporal Resolution	Example Values
Year	Year of crime incident	Royal Malaysia Police (RMP), Bukit Aman	Annual	2015-2020	2015, 2016
Crime Type	Legal classification under Penal Code (e.g., Section 379, 379A, 380, 457)	Property Crime Index (RMP, 2021)	-	-	Theft (379), Vehicle Theft (379A), Burglary (457)
Number of Incidents	Total property crimes reported per year	RMP, 2021	Aggregated	Annual	58,130 (2015-2020 total)
Location	Federal Territories in Malaysia	RMP, MyGDI, and ESRI	Kuala Lumpur, Putrajaya	-	Jalan Tuanku Abdul Rahman, Chow Kit
Land Use Type	Classification based on land use maps	MyGDI=Land Use Data (2018)	Categorical	Static (2018 snapshot)	Commercial, Transport/ Roads
X and Y Coordinates	Geographical coordinates of crime incidents	GIS Geocoding	Point level	Continuous	Latitude/Longitude
Police Station Boundaries	Administrative unit of spatial aggregation	KLPCH GIS Data	24 Police Stations	Fixed (Spatial)	DPH Dang Wangi, Cheras
Time of Day	Hour of crime occurrence	RMP Hourly Records	Hourly	24-hour cycle	8:00 PM, 4:00 AM

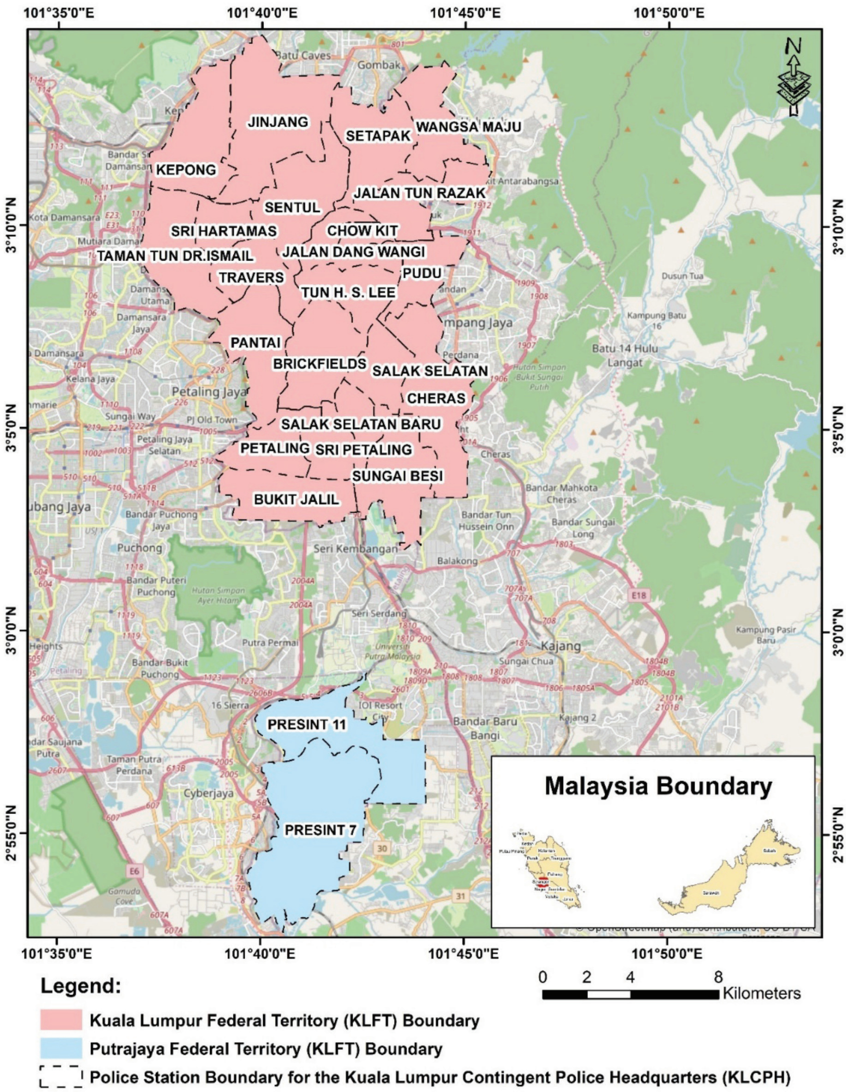


Figure 1: Police station boundaries for the Kuala Lumpur Police Contingent Headquarters (KLPCH)

et al., 2025). The index comprises a series of specific offences classified under various sections of the Malaysian Penal Code, which are used systematically to record, analyse, and monitor property crime trends across the country. These categories serve as the official reference for crime statistics reported by law enforcement agencies and play a crucial role in criminological research, policy formulation, and spatial crime analysis.

The index includes offences such as theft and burglary, which are further disaggregated based on the nature, location, and context of the crime. Theft offences are prominently represented under Section 379 and Section 379A of the Penal Code. Section 379 refers to "stealing off the premises", typically involving incidents where property is unlawfully taken from open or public spaces such as parked bicycles, unattended bags in public areas, or

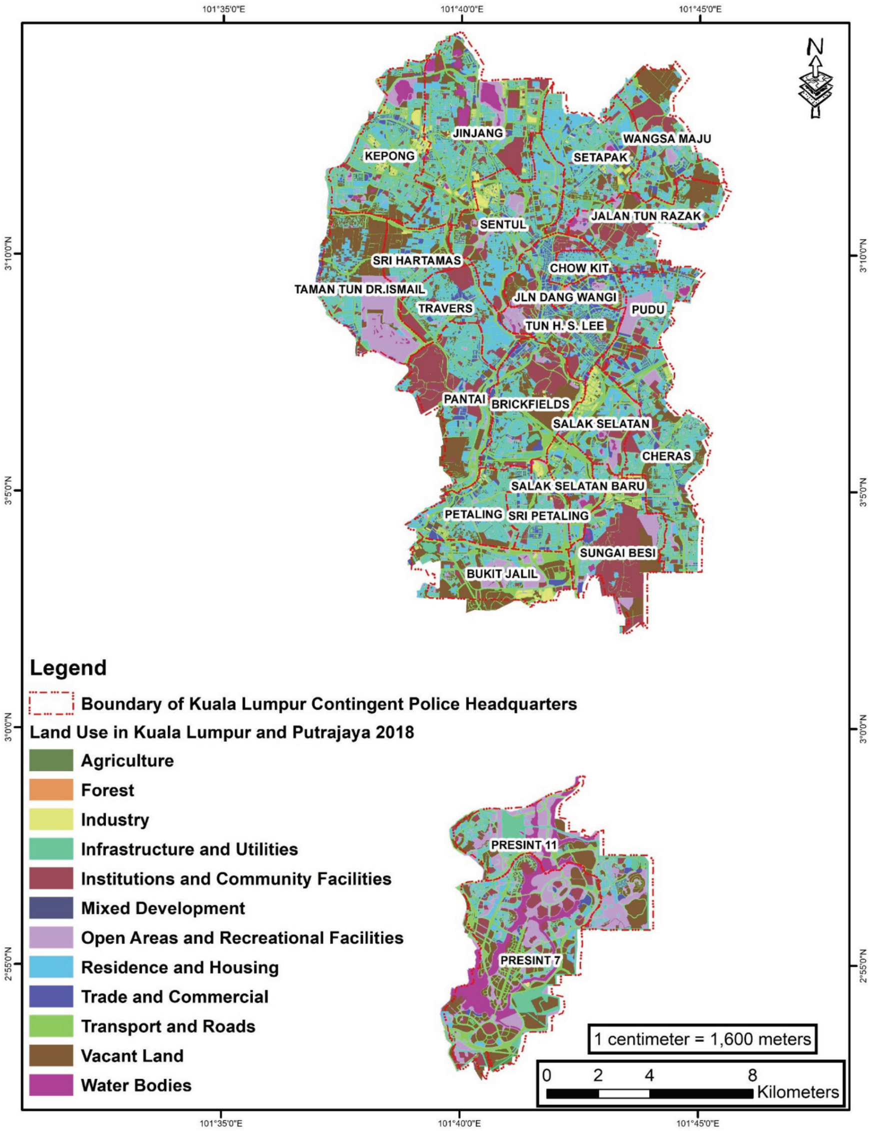


Figure 2: Land use data for Kuala Lumpur Federal Territory (KLFT) and Putrajaya Federal Territory (PFT) areas for (2018)

Source: MyGDI Program (Malaysian Geospatial Data Infrastructure)

equipment stored outdoors. Meanwhile, Section 379A specifically addresses vehicle theft, which is further classified into three subcategories: Motorcycle theft, motorcar theft, and theft of vans, trucks, or heavy machinery. These vehicle-related crimes are among the most frequently reported and are often prioritised in policing strategies due to their economic impact and connection to organised crime syndicates.

In addition, the index recognises "stealing on the premises" under Section 380 of the Penal Code. This category involves theft occurring within secured or enclosed areas such as residential homes, business premises, or institutions. Such crimes often involve breaches of physical barriers or trust and can vary in scale depending on the location and type of property stolen. Burglary, another significant form of property crime is classified under Section 457 and is further divided into daytime and nighttime occurrences. This distinction acknowledges the differing social and psychological impacts of burglary based on the time of day, with nighttime burglaries typically perceived as more severe due to the higher risk to occupants' safety and the potential for confrontation (Intelligence/Operations/Criminal Records (D4) (RMP CID, Bukit Aman Headquarters, 2021).

Overall, the Property Crime Index serves as a critical tool for understanding the scope and nature of property-related offences in Malaysia. By segmenting crimes according to specific legal sections, the index facilitates more accurate crime reporting, enhances data consistency, and supports targeted law enforcement interventions. Furthermore, this classification aids researchers in identifying spatial patterns and temporal trends in property crime, thereby contributing to the broader goals of crime prevention and urban safety planning.

Results

Temporal Considerations-Property Crime by Time (Hours)

The temporal distribution of property crimes in Kuala Lumpur and Putrajaya from 2015 to 2020 demonstrates distinct peaks and troughs over the 24-hour cycle, indicating strong diurnal patterns. Figure 3 illustrates this 24-hour temporal pattern: Evening hours see a clear spike, especially around 20:00 while late night and early morning hours have minimal crimes. For example, our data show 8:00 p.m. as the single peak (8.12% of incidents). This aligns with routine activity theory, which posits that crimes occur when motivated offenders encounter targets with low guardianship (Felson *et al*., 2020).

The hourly distribution of property crimes (2015-2020, KLFT & Putrajaya) is depicted in Figure 3, which presents a line (or bar) chart showing the percentage of total property crimes occurring in each hour of the day. This highlights the pronounced diurnal pattern: The highest crime rate occurs at 8:00 p.m. (8.12% of incidents) while the lowest occurs at 4:00 a.m. (0.61%), consistent with routine activity theory.

A total of 58,130 property crime incidents were reported during this period (Intelligence/Operations/Criminal Records (D4) (RMP CID, Bukit Aman Headquarters, 2021). Peak activity reflects the highest concentration of property crimes at 8:00 p.m., with a total of 4,722 incidents recorded, accounting for 8.12% of all property crimes during the period. This is the most significant spike observed in the entire 24-hour cycle. Additionally, the period between 6:00 p.m. and 9:00 p.m. consistently shows elevated crime rates, with percentages ranging from 6.7% to 8.1%. In contrast, property crime incidents drop to their lowest levels between 12:00 a.m. and 4:00 a.m., with the lowest point observed at 4:00 a.m., where only 357 incidents were reported, representing a mere 0.61% of the total crimes. The hours between 2:00 a.m. and 5:00 a.m. consistently see less than 1% of crimes reported.

Beginning at 6:00 a.m., property crime incidents rise steadily, peaking at 10:00 a.m. with 3,363 incidents, which account for 5.79% of the total. This trend continues throughout the morning, with consistently high crime rates between 8:00 a.m. and 12:00 p.m., culminating at 12:00 p.m. with 6.39% of total incidents. In the afternoon, particularly between 2:00 p.m. and 5:00 p.m., there is another significant surge in property crime, with percentages fluctuating between 6.4% and 6.8%.

The volume of incidents remains high throughout the early evening, peaking again at 8:00 p.m. Interestingly, the early night period (from 9:00 p.m. onwards) sees a gradual decline in criminal activity, falling to 2.11% by 11:00 p.m. The temporal concentration of property crimes during the evening hours suggests that this period is the most vulnerable time for the occurrence of property crimes, particularly at 8:00 p.m., when incidents peak sharply. Conversely, the early morning hours present a period of relative safety, with significantly fewer crimes being reported.

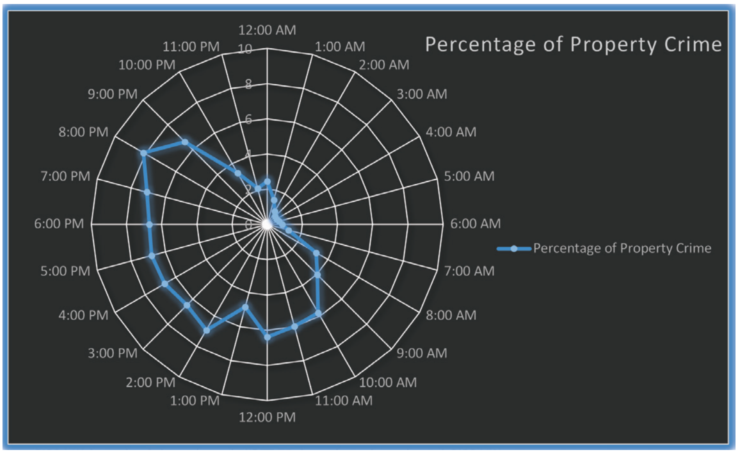


Figure 3: Percentage of property crime
Source: Intelligence/Operations/Criminal Records (D4) (Criminal Investigation Department) (RMP CID, Bukit Aman Headquarters, 2021)

Standard Deviational Ellipse (SDE) and Mean Centre (MC)

The analysis of the MC and SDE for property crime from 2015 to 2020 reveals significant insights into the spatial dynamics and dispersion patterns of crime incidents within the study area. This map shows, for each year, the mean centre of that year's crime incidents (solid points) and the corresponding 1-standard-deviation ellipse (thin outline). Different colours distinguish the years (Figure 4). The background land-use map (2018) helps relate shifts to the urban context. Visualising the ellipses year by year clarifies how areas of crime concentration move and spread over time (e.g., northward shifts or rotations). Figure 4, together with Table 2 summarises the spatial movement of crime. Each year's mean centre (black dot) and ellipse orientation/area illustrate how hotspots drift (e.g., from central commercial areas toward transport corridors).

Table 2 lists the key hotspot locations and SDE parameters annually, making these trends explicit. For example, it shows a decrease in ellipse area in 2018 and a rapid expansion by 2020, signalling a contraction followed by a widening of crime spread. Table 2 provides a summary of spatial crime metrics (2015-2020). Each row lists the year's dominant hotspot location(s), associated land-use type, relevant police stations, the X and Y standard deviations (ellipse axes), rotation angle, and total ellipse area (km²). This detailed breakdown highlights year-to-year changes: For example, 2018's smaller area compared to the larger area in 2020. The caption and table have been expanded to explain each column, allowing readers to easily see how the crime "centre of gravity" and dispersion evolve annually.

In 2015, property crime incidents were mainly concentrated around Jalan Tuanku Abdul Rahman, Brazilian Beauty House, and Tengah 4, indicating high crime rates in commercial zones (Table 2 and Figure 4). The SDE for 2015 covered an area of 113.55 km², with a rotation angle of 176.00 degrees, reflecting the spread of crime along major commercial corridors. In 2016, there was a shift in crime hotspots towards Habib Jewel, My Foodloft, Capsquare Residence, and Capsquare Promenade, suggesting a redistribution of criminal activities. The SDE area increased to 115.31 km², with a rotation angle of 179.87 degrees, indicating a northward movement and broader dispersion.

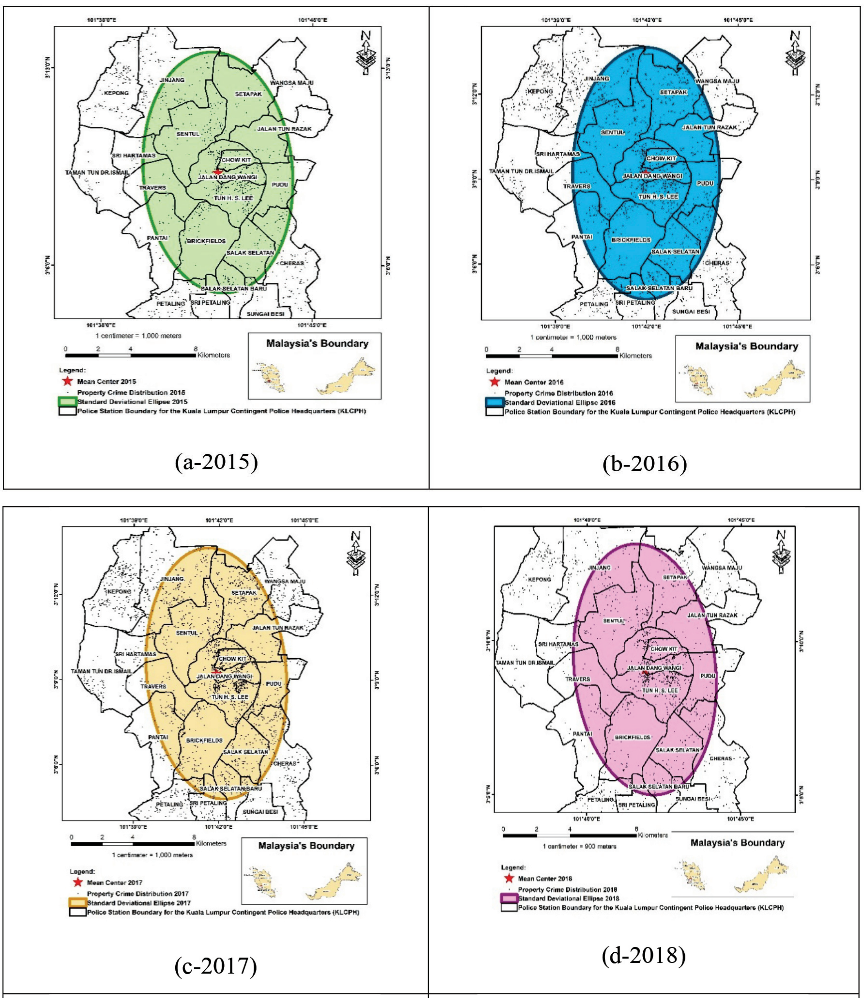
Property crimes in 2017 redistributed towards Kamdar Sdn. Bhd. and Jalan Tuanku Abdul Rahman, reflecting changes in land use

Table 2: Movement of Mean Centre (MC) and Standard Deviational Ellipse (SDE) for property crime in (2015-2020)

No.	Year	Location Name	Land Use Type	Police Stations Involved	XStdDist	YStdDist	Rotation	Area (km^2)
1	2015	Jalan Tuanku Abdul Rahman, Brazilian Beauty House and Tengah 4	Trade and Commercial	Jalan Dang Wangi	4584.963391	7883.976436	176.001623	113.55292
2	2016	Habib Jewel, My Foodloft, Capsquare Residence and Persiaran Capsquare	Trade and Commercial	Jalan Dang Wangi	4480.103036	8193.093642	179.869092	115.305536
3	2017	Kamdar Sdn. Bhd. and Jalan Tuanku Abdul Rahman	Transport and Roads	Jalan Dang Wangi	4550.104866	8186.434074	174.889361	117.01222
4	2018	Tingkat 11, Wisma Yakin and Jalan Melayu	Transport and Roads	Jalan Dang Wangi	4245.675677	7559.368538	173.928142	100.820275
5	2019	Chow Kit and Jalan Raja Laut	Transport and Roads	Jalan Dang Wangi	4505.933684	7393.055064	168.863868	104.647237
6	2020	Pertama Complex and Tengah 4	Trade and Commercial	Jalan Dang Wangi	7452.791804	7452.791804	170.530942	106.228545

and urban development. The SDE area increased to 117.01 km^2, with a rotation angle of 174.89 degrees, indicating a reorientation towards transportation routes. In 2018, a contraction in the spatial extent of property crimes was noted, with focal points at Tingkat 11, Wisma Yakin, and Jalan Melayu. The SDE area reduced to 100.82 km^2 and the rotation angle adjusted to 173.93 degrees, aligning more closely with transport routes and road networks. Crime clusters shifted to Chow Kit and Jalan Raja Laut in 2019, influenced by socio-economic changes. The SDE area was 104.65 km^2, with a rotation angle of 168.86 degrees, showing significant reorientation towards new urban areas. In 2020, Complex Pertama and Tengah 4 emerged as major crime hotspots, indicating dynamic shifts in commercial areas. The SDE area expanded to 106.23 km^2, with a drastic increase in both X and Y standard deviations (XStdDist: 7452.79), reflecting broader dispersion and significant shifts in crime patterns due to socio-economic impacts such as the COVID-19 pandemic. The rotation angle of 170.53 degrees highlighted the influence of the pandemic on crime distribution, with a notable reorientation of crime clusters.

To quantify the stability of the spatial-dispersion metrics, we generated bootstrap-derived 95% confidence ellipses for each year's mean centre and SDE axes by resampling incident locations 1,000 times (Efron & Tibshirani, 1998). The resulting standard errors (e.g., ± 312 m for 2020's major axis) were used to plot dashed confidence bounds around the solid SDE outlines (Figure 4), demonstrating that the observed expansion in 2020 remains statistically significant at $p < 0.05$. The parallel application of Local Moran's I—with 999 Monte Carlo permutations—confirmed that the years showing northward ellipse rotations (2016-2017) coincide with high–high clusters along emerging transport corridors (Anselin, 1995) while the contraction in 2018 corresponds to a marked reduction in cluster significance ($p < 0.10$). Finally, kernel density overlays (bandwidth = 1 km) align closely with our SDE contours, further validating the spatial shifts in property crime concentration over 2015-2020 (Silverman, 1986).



(a-2015) (b-2016)

(c-2017) (d-2018)

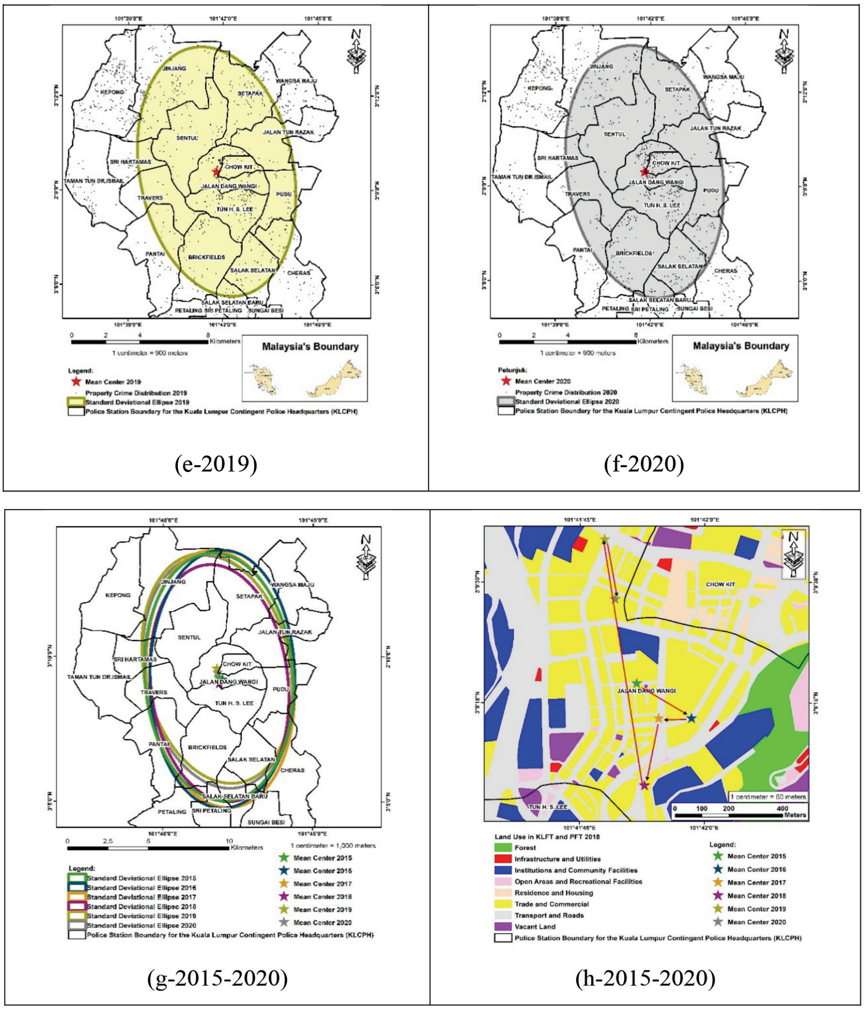


Figure 4: Movement of Mean Centre (MC), Standard Deviational Ellipses (SDE) for property crime from 2015 to 2020 based on land use in 2018

Discussion

Property Crime by Time (Hours)

The early morning decline in property crime (from 12:00 a.m. to 6:00 a.m.) reflects a period of reduced human activity in public spaces. The drop to the lowest point at 4:00 a.m. may coincide with the fact that most people are indoors, sleeping, resulting in fewer opportunities for crime. Additionally, law enforcement patrols tend to be more focused and effective during late-night hours, particularly in urban areas like Kuala Lumpur and Putrajaya, where police surveillance may increase during times of reduced public movement. This temporal gap in crime suggests that offenders prefer to avoid these hours due to the high risk of detection and the lack of accessible targets (Tompson & Bowers, 2013).

The morning resurgence in property crime, particularly starting at 6:00 a.m. could reflect the start of daily activities as people leave their homes for work or school, leaving their residences and vehicles unattended. This period also aligns with peak traffic times, potentially increasing the incidence of opportunistic crimes such as theft from vehicles or residential burglaries in quiet neighbourhoods. The continuation of elevated crime rates throughout the morning and into the early afternoon could indicate commercial crime, targeting businesses during operating hours (Felson *et al*., 2020). The second spike in property crime during the late afternoon and early evening hours may reflect increased activity in residential areas as people return home. The rise in incidents from 4:00 p.m. to 8:00 p.m. suggests that criminals may exploit the routine transitions of daily life, targeting homes and vehicles when individuals are more likely to be distracted or away from their residences. The high rate of crime during these periods underscores the need for targeted interventions, particularly in residential and commercial zones (Yim & Riddell, 2024).

The spatial dynamics we observe largely parallel recent findings in urban crime research. The strong evening peak (20:00) and low early-morning rate mirror patterns documented in other cities, consistent with routine-activity theory. For instance, studies of burglary patterns similarly find evening hours to be most active, aligning with observed routine transitions. The shifting MC from commercial hubs toward transport corridors (and back to mixed-use areas) resemble trends in other developing cities undergoing rapid change.

For example, Masron *et al*. (2025) analysed property crimes in Kuala Lumpur using regression methods and also noted central business districts as perennial hotspots, especially for vehicle theft. Similarly, Alazawi *et al*. (2022) found that spatial crime clusters often coincide with high-density commercial or transit zones, even in Southeast Asian settings. Our observed reorientation of the ellipse in 2019-2020 (with a marked northward tilt) is consistent with pandemic-driven mobility changes reported else, where X. Zhang and Chen (2023) and others noted that COVID-19 disruptions can push crime into new areas as human activity patterns shift.

Standard Deviational Ellipse (SDE) and Mean Centre (MC)

The analysis of MC and SDE for property crime from 2015 to 2020 offers crucial insights into the shifting dynamics of urban crime. The spatial and temporal changes in crime hotspots underscore the influence of socio-economic and environmental factors, highlighting the need for adaptive strategies in crime prevention and urban management (Lama & Rathore, 2017).

The dynamic nature of crime is illustrated by the movement of the mean centre and the changing dispersion patterns reveal the evolving landscape of property crime. This necessitates tailored and responsive law enforcement strategies to address emerging hotspots effectively (Kounadi *et al*., 2020; Ying, 2021). Understanding the spatial dynamics of crime enables law enforcement agencies to allocate resources more efficiently. By identifying high-risk areas, targeted interventions such as enhanced lighting, surveillance, and community engagement programmes can be implemented to deter criminal activities (Ali & Rais, 2018; Fitzpatrick *et al*., 2020).

Urban planners and policymakers can utilise these insights to inform land use planning and urban development. Creating safer urban environments through strategic planning can mitigate the factors contributing to crime (Cozens *et al*., 2005; Shamsuddin & Hussin, 2013; Cozens & Love, 2015; Sohn, 2016; Cozens & Love, 2017; Piroozfar *et al*., 2019; Sakina, 2020; Mohamad Bahari *et al*., 2021; Hua & Abas, 2022; Sebastian *et al*., 2022; Lee *et al*., 2023). This study emphasises the importance of collaboration between law enforcement, urban planners, policymakers, and local communities.

Addressing the root causes of property crime requires a multifaceted approach involving all stakeholders (Sakala & La Vigne, 2019; Gupta & Sayer, 2024). Regular monitoring of spatial crime patterns and the movement of the mean centre can provide early warning indicators of shifting crime trends. This proactive approach allows for timely interventions and the effective allocation of resources (Ratcliffe, 2004; Sheikh *et al*., 2017; Hutt *et al*., 2018; Braga *et al*., 2019).

Recent GIS-based mixed-methods studies reveal that urban crime in Southeast Asia tends to concentrate in central business districts and along major transport routes, that these patterns persisted even as travel restrictions changed. For example, Redzuan *et al*. (2025) found that violent crime in Kuala Lumpur and Putrajaya was initially "concentrated in commercial districts" and only later spread into transportation corridors and new suburban areas. Similarly, burglary in Kuching was strongly clustered in the urban core (Jubit *et al*., 2020). When COVID-19 hit, stricter lockdowns dramatically reduced overall crime–global analyses report drops of up to 57%-65% under full restrictions (Nivette *et al*., 2021)–and Malaysian data show property crimes in Kuching fell sharply during the Movement Control Order (Ahmad *et al*., 2024b).

Nonetheless, key hotspots remained active: Even during the lockdown, Kuching's central market and downtown areas continued to be targeted (Ahmad *et al*., 2024b). Jakarta likewise exhibited spatial variation driven by land use, with greener suburban districts experiencing much lower crime than dense central sectors (Fitriyyah & Pramana, 2025). In summary, these peer-reviewed GIS studies of cities like Kuala Lumpur, Kuching, and Jakarta suggest a regional pattern: Crime hotspots adhere to commercial hubs and major roads while pandemic travel restrictions depress crime citywide (especially under strict lockdowns), the remaining incidents still cluster around essential centres and transit nodes (Nivette *et al*., 2021; Redzuan *et al*., 2025).

In conclusion, our findings on Kuala Lumpur and Putrajaya align with recent Southeast Asian and developing-country research on urban crime. High-density commercial areas and major transit corridors consistently emerge as hotspots across studies. The movement of these hotspots over time–as captured by our mean centre and SDE metrics–reflects broader socio-economic changes (urban development, pandemic responses) and is similar to patterns reported in cities of neighbouring countries. These consistencies reinforce the validity of using GIS-based SDE/MC methods for crime analysis in Malaysia and suggest that policy lessons (such as focused policing of transport hubs) may transfer regionally.

Implications for Practice

The temporal analysis of property crime in Kuala Lumpur and Putrajaya has several practical implications for law enforcement, urban planning, and public safety strategies. Optimised Law Enforcement Resource Allocation: The findings suggest that law enforcement agencies should prioritise patrols and surveillance efforts during peak crime periods, particularly in the evening hours between 6:00 p.m. and 9:00 p.m. Focusing resources during these times could help prevent crimes of opportunity and deter potential offenders. Conversely, reduced manpower may be allocated during the early morning hours, when crime rates are consistently low (Dominguez & Asahi, 2017).

Community Engagement and Crime Prevention Programs: Awareness campaigns targeting the public, particularly during high-risk periods such as 10:00 a.m. to 3:00 p.m. and 6:00 p.m. to 9:00 p.m. could be implemented to encourage proactive crime prevention behaviours. Residents can be advised to adopt security measures such as locking doors, activating alarm systems, and being vigilant when parking or returning home (Sakala & La Vigne, 2019).

Urban Design and Infrastructure Improvements: The crime spikes observed during the afternoon and evening hours highlight potential vulnerabilities in urban infrastructure such as poorly lit streets, inadequate surveillance systems, and weak neighbourhood watch programmes. By improving street lighting, CCTV coverage, and traffic flow management, city planners could mitigate the environmental factors that contribute to property crime during peak hours (Zainudin & Abdul Malek, 2012; Chalfin *et al*., 2022).

Technological Solutions for Predictive Policing: The data provides a strong case for the adoption of predictive policing models that use machine learning and temporal crime patterns to optimise patrol schedules and resource deployment. Predictive analytics can allow law enforcement to pre-emptively target high-crime periods and reduce the likelihood of incidents occurring (Mastrobuoni, 2020; Shah *et al*., 2021).

Policy Recommendations for Safer Urban Environments: Policymakers should consider implementing crime reduction strategies tailored to the specific temporal trends in property crime. This may include zoning laws that encourage the development of mixed-use neighbourhoods, where residential, commercial, and recreational areas are integrated, leading to increased natural surveillance and a lower risk of crime (J. MacDonald, 2015; Humphrey *et al*., 2020).

The findings suggest that continuous analysis and monitoring of crime patterns are essential for developing effective crime prevention strategies. Collaborative efforts are crucial in fostering safer and more resilient neighbourhoods, addressing the complexity of crime, and promoting community well-being. By understanding the socio-economic factors driving crime and implementing targeted interventions, stakeholders can enhance public safety and urban livability (Weatherburn & Grabosky, 1999; Bainbridge *et al*., 2004; Ibrahim & Shafiq, 2019).

Future Recommendations

Enhanced policing strategies involve adopting flexible and responsive approaches to adapt to emerging crime trends. This includes increasing patrols in hotspot areas and utilising predictive policing technologies (Police Executive Research Forum, 2014; Fitzpatrick *et al*., 2019; Ikuesan *et al*., 2020). Urban planning and design should integrate crime data into urban design, focusing on improved street lighting, surveillance, and environmental design to deter criminal activities (Cozens, 2008; Ibimilua, 2008; Welsh & Farrington, 2008; Chalfin *et al*., 2022). Community engagement should involve implementing neighbourhood watch programs and community policing, promoting awareness campaigns, and encouraging community participation to create a safer environment (Bonsu *et al*., 2020; Mussa, 2023).

Technological integration entails utilising advanced technologies such as CCTV, drones, and crime mapping software to monitor and respond to criminal activities in real time. Data analytics can be employed to predict future crime trends and allocate resources effectively (Anderez *et al*., 2021; Serebrennikova & Serebrennikova, 2021). Economic and social interventions should address the root causes of crime through economic and social programmes such as job creation, education, and social services, particularly in high-crime areas (Landes, 1978; Mixon Jr & Mixon, 1996; Imran *et al*., 2018; Abdul Lasi & Yunusi, 2020).

The inclusion of uncertainty measures (or their proxies) would further strengthen such comparisons. Future work could apply bootstrapped confidence intervals or Monte Carlo simulations (Wang *et al*., 2015) to test whether observed MC shifts or SDE area changes are statistically significant. In lieu of formal uncertainty bounds, the multi-year consistency of our trends (alignment with theory and external studies) adds credibility. For example, the clear evening crime peak has persisted every year and the 2020 expansion of the ellipse matches broad COVID-era crime reports elsewhere. Incorporating more quantitative uncertainty analysis (e.g., using CrimeStat IV or spatial regression models) would be a useful extension, as noted in recent literature on crime pattern analysis (Kounadi *et al*., 2020; Masron *et al*., 2025).

Conclusions

This study highlights the importance of temporal analysis in understanding the dynamics of property crime in rapidly urbanising areas like Kuala Lumpur and Putrajaya. The data reveals significant diurnal patterns in crime, with two distinct peaks in the late afternoon and evening, and a trough during the early morning hours. These findings suggest that property crime is closely linked to the routine activities of urban residents, and that targeted interventions during specific time windows could significantly reduce crime rates. Understanding the Mean Centre (MC) and Standard Deviational Ellipse (SDE) for property crime from 2015 to 2020 offers valuable insights for developing evidence-based crime prevention strategies. These findings are essential for informing policing strategies, urban planning, and community engagement efforts, ultimately improving urban liveability and promoting community well-being.

The analysis reveals significant spatial and temporal variations in crime patterns that emphasise the need for adaptable and responsive measures. Effective crime prevention requires a combination of urban planning considerations, community engagement, technological integration, and socio-economic interventions. Continuous monitoring and analysis of crime patterns are necessary to inform adaptive strategies. By identifying emerging hotspots and understanding the socio-economic drivers of crime, stakeholders can implement targeted interventions to enhance community safety and urban liveability.

Future research should focus on understanding the underlying causes of these shifts and implementing comprehensive strategies to address property crime. Integrating advanced technologies and fostering community engagement will further strengthen crime prevention efforts and contribute to safer urban environments. Future research could explore the spatial correlation between different types of land use (e.g., commercial vs. residential) and property crime hotspots, as well as assess the effectiveness of crime prevention measures implemented based on temporal patterns.

Acknowledgements

This paper was funded under Fundamental Research Grant Scheme (FRGS) FRGS/1/2020/SS0/UNIMAS/01/1. The authors wish to express appreciation to Royal Malaysia Police Headquarters, Bukit Aman, the Criminal Investigation Department (Intelligence/Operations/Records-D4 Division JSJ), Contingent Police Headquarters in Kuala Lumpur, Malaysia Geospatial Data Infrastructure (MyGDI Program), and National Geospatial Centre (NGC) for giving support and cooperation.

Conflict of Interest Statement

The authors declare that they have no conflict of interest.

References

Abdul Lasi, M., & Yunusi, E. (2020). Factors influencing high crime rate in Kuala Lumpur urban community. *International Journal of Publication and Social Studies*, *5*(2), 147-153. https://doi.org/10.18488/journal.135.2020.52.147.153

Abdullah, S. N. H. S., Bohani, F. A., Nazri, Z. A., Jeffry, Y., Abdullah, M. A., Junoh, N., & Kasim, Z. A. (2018). Amenities surrounding commercial serial crime prediction at Klang Valley and Kuala Lumpur using K-Means clustering/Pengecaman kemudahan awam sekitar lokasi jenayah komersial bersiri di Lembah Klang dan Kuala Lumpur menggunakan kaedah gugusan K-Means. *Jurnal Teknologi*, *80*(4), 43-53. https://doi.org/10.11113/jt.v80.11484

Ahmad, A., Masron, T., Junaini, S. N., Kimura, Y., Barawi, M. H., Jubit, N., Redzuan, M. S., Bismelah, L. H., & Mohd Ali, A. S. (2024a). Mapping the unseen: Dissecting property crime dynamics in urban Malaysia through spatial analysis. *Transactions in GIS*, *28*(6), 1486-1509. https://doi.org/10.1111/tgis.13197

Ahmad, A., Kelana, M. H., Soda, R., Jubit, N., Mohd Ali, A. S., Bismelah, L. H., & Masron, T. (2024b). Mapping the impact: Property crime trends in Kuching, Sarawak, during and after the COVID-19 period (2020-2022). *Indonesian Journal of Geography*, *56*(1), 127-137. https://doi.org/10.22146/ijg.90057

Alanezi, F. (2010). Juvenile delinquency in Kuwait: Applying social disorganisation theory. *DOMES: Digest of Middle East Studies*, *19*(1), 68-81. https://doi.org/10.1111/j.1949-3606.2010.00006.x

Alazawi, M. A., Jiang, S., & Messner, S. F. (2022). Identifying a spatial scale for the analysis of residential burglary: An empirical framework based on point pattern analysis. *PLOS ONE*, *17*(2), 1-22. https://doi.org/10.1371/journal.pone.0264718

Ali, M. I., & Rais, M. (2018). Spatial pattern of crime with Geographic Information System (GIS) in Makassar, Indonesia. *International Journal of Science and Research (IJSR)*, *7*(4), 451-457.

Anderez, D. O., Kanjo, E., Anwar, A., Johnson, S. D., & Lucy, D. (2021). The rise of technology in crime prevention: Opportunities, challenges and practitioners perspectives. *Computer Science, Computers and Society*. https://arxiv.org/abs/2102.04204

Anselin, L. (1995). Local indicators of Spatial Association-LISA. *Geographical Analysis*, *27*(2), 93-115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Aos, S., Phipps, P., Barnoski, R., & Lieb, R. (2001). *The comparative costs and benefits of programs to reduce crime, version 4.0*. https://www.wsipp.wa.gov/ReportFile/756/Wsipp_The-Comparative-Costs-and-Benefits-of-Programs-to-Reduce-Crime-v-4-0_Full-Report.pdf

Bainbridge, B., Battle, W., Brown, S., Datesman, C., Davis, A., Evans, K., Fox, A., Giles, C., Hall, D., Mims, J., Perry, P. J., & Werts, T. (2004). Ending the culture of street crime: The lifers public safety steering committee of the state correctional institution. *The Prison Journal*, *84*(4), 48S-68S. https://doi.org/10.1177/0032885504269950

Balocchi, C., & Jensen, S. T. (2019). Spatial modeling of trends in crime over time in Philadelphia. *Annals of Applied Statistics*, *13*(4), 2235-2259. https://doi.org/10.1214/19-AOAS1280

Bhati, A. S. (2005). 4. Robust spatial analysis of rare crimes: An information-theoretic approach. *Sociological Methodology*, *35*(1), 227-289. https://doi.org/10.1111/j.0081-1750.2006.00169.x

Bonsu, G. A., Abaitey, A. K., & Chisin, A. V. (2020). Exploring community security interventions using design thinking approach. *Journal of Applied Security Research*, *15*(1), 73-83. https://doi.org/10.1080/19361610.2019.1689760

Braga, A. A., Turchan, B., Papachristos, A. V., & Hureau, D. M. (2019). Hot spots policing of small geographic areas effects on crime. *Campbell Systematic Reviews*, *15*(3). https://doi.org/10.1002/cl2.1046

Cesario, E. (2023). Big data analytics and smart cities: Applications, challenges, and opportunities. *Frontiers in Big Data*, *6*. https://doi.org/10.3389/fdata.2023.1149402

Chalfin, A., Hansen, B., Lerner, J., & Parker, L. (2022). Reducing crime through environmental design: Evidence from a randomised experiment of street lighting in New York City. *Journal of Quantitative Criminology*, *38*, 127-157. https://doi.org/10.1007/s10940-020-09490-6

Chemin, M., Kimalu, P., & Newman-Bachand, S. (2024). Courts, crime and economic performance: Evidence from a judicial reform in Kenya. *Journal of Public Economics*, *231*, 105035. https://doi.org/10.1016/j.jpubeco.2023.105035

Cozens, P. (2008). Crime prevention through environmental design in Western Australia: Planning for sustainable urban futures. *International Journal of Sustainable Development and Planning*, *3*(3), 272-292. https://doi.org/10.2495/SDP-V3-N3-272-292

Cozens, P., & Love, T. (2015). A review and current status of Crime Prevention through Environmental Design (CPTED). *Journal of Planning Literature*, *30*(4), 393-412. https://doi.org/10.1177/0885412215595440

Cozens, P., & Love, T. (2017). The dark side of Crime Prevention Through Environmental Design (CPTED). *Oxford Research Encyclopedia of Criminology and Criminal Justice*. https://doi.org/10.1093/acrefore/9780190264079.013.2

Cozens, P., Saville, G., & Hillier, D. (2005). Crime Prevention Through Environmental Design (CPTED): A review and modern bibliography. *Property Management*, *23*(5), 328-356. https://doi.org/10.1108/02637470510631483

da Silva, B. F. A. (2014). Social disorganisation and crime: Searching for the determinants of crime at the community level. *Latin American Research Review*, *49*(3), 218-230. https://doi.org/10.1353/lar.2014.0041

Dominguez, P., & Asahi, K. (2017). Crime time: How ambient light affect criminal activity. *Social Science Research Network (SSRN)*, 1-70. https://doi.org/10.2139/ssrn.2752629

Drozdowski, R., Wielki, R., & Tukiendorf, A. (2023). Overlapped Bayesian Spatio-Temporal Models to detect crime spots and their possible risk factors based on the Opole Province, Poland, in the years 2015–2019. *Crime Science*, *12*(10), 10. https://doi.org/10.1186/s40163-023-00189-0

Efron, B., & Tibshirani, R. J. (1998). *An Introduction to the Bootstrap*. Chapman & Hall. https://www.hms.harvard.edu/bss/neuro/bornlab/nb204/statistics/bootstrap.pdf

Elfversson, E., & Höglund, K. (2023). Urban growth, resilience, and violence. *Current Opinion in Environmental Sustainability*, *64*(101356). https://doi.org/10.1016/j.cosust.2023.101356

ESRI. (2022a). *How Directional Distribution (Standard Deviational Ellipse) Works*. Environmental Systems Research Institute, Inc. (ESRI). https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-directional-distribution-standard-deviationa.htm#:~:text=These%20measures%20define%20the%20axes,the%20axes%20of%20the%20ellipse

ESRI. (2022b). *How Mean centre Works*. Environmental Systems Research Institute, Inc. (ESRI). https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-mean-center-spatial-statistics-works.htm#:~:text=The%20mean%20center%20is%20the,of%20different%20types%20of%20features

Felson, M., Jiang, S., & Xu, Y. (2020). Routine activity effects of the COVID-19 pandemic on burglary in Detroit, March, 2020. *Crime Science*, *9*(10). https://doi.org/10.1186/s40163-020-00120-x

Fitriyyah, N. R., & Pramana, S. (2025). Green spaces and crime: Spatial modeling of socio-economic influences in Jakarta's urban areas, 2022. *The Journal of Indonesia Sustainable Development Planning*, *6*(1), 116-137. https://doi.org/10.46456/jisdep.v6i1.609

Fitzpatrick, D. J., Gorr, W. L., & Neill, D. B. (2019). Keeping score: Predictive analytics in policing. *Annual Review of Criminology*, *2*, 473-491. https://doi.org/10.1146/annurev-criminol-011518-024534

Fitzpatrick, D. J., Gorr, W. L., & Neill, D. B. (2020). Policing chronic and temporary hot spots of violent crime: A controlled field experiment. *Stat, arXiv*, 1-15. https://doi.org/10.48550/arXiv.2011.06019

Furfey, P. H. (1927). A note on Lefever's "Standard Deviational Ellipse". *American Journal of Sociology*, *33*(1), 94-98. https://www.jstor.org/stable/2765043?seq=3

Glaeser, E. L., & Sacerdote, B. (1999). Why is there more crime in cities? *Journal of Political Economy*, *107*(S6), S225-S258. https://doi.org/10.1086/250109

Gupta, S., & Sayer, S. (2024). Machine learning for public good: Predicting urban crime patterns to enhance community safety. *arXiv, Computer Science, Machine Learning*, 1-19. https://doi.org/10.48550/arXiv.2409.10838Focustolearnmore

He, Z., Tao, L., Xie, Z., & Xu, C. (2020). Discovering spatial interaction patterns of near repeat crime by spatial association rules mining. *Scientific Reports*, *10*(17262), 1-11. https://doi.org/10.1038/s41598-020-74248-w

He, Z., Wang, Z., Gu, Y., & An, X. (2023). Measuring the influence of multiscale geographic space on the heterogeneity of crime distribution. *ISPRS International Journal of Geo-Information*, *12*(10), 437. https://doi.org/10.3390/ijgi12100437

Hew, W. W. L., Lau, S. H., Goh, G. G. G., & Low, B. Y. (2019). Managing crime for urban wellbeing and sustainable housing delivery: Through the lens of housing residents and developers in Malaysia. *Geografia: Malaysian Journal of Society and Space*, *15*(4), 106-121. https://doi.org/10.17576/geo-2019-1504-08

Hua, T. W., & Abas, H. (2022). Systematic literature review Crime Prevention Through Environmental Design (CPTED) in physical security for IT organisation article history. *Open International Journal of Informatics (OIJI)*, *10*(1), 69-83. https://doi.org/10.11113/oiji2022.10n1.189

Humphrey, C., Jensen, S. T., Small, D. S., & Thurston, R. (2020). Urban vibrancy and safety in Philadelphia. *Environment and Planning B: Urban Analytics and City Science*, *47*(9), 1573-1587. https://doi.org/10.1177/2399808319830403

Hutt, O., Bowers, K., Johnson, S., & Davies, T. (2018). Data and evidence challenges facing place-based policing. *Policing: An International Journal*, *41*(3), 339-351. https://doi.org/10.1108/PIJPSM-09-2017-0117

Ibimilua, A. F. (2008). The ideal design of a potentially safe community. *Journal of Applied Security Research*, *4*(1-2), 129-140. https://doi.org/10.1080/19361610802210293

Ibrahim, R., & Shafiq, M. O. (2019). Extended results from the measurement and analysis of safety in a large city. *International Journal of Big Data Intelligence (IJBDI)*, *6*(2), 86-101. https://doi.org/10.1504/ijbdi.2019.098891

Ikuesan, R. A., Ganiyu, S. O., Majigi, M. U., Opaluwa, Y. D., & Venter, H. S. (2020). Practical approach to urban crime prevention in developing nations. *NISS '20: Proceedings of the 3rd International Conference on Networking, Information Systems & Security*, 1-8. https://doi.org/10.1145/3386723.3387867

Imran, M., Hosen, M., & Chowdhury, M. A. F. (2018). Does poverty lead to crime? Evidence from the United States of America. *International Journal of Social Economics*, *45*(10), 1424-1438. https://doi.org/10.1108/IJSE-04-2017-0167

Jamru, L. R., Hashim, M., Phua, M. H., Jafar, A., Sakke, N., Eboy, O. V., Imang, U., Natar, M., Ahmad, A., & Mohd Najid, S. A. (2024). Exploring intensity metrics in raw LiDAR data processing for tropical forest. *IOP Conference Series: Earth and Environmental Science, 12th IGRSM International Conference and Exhibition on Geospatial & Remote Sensing 29/04/2024 - 30/04/2024 Kuala Lumpur, Malaysia*, *1412*(012005), 1-13. https://doi.org/10.1088/1755-1315/1412/1/012005

Johnson, S. D. (2010). A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics*, *21*(4-5), 349-370. https://doi.org/10.1017/S0956792510000082

Jubit, N., Masron, T., & Marzuki, A. (2020). Spatial pattern of residential burglary. The case study: Kuching, Sarawak. *Planning Malaysia: Journal of the Malaysian Institute of Planners*, *18*(3), 190-201. https://doi.org/10.21837/pm.v18i13.785

Kounadi, O., Ristea, A., Araujo, A., & Leitner, M. (2020). A systematic review on spatial crime forecasting. *Crime Science*, *9*(7), 1-22. https://doi.org/10.1186/s40163-020-00116-7

Lama, S., & Rathore, S. S. (2017). Crime mapping and crime analysis of property crimes in Jodhpur. *International Annals of Criminology*, *55*(2), 205-219. https://doi.org/10.1017/cri.2017.11

Landes, W. M. (1978). An economic study of U.S aircraft hijacking, 1961-1976. *The Journal of Law and Economics*, *21*(1), 1-31. https://doi.org/10.1086/466909

Lee, S., Lee, C., Nam, J. W., Moudon, A. V., & Mendoza, J. A. (2023). Street environments and crime around low-income and minority schools: Adopting an environmental audit tool to assess Crime Prevention Through Environmental Design (CPTED). *Landscape and Urban Planning*, *232*. https://doi.org/https://doi.org/10.1016/j.landurbplan.2022.104676

MacDonald, J. (2015). Community design and crime: The impact of housing and the built environment. *Crime and Justice*, *44*(1), 333-383. https://doi.org/10.1086/681558

MacDonald, J. M., Knorre, A., Mitre-Becerril, D., & Chalfin, A. (2024). Place-based approaches to reducing violent crime hot spots: A review of the evidence on public health approaches. *Aggression and Violent Behavior*, *78*(101984). https://doi.org/10.1016/j.avb.2024.101984

Mansourihanis, O., Maghsoodi Tilaki, M. J., Sheikhfarshi, S., Mohseni, F., & Seyedebrahimi, E. (2024). Addressing urban management challenges for sustainable development: Analysing the impact of neighborhood deprivation on crime distribution in Chicago. *Societies*, *14*(8), 139. https://doi.org/10.3390/soc14080139

Marzuki, F. N. (2016, June 10). Public housing projects becoming crime haunts. *The Star Online*. https://www.thestar.com.my/news/nation/2016/06/10/public-housing-projects-becoming-crime-haunts

Masron, T., Ahmad, A., Abdillah, K. K., Mohd Ali, A. S., Junaini, S. N., & Kimura, Y. (2025). Deciphering property crime through OLS regression: A demographic study. *International Social Science Journal*, *75*(256), 395-412. https://doi.org/10.1111/issj.12558

Masron, T., Ahmad, A., Jubit, N., Sulaiman, M. H., Rainis, R., Redzuan, M. S., Junaini, S. N., Jamian, M. A. H., Mohd Ali, A. S., Salleh, M. S., Zaini, F., Soda, R., & Kimura, Y. (2024). *Crime Map Book*. Centre for Spatially Integrated Digital Humanities (CSIDH), Faculty of Social Sciences and Humanities, Universiti Malaysia Sarawak. https://www.researchgate.net/publication/384572873_Crime_Map_Book

Mastrobuoni, G. (2020). Crime is terribly revealing: Information technology and police productivity. *The Review of Economic Studies*, *87*(6), 2727-2753. https://doi.org/10.1093/restud/rdaa009

Mburu, E., & Mutua, F. (2023). Investigating the influence of land use and alcohol outlet density on crime in Juja sub-county, Kenya. *Journal of Geovisualisation and Spatial Analysis*, *7*(10). https://doi.org/10.1007/s41651-023-00141-5

Melo, S. N. de, Frank, R., & Brantingham, P. (2017). Voronoi diagrams and spatial analysis of crime. *Professional Geographer*, *69*(4), 579-590. https://doi.org/10.1080/00330124.2017.1288578

Mixon Jr, F. G., & Mixon, D. C. (1996). The economics of illegitimate activities: Further evidence. *The Journal of Socio-Economics*, *25*(3), 373-381. https://doi.org/10.1016/S1053-5357(96)90011-6

Mohamad Ali, S. N., Tarmidi, Z., & Mat Nor, N. A. (2020). Review of conceptual model to spatially assessing safe city level of affordable housing in Malaysia. *IOP Conference Series: Earth and*

Environmental Science, Volume 540, 10th IGRSM International Conference and Exhibition on Geospatial & Remote Sensing 20-21 October 2020, *540*(1), 1-9. https://doi.org/10.1088/1755-1315/540/1/012046

Mohamad Bahari, N. A., Zainol, H., Sakip, S. R., Ahmad, A., Sallehudin, N. S., & Muhammad Soffian, N. S. (2021). The key contribution factors of safety through crime prevention towards higher quality of life in neighborhood residential. *International Journal of Academic Research in Business and Social Sciences*, *11*(6), 315-324. https://doi.org/10.6007/ijarbss/v11-i6/10126

Muhamad Ludin, A. N., Abd. Aziz, N., Hj Yusoff, N., & Wan Abd Razak, W. J. (2013). Impacts of urban land use on crime patterns through GIS application. *Planning Malaysia: Journal of the Malaysian Institute of Planners (Special Issue 2: 2013, Geospatial Analysis in Urban Planning)*, *11*(2), 1-22. https://doi.org/10.21837/pm.v11i2.113

Mussa, M. A. (2023). Neighborhood watch as a strategy of community policing program: A case of Zanzibar. *East African Journal of Education and Social Sciences*, *4*(2), 52-57. https://doi.org/10.46606/eajess2023v04i02.0275

Nader, E., Wasileski, G., & Poteyeva, M. (2023). Community perceptions, concerns for privacy, and support for law enforcement use of aerial surveillance in Baltimore. *Crime & Delinquency*. https://doi.org/10.1177/00111287231189720

Nagulendran, K., Padfield, R., Aziz, S. A., Amir, A. A., Abd. Rahman, A. R., Latiff, M. A., Zafir, A., Quilter, A. G., Tan, A., Arifah, S., Awang, N., Azhar, N., Balu, P., Gan, P. C., Hii, N., Reza, M. I. H., Lakshmi Lavanya, R. I., Lim, T., & Mahendra, S., *et al*. (2016). A multi-stakeholder strategy to identify conservation priorities in Peninsular Malaysia. *Cogent Environmental Science*, *2*(1), 1-19. https://doi.org/10.1080/23311843.2016.1254078

Nivette, A. E., Zahnow, R., Aguilar, R., Ahven, A., Amram, S., Ariel, B., Burbano, M. J. A., Astolfi, R., Baier, D., Bark, H. M., Beijers, J. E. H., Bergman, M., Breetzke, G., Concha-Eastman, I. A., Curtis-Ham, S., Davenport, R., Díaz, C., Fleitas, D., Gerell, M., *et al*. (2021). A global analysis of the impact of COVID-19 stay-at-home restrictions on crime. *Nature Human Behaviour*, *5*, 868-877. https://doi.org/10.1038/s41562-021-01139-z

Oliveira, M., & Menezes, R. (2019). Spatial concentration and temporal regularities in crime. *Understanding Crime through Science*, 1-13. https://doi.org/10.48550/arXiv.1901.03589

Piroozfar, P., Farr, E. R. P., Aboagye-Nimo, E., & Osei-Berchie, J. (2019). Crime prevention in urban spaces through environmental design: A critical UK perspective. *Cities*, *95*. https://doi.org/10.1016/j.cities.2019.102411

Police Executive Research Forum. (2014). *Future Trends in Policing*. U.S. Department of Justice, Office of Community Oriented Policing Services. https://www.policeforum.org/assets/docs/Free_Online_Documents/Leadership/future%20trends%20in%20policing%202014.pdf

Pooja, B. S., Guddattu, V., & Rao, K. A. (2024). Crime against women in India: District-level risk estimation using the small area estimation approach. *Frontiers in Public Health*, *12*. https://doi.org/10.3389/fpubh.2024.1362406

Ratcliffe, J. H. (2004). The hotspot matrix: A framework for the spatio-temporal targeting of crime reduction. *Police Practice and Research: An International Journal*, *5*(1), 5-23. https://doi.org/10.1080/1561426042000191305

Ray, B. (2016). Quality of life in selected slums of Kolkata: A step forward in the era of pseudo-urbanisation. *Local Environment: The International Journal of Justice and Sustainability*, *22*(3), 365-387. https://doi.org/10.1080/13549839.2016.1205571

Redzuan, M. S., Masron, T., Yusuf, A., Junaini, S. N., Kimura, Y., Barawi, M. H., Salleh, M. S., Rainis, R., & Ahmad, A. (2025). Urban violent crime dynamics in Kuala Lumpur and Putrajaya: Utilising spatial temporal techniques. *Forum Geografi: Indonesian Journal of Spatial and Regional Analysis*, *39*(1), 1-19. https://doi.org/10.23917/forgeo.v39i1.6456

Royal Malaysia Police Criminal Investigation Department (RMP CID) Bukit Aman Headquarters. (2021). Crime record for Kuala Lumpur and Selangor Contingent Police Headquarters 2015-2020. https://www.rmp.gov.my/infor-korporate/

Sakala, L., & La Vigne, N. (2019). Community-driven models for safety and justice. *Du Bois Review: Social Science Research on Race*, *16*(1), 253-266. https://doi.org/10.1017/S1742058X19000146

Sakina, B. (2020). A study on crime prevention through environmental design concept application in a private house in Yogyakarta, Indonesia. *IOP Conference Series: Earth and Environmental Science, Volume 426, The 3rd International Conference on Eco Engineering Development 13-14 November 2019*, *426*(1). https://doi.org/10.1088/1755-1315/426/1/012093

Sebastian, T., Love, H., Washington, S., Barr, A., Rahman, I., Paradis, B., Perry, A. M., & Cook, S. (2022). *A new community safety blueprint: How the federal government can address violence and harm through a public health approach*. Brookings. https://www.brookings.edu/articles/a-new-community-safety-blueprint-how-the-federal-government-can-address-violence-and-harm-through-a-public-health-approach/

Serebrennikova, A. V., & Serebrennikova, M. S. (2021). Criminological innovations in criminality prevention: Status and perspectives. *SHS Web of Conferences*, *108*, 03002. https://doi.org/10.1051/shsconf/202110803002

Shah, N., Bhagat, N., & Shah, M. (2021). Crime forecasting: A machine learning and computer vision approach to crime prediction and prevention. *Visual Computing for Industry, Biomedicine, and Art*, 4(1), 1-14. https://doi.org/10.1186/s42492-021-00075-z

Shamsuddin, S., & Hussin, N. A. (2013). Safe city concept and Crime Prevention Through Environmental Design (CPTED) for urban sustainability in Malaysian cities. *American Transactions on Engineering & Applied Sciences*, *2*(3), 223-245. https://tuengr.com/ATEAS/V02/223-245M.pdf

Sheikh, J. A., Shafique, I., Sharif, M., Zahra, S. A., & Farid, T. (2017). IST: Role of GIS in crime mapping and analysis. *International Conference on Communication Technologies (ComTech - 2017): 19-21 April 2017, Military College of Signals, National University of Sciences & Technology*, 126-131. https://doi.org/10.1109/COMTECH.2017.8065761

Sheykhi, M. (2016). Increasing crimes vs. population density in megacities. *Sociology and Criminology-Open Access*, *4*(1), 1-2. https://doi.org/10.4172/2375-4435.1000136

Sohn, D. W. (2016). Residential crimes and neighbourhood-built environment: Assessing the effectiveness of Crime Prevention Through Environmental Design (CPTED). *Cities*, *52*, 86-93. https://doi.org/10.1016/j.cities.2015.11.023

Tabangin, D. R., Flores, J. C., & Emperador, N. F. (2008). Investigating crime hotspot places and their implication to urban environmental design: A geographic visualisation and data mining approach. *International Journal of Information, Control and Computer Sciences*, *2*(12), 4004-4012. https://doi.org/10.5281/zenodo.1330639

Tacoli, C., Mcgranahan, G., & Satterthwaite, D. (2014). *Urbanisation, rural-urban migration and urban poverty.* World Migration Report

2015 (Background Paper). https://www.iom.int/sites/default/files/our_work/ICP/MPR/WMR-2015-Background-Paper-CTacoli-GMcGranahan-DSatterthwaite.pdf

Tan, K. G., Chuah, H. Y., & Luu, N. T. D. (2018). A case study on Malaysia and Singapore: Nexus amongst competitiveness, cost of living, wages, purchasing power and liveability. *Competitiveness Review*, *28*(2), 172-193. https://doi.org/10.1108/CR-09-2017-0062

Tompson, L., & Bowers, K. (2013). A stab in the dark?: A research note on temporal patterns of street robbery. *Journal of Research in Crime and Delinquency*, *50*(4), 616-631. https://doi.org/10.1177/0022427812469114

Vanderschueren, F. (1996). From violence to justice and security in cities. *Environment and Urbanisation*, *8*(1), 93-112. https://doi.org/10.1177/095624789600800119

Wang, B., Shi, W., & Miao, Z. (2015). Confidence analysis of standard deviational ellipse and its extension into higher dimensional euclidean space. *PLOS ONE*, *10*(3), e0118537. https://doi.org/10.1371/journal.pone.0118537

Weatherburn, D., & Grabosky, P. (1999). Strategic approaches to property crime control. *Policing and Society: An International Journal of Research and Policy*, *9*(1), 77-96. https://doi.org/10.1080/10439463.1999.9964803

Welsh, B. C., & Farrington, D. P. (2008). Effects of improved street lighting on crime. *Campbell Systematic Reviews*, *4*(1), 1-51. https://doi.org/10.4073/csr.2008.13

Wen, Y., Qi, H., Long, T., & Zhang, X. (2024). Designed for safety: Characteristics and trends in crime prevention through environmental design research. *Journal of Asian Architecture and Building Engineering*, 1-19. https://doi.org/10.1080/13467581.2024.2366823

Witte, A. D. (1996). Urban crime: Issues and policies. *Housing Policy Debate*, *7*(4), 731-748. https://doi.org/10.1080/10511482.1996.9521241

Wong, D. W. S., & Lee, J. (2005). *Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS*. John Wiley and Sons, Inc. https://www.wiley.com/en-us/Statistical+Analysis+of+Geographic+Information+with+ArcView+GIS+and+ArcGIS-p-9780471468998

Yim, H. N., & Riddell, J. R. (2024). The spatial dynamics of commercial burglary during the COVID-19 lockdown in San Francisco. *Journal of Experimental Criminology*, *20*, 187-205. https://doi.org/10.1007/s11292-022-09530-0

Ying, L. H. (2021). Discovering spatio-temporal pattern of city crime. *Preprints 2021*, 2021010292. https://doi.org/10.20944/preprints202101.0292.v1

Zainudin, A. Z., & Abdul Malek, J. (2012). Keberkesanan program bandar selamat dari persepsi penduduk. Kajian Kes: Bandaraya Shah Alam. *Jurnal Teknologi (Sciences & Engineering)*, *53*(1), 13-34. https://doi.org/10.11113/jt.v53.111

Zhang, X., & Chen, P. (2023). The impact of urban facilities on crime during the pre and pandemic periods: A practical study in Beijing. *International Journal of Environmental Research and Public Health*, *20*(3). https://doi.org/10.3390/ijerph20032163

Zhang, Z., Zhao, M., Zhang, Y., & Feng, Y. (2023). How does urbanisation affect public health? New evidence from 175 countries worldwide. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.1096964

Zhou, Y., Wang, F., & Zhou, S. (2023). The spatial patterns of the crime rate in London and its socio-economic influence factors. *Social Sciences*, *12*(6), 340. https://doi.org/10.3390/socsci12060340