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GEOGRAPHICAL INVESTIGATION OF CRIME CONCENTRATION AND DISPERSION: MAPPING HOTSPOTS OF PROPERTY OFFENCES IN SAIFABAD CIRCLE OF HYDERABAD

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Abstract:

The field of crime studies has witnessed significant advancements in recent years, embracing a comprehensive and interdisciplinary approach. However, notable gaps remain in the investigation of property related criminal offences within their spatial context in India. This study investigates the complex relationship between geographic factors and the nature, type, and intensity of property related offences within the administrative jurisdiction of the Hyderabad Police Commissionerate, using crime data collected from 2016 to 2018. The study aims to generate insights into the relative significance and influence of the area's morphology and socio-cultural-governance structures on property crime incidence. To facilitate spatial understanding, crime analysis tools, including hotspot analysis and gradient analysis, were employed. The thematic layers obtained from the Telangana State Remote Sensing Applications Centre (TSRSAC) were utilised for spatial analysis. The results of the study shedding light on the spatio-temporal dimensions of property related crime in the study area. The crime patterns were found to be closely linked to land use and socio-economic conditions, with dense mixed-use and informal areas exhibiting higher incidences of robbery and theft. Vulnerability was observed to rise in zones characterised by informal employment and gentrification. Weekday crime rate peaks corresponded to commuting activity, while monthly spikes aligned with salary disbursement and festival cycles. Predictive analysis revealed elevated crime intensity in March, July, and October, as well as on Tuesdays during the first and last weeks of each month in certain sectors. Peripheral and transit corridors remained persistent hotspots for crimes, possibly due to transient populations and limited surveillance. The findings contribute to a deeper understanding of the dynamics underlying property related criminal offences in the study area and serve as an empirical resource for future advancements in spatial crime studies.

Key Words: Crime and Space – Hotspots – Land Use - Impactors- Challenges

1. Introduction:

The growing concern over urban crime has spurred a substantial body of literature

emphasizing spatial analysis, data-driven policing, and socio-economic correlations to enhance public safety strategies. However, there appears to be a lack of evolved research models and methods in the sphere of spatiality of crime in urban areas. Oliveira (2021) critiques the traditional per capita rankings of crime, arguing that such measures are inadequate when comparing cities of differing scales. The study reveals that crime does not necessarily increase linearly with population, highlighting the need for more uncommon approaches that incorporate scaling laws to better understand crime patterns. Similarly, Sharma et al. (2016) explore spatial crime mapping and hotspot analysis in Ajmer City, demonstrating how geospatial techniques can support local law enforcement in identifying high-risk zones and optimising surveillance strategies. Their findings stress the utility of mapping historical crime data to predict future incidents and inform resource deployment based on proximity and intensity of crime occurrences. Complementing these insights, Cheng and Chen (2021) provide a comprehensive examination of urban crime in the context of urban informatics. They trace the evolution of crime prevention from traditional criminology to modern data-driven policing, emphasising the effectiveness of analytical tools and big data technologies in urban security management. The authors advocate for a shift toward evidence-based strategies that align with the complexities of modern cities. Supporting this direction, Gupta (2020) investigates the relationship between urbanisation and crime in Delhi, establishing a strong correlation between crime incidence and factors like population growth, mobility, and vehicle density. The study integrates GIS and GPS technologies, and the results reveal that areas with high population density and public neglect are especially vulnerable to crime. He also identifies public perceptions of safety, showing that while police presence can enhance the feeling of security, there is considerable dissatisfaction with the response time and accessibility of law enforcement.

Collectively, these studies underscore the multidimensional nature of urban crime and the value of integrating spatial data, technology, and community feedback in crafting effective crime prevention and control measures. Crime Prevention Through Environmental Design (CPTED) has emerged as a promising framework for mitigating crime. Cozens and Love (2015) highlight the importance of environmental interventions, such as improved street lighting and the strategic placement of surveillance cameras, in deterring criminal behaviour. Crowe (2000) emphasizes that urban spaces should be designed with safety in mind, ensuring that public areas are well-lit, visible, and actively monitored by both authorities and the community. This design philosophy aligns with Weisburd and Bernasco's (2018) findings that well-planned environments reduce opportunities for crime, particularly in residential areas with limited surveillance.

In these backdrops, the objective of the study is set as to analyse the spatio-temporal dynamics of property offence-related crime in the Saifabad Circle of Hyderabad. It conducts a temporal assessment of offences from 2016 to 2018 and examines spatial variations to identify dominant sectors and key crime zones. The research further explores crime patterns across different time frames, like diurnal, date-wise, and month-wise, to capture behavioural and situational trends. Sector-wise hotspot mapping is undertaken to visualise crime concentration, followed by the determination of preference scores to rank

vulnerability levels within the study area. The study also intends to examine the potential for predictive analysis in strategic urban crime management.

2. Study Area:

The study area of Saifabad Circle falls within the Hyderabad Police Commissionerate. The total extent of the study area is approximately 3.21 sq.km. bordering Panjagutta, Nampalli, Abid road, Narayanguda, Chikkadpally, and Ramgopalpet police station limits. The study area is bounded on the north by Hussain Sagar Lake, known for its parks and recreational zones. The western side is predominantly occupied by middle-income residential neighbourhoods, while the southern part features government institutions, hostels, and stadiums. To the east lies the Birla Mandir, set amidst undulating terrain and surrounded by a mix of residential and commercial buildings. The study area does not align with the existing mandal divisions used in the district's census structure. Therefore, the demographic data sourced from the mandal census had to be adjusted to correspond to the mapped area in this case study.

The study area is dynamic due to its central location within the central business district (CBD) of Metropolitan Hyderabad (Fig. 1). It is characterised by a unique blend of residential and commercial establishments, as well as serving as the administrative headquarters for the states of Andhra Pradesh and Telangana during the study period. Specifically, one sector of the study area encompasses significant administrative and cultural centres, including various central and state government offices. Another sector has been known for accommodating short-term commuters, such as those staying in hotels and lodges, who visit the state capital for political, administrative, and business purposes.

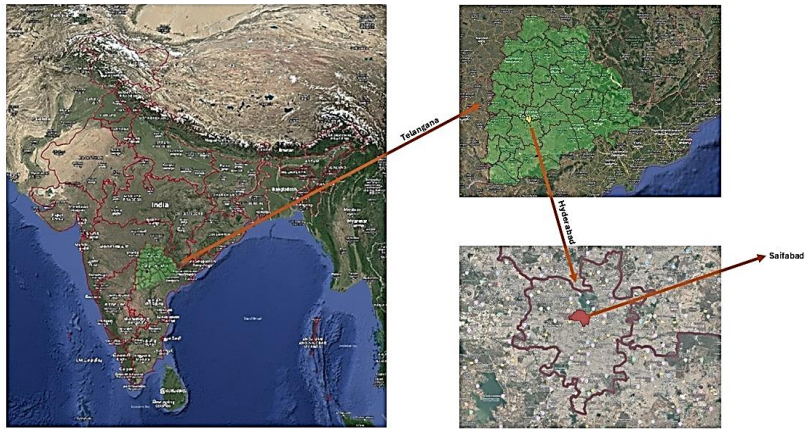


Fig. 1: Location Map of the Study Area.

While the movement of people in this locality has undergone significant changes, particularly with a reduction in commuters following the shift of Andhra Pradesh's capital city

from Hyderabad to Amaravathi in 2018—this study does not delve into the dynamics of people's movement and its impact on local businesses. The focus of this study is primarily on understanding the spatial aspects of property crime and the societal implications of offences. Relevant references from related studies are used to test or support the arguments and structure the study, ensuring consistency in the incidence of crime analysis.

Saifabad jurisdiction is classified into seven sectors by analysing its demographic characteristics and land use patterns. Based on this assessment, a broad and interpretive typology of land use was developed, as summarised in Table 1. The classification incorporates key parameters such as the dominant land use type, sector designation, demographic and socio-economic attributes, and notable spatial or functional features.

Table 1: Sector-wise Summary Table with Socio-Economic Profiles:

Sector	Dominant Land Use	Title	Demographic & Socio-Economic Profile	Key Features
1	Urban Core with Dense Mixed Housing and Administrative Concentration	Central Business Districts (CBDs)-Residential with roadside commercial and slum clusters	Predominantly middle- and lower-income groups; high population density; informal and semi-formal employment	Slums (Chintal Basti), major state roads, religious sites, GHMC & State Stats Office
2	Transitional Residential Zone with Emerging Commercial Pressure	Informal Settlements / Slum Clusters - Residential with increasing commercial use	Mixed-class residents; signs of gentrification; student and working-class populations	Govt. Degree College, HMWSSB, demarcation issues; triangular configuration
3	Mixed-Use Entertainment and Residential Hub with Demographic Variability	Entertainment and Leisure Districts - Mixed residential and entertainment	Socio-economically diverse; the West is more densely populated with middle/lower classes; the eastern institutional zone	NTR Garden, IMAX, Secretariat, Post Office
4	Service-Oriented Transit Corridor with Moderate Density	Transit Hubs - Residential and service-oriented	Predominantly working class; renters and service workers; moderate housing density	Lakdikapool railway station, hotels, educational institutions, and the Khairatabad metro proximity
5	High-Activity Mixed Zone with Cultural and Governmental Anchors	Religious and cultural Hubs - Mixed-use: residential, service, entertainment	High population density; mix of slum dwellers, govt. employees, and service workers	Birla Temple, Birla Science Museum, Nizam Club, Income Tax Office
6	Low-Density Institutional and Recreational Axis	Industrial/Institutional Zones - Entertainment, govt. and residential mix	Sparse southern population; north has govt. employees, professionals, and recreational users	LB Stadium, Public Garden, Assembly, DGP Office, RBI, AG Office
7	Peripheral Government-Commercial Fringe with Pockets of Informality	Govt. Offices with Slum Clusters - Mixed-use: Govt., residential, commercial	Mixed socio-economic class; informal workers in slum areas; govt. staff and business class in commercial zones	Govt. offices, eastern commercial strip, southwest slum clusters and open spaces

3. Database and Methodology:

The property offence-related crime data used in this study were collected from the Telangana State Remote Sensing Applications Centre (TSRSAC) website. The study focuses on ten types of offences, including Ordinary Theft, Attention Diverting, Robbery and Snatching, Automobile Theft, Dacoity, Extortion, Housebreak in Day, Housebreak in Night, and Pseudo Police. Detailed information, such as the incidence location (address with latitude and longitude) and occurrence date, was considered for the spatio-temporal analysis.

Land use type data, including residential, commercial, entertainment, government administrative areas, density of built-up areas, and different types of roads, were obtained from the ArcGIS Pro base map layer and from the field data collected in 2018.

The collected data were analysed based on date, weekday, month, and subdivision, integrating spatial and non-spatial data. GIS techniques were employed, utilising ArcGIS Pro software for overlay and geo-querying, as well as statistical methods such as standard deviation. Furthermore, spatial analysis models such as the urban crime heat-intensity map and crime prediction models were employed, leveraging tools such as Kernel Density Estimation (KDE) to calculate the intensity of crime at each location (point of crime) based on proximity and frequency, through weighted allocation using a Gaussian kernel function.

3.1 Kernel Density and Gradient Change

Kernel Density and density change tools were utilised for crime analysis, identifying dense clusters of different crime types in the study area (Nakaya and Yano 2010). Density change analysis was conducted to detect temporal changes in crime patterns (Hu et al. 2018). The KDE algorithm calculates the intensity of crime at each location based on the proximity and frequency of nearby crime points, using a specified search radius (bandwidth).

The Kernel Density Estimation (KDE) formula is as follows:

Crime Heat Intensity (I) at location x:

$$I(x) = k \sum_{i=1}^{n} \frac{1}{h^2} \left(\frac{d(x, x_i)}{h} \right)$$

Where, x: Location where intensity is estimated; x_i: Location of crime event I; d (x, x_i): Distance between x and crime event x_i; h: Bandwidth (search radius or smoothening parameter); K: Kernel function (usually Gaussian or quadratic)

A Gaussian kernel function was employed to assign greater weight to crimes closer to the location of interest. The resulting output is a continuous raster surface, with areas of

higher density represented by warmer colours on the heat map. This method effectively highlights crime-prone zones, assisting in hotspot detection and spatial trend analysis.

3.2 Standard Deviation and Frequency Analysis

The study employed standard deviation analysis to assess the variability in crime frequency across different sectors from 2016 to 2018. Standard deviation measures the dispersion of data points from the mean, used to evaluate how consistently or inconsistently crimes were distributed spatially within each crime category. This statistical approach enabled the identification of sectors that significantly deviated from the average crime incidence, offering critical insights into the temporal and spatial fluctuations in criminal activity (Leitner 2013; Santos 2016). The standard deviations of crime data were used to identify below average Sectors (< Mean), above average Sectors (+ 1σ), high concentration Sectors (+ 2 σ), and very high concentration Sectors (+ 3 σ).

3.3 Hotspot Analysis

The optimised hotspot tool in ArcGIS Pro was employed to identify significant clusters of hot and cold spots, indicating overall positive and negative confidence in crime occurrences. The hotspot analysis presents a comprehensive examination of the spatial characteristics of offences, identification of crime hotspots, and crime gradients (Chainey 2008).

3.4 Predictive Analysis and Spatial Correlation Techniques

Predictive analysis in this study was conducted using trend extrapolation and spatial correlation techniques to forecast potential crime hotspots based on historical crime data from 2016 to 2018. By applying linear regression and GIS-based mapping, the method identifies patterns and projects future crime-prone sectors with reasonable accuracy (Hu et al. 2018).

Formula (Z-Score Normalisation for Crime Prediction):

$$z_{ij} = \frac{C_{ij} - u_j}{\sigma_j}$$

Where, z_{ij}: Standardised crime score (Z-score) for sector I during time period j (month, day of week, or date range); C_{ij}: Actual or predicted number of crimes in sector i during time j; u_j: Mean number of crimes across all the sectors for the time period j; σ_j: Standard deviation of crimes across all sectors for time period j.

3.5 Crime Heat Intensity Map of Kernel Density Estimation (KDE)

The Crime Heat Intensity Map was generated using Kernel Density Estimation (KDE), a spatial analysis method that calculates the density of crime incidents over a

defined area by applying a smoothening function around each data point. This method highlights high-risk zones (hotspots) by converting discrete crime occurrences into a continuous surface, enabling visualisation of spatial crime concentration across sectors (Martin and Ralphs 2014).

4. Results and Discussion:

4.1 Crime Incidence and Dispersion

The investigation of property crime through spatial and temporal analysis is crucial in understanding the underlying factors contributing to crime within urban areas. The study area is situated in the heart of Hyderabad, provides an ideal case study due to its diverse socio-economic landscape and dense population. As Brantingham and Brantingham (1995) highlight, urban spaces, particularly those characterised by high foot traffic or poorly lit areas, often serve as "crime generators" and "crime attractors." This concept aligns with Cohen and Felson's (1979) Routine Activity Theory, which suggests that crime is the result of a convergence between motivated offenders, suitable targets, and the lack of capable guardians.

A consolidated 3-year data of the property offences for 2016, 2017, and 2018 that occurred in the Saifabad area has been mapped and presented in Fig. 2, 3, 4 and 5.

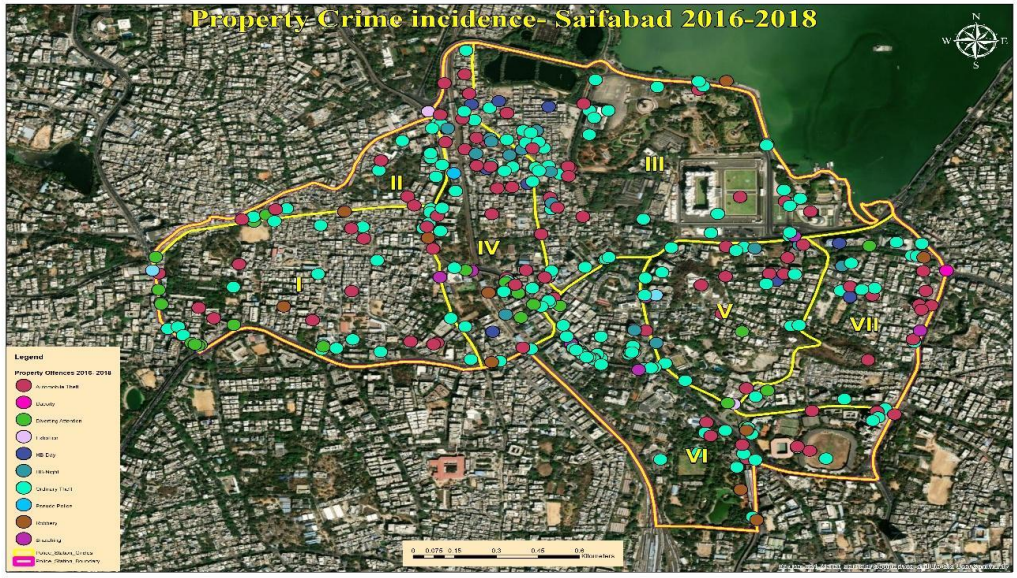


Fig. 2: Property Crime Incidence Study Area 2016-2018

In India, research into the spatial dynamics of crime has grown in importance, with studies from cities like Chennai and Delhi beginning to leverage GIS and spatial data. Gandhirajan's (2002) pioneering work in Chennai laid the groundwork for understanding

how territoriality within criminal gangs could influence crime patterns. While such research has yet to be fully integrated into law enforcement strategies in many Indian cities, there is growing recognition of the value of spatial analysis in understanding property crimes. In the study area, for instance, a combination of commercial activity, infrastructure, and socio-economic vulnerability creates conditions conducive to theft and robbery. These findings align with global research, which suggests that crime is often a product of a city's-built environment, as well as the socio-economic status of its residents.

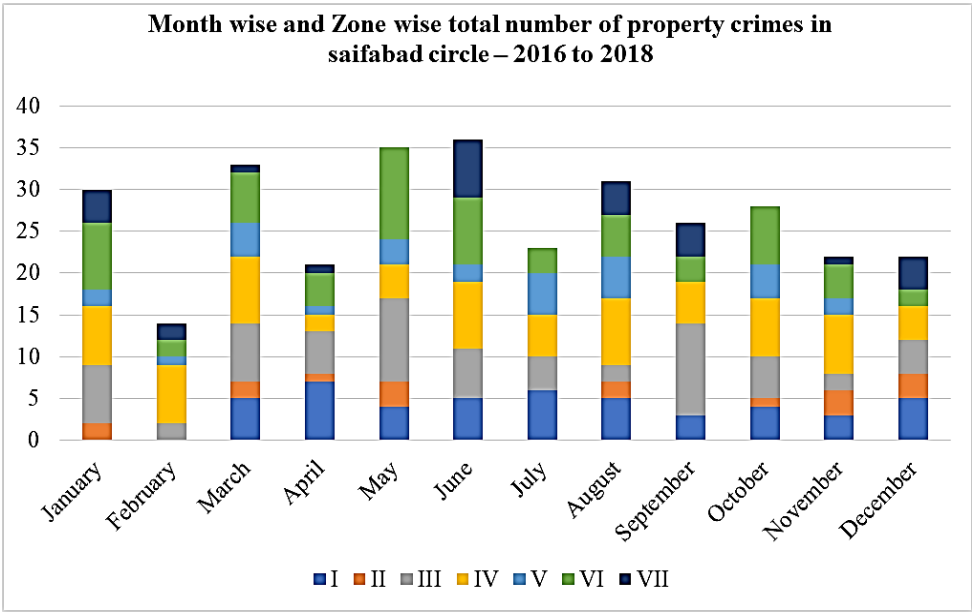


Fig. 3: Month-wise and zone-wise total number of property crimes in Study Area 2016-2018

From the Fig. 3, it can be observed that of the three years' aggregate, the highest number of offences was 36, representing the 11.21 % of the total offences that occurred in the month of June alone in all the years 2016, 2017 and 2018. The second highest occurrences were 35 instances (10.90 %) in May, followed by 33 offences (10.28 %) in March. The months of February and April recorded the lowest offences of 14 (4.36 %) and 21 (6.54 %) respectively.

In all three years (2016, 2017 and 2018), (fig.04) the highest number of offences committed was 72 (22.43%), in Sector IV alone. The second largest number were committed in Sector II - 65 instances (20.25 %) in Sector III, the third highest number of crimes were 63 (19.63%) in Sector VI, and the least number of offences were 17 (5.30 %) in Sector II, the second lowest number of offences were 28 (8.72 %) in Sector V, of the total crimes in the study area.

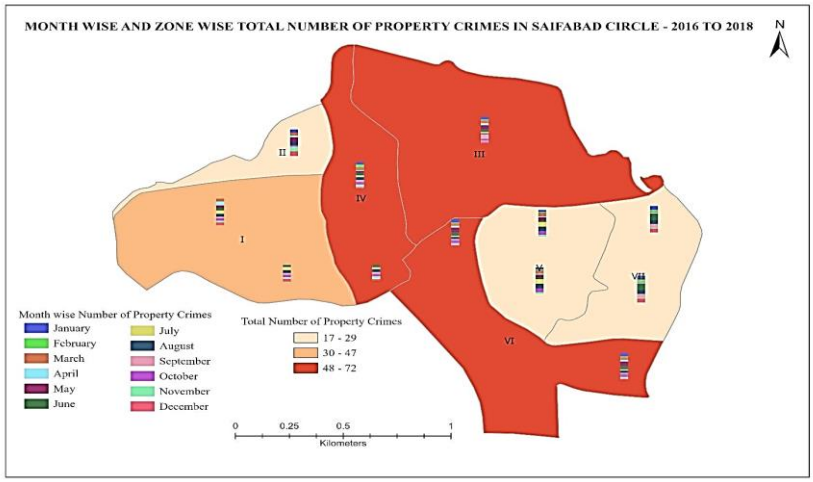


Fig. 4: Month-wise and zone-wise total number of property crimes in Study Area 2016-2018

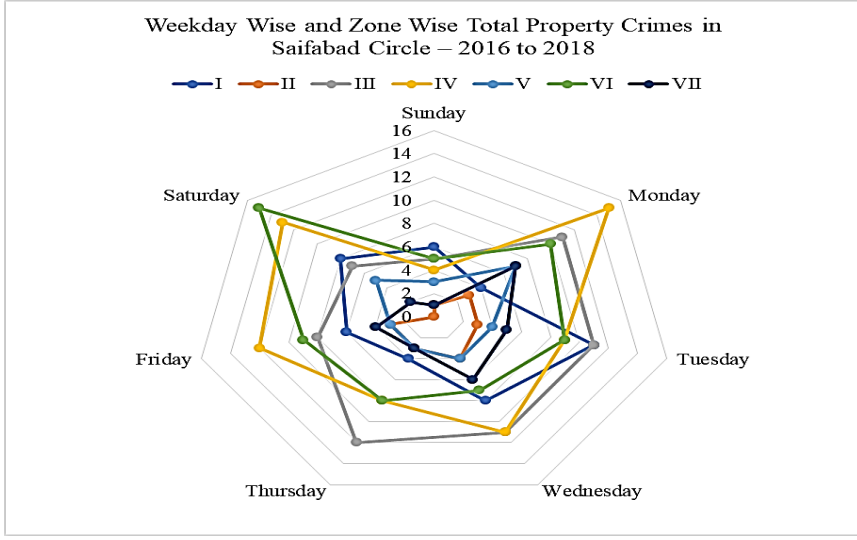


Fig. 5: Weekday Wise and Zone Wise Total Property Crimes in Study Area 2016-2018

An analysis of crime incidence in relation to weekdays was undertaken to examine both the frequency and temporal distribution of offences. The results, as illustrated in the above Fig. 5, highlight variations in crime intensity across different days of the week, offering insights into the temporal patterns and potential routine activity influences on criminal behaviour.

In the three years 2016, 2017 and 2018, the highest number of offences, 57 (17.76 %) of the total crimes, were committed on Mondays. The second highest number of offences was 52 (16.20 %) of the total crimes were committed on Tuesdays, the third

highest instances of 51 (15.89 %) of the total crimes were committed on Wednesdays, and the least number of crimes was 25 (7.79 %) of the total crimes, committed on Sundays. The second least number of crimes was 41 (12.77 %) committed on Wednesdays and Thursdays.

4.2 Hotspot Analysis

The Crime Hotspot Map was generated using Kernel Density Estimation, highlights high-risk zones (hotspots) by converting discrete crime occurrences into a continuous surface, enabling visualisation of spatial crime concentration across sectors.

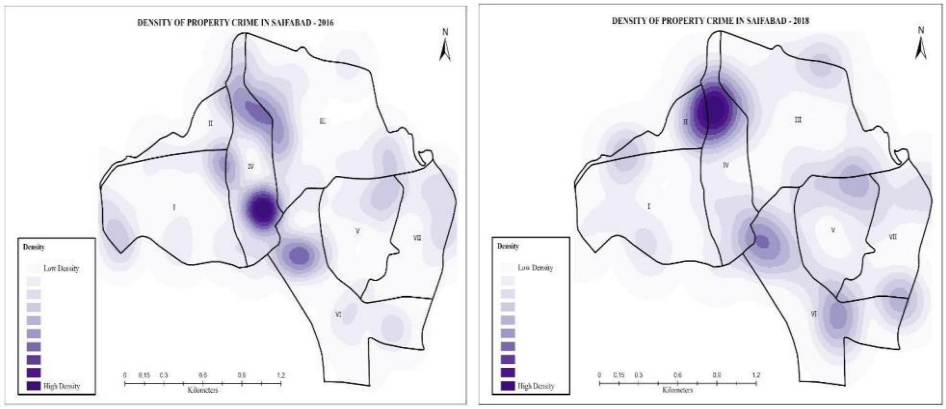


Fig. 6: Density of Property Crime in Study Area – 2016 & 2018

Between 2016 and 2018, the spatial distribution of property crimes (Fig. 6) in the Saifabad police station jurisdiction revealed consistent high-density zones in Sectors IV and VI, particularly along their southern and eastern sides. In contrast, Sectors V and VII consistently displayed low crime densities across all three years, while Sectors I and II generally remained low-density areas, except for localised increases in 2018. Overall, crime hotspots remained concentrated in specific peripheral and sectoral zones, with limited spread into central or traditionally low-density areas.

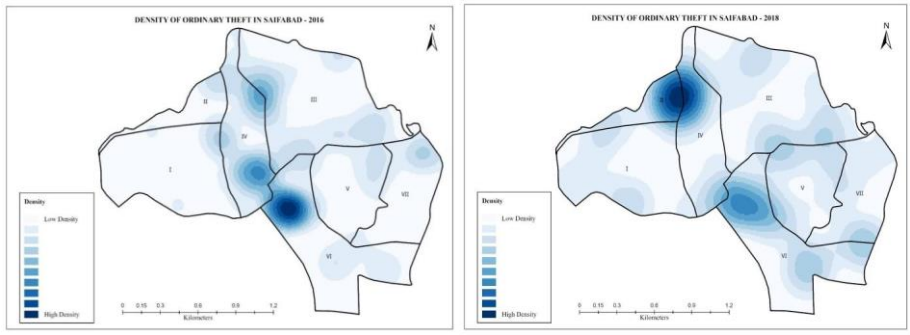


Fig. 7: Density of Ordinary Theft in Study Area – 2016 & 2018

In 2016, ordinary theft (Fig. 7) accounted for 42.67% of all property-related crimes, with higher concentrations observed in Sectors IV and VI. In 2017, the share of ordinary theft rose to 64.04% and by 2018, Sector II emerged as a new hotspot, with its northern, eastern, and southern parts showing high crime intensity. Sector IV maintained its high-density status, particularly along the west–east stretch. Despite fluctuations in total crime share, the spatial concentration of ordinary theft remained centred in key sectors like IV and VI, with new emerging pockets in Sector II.

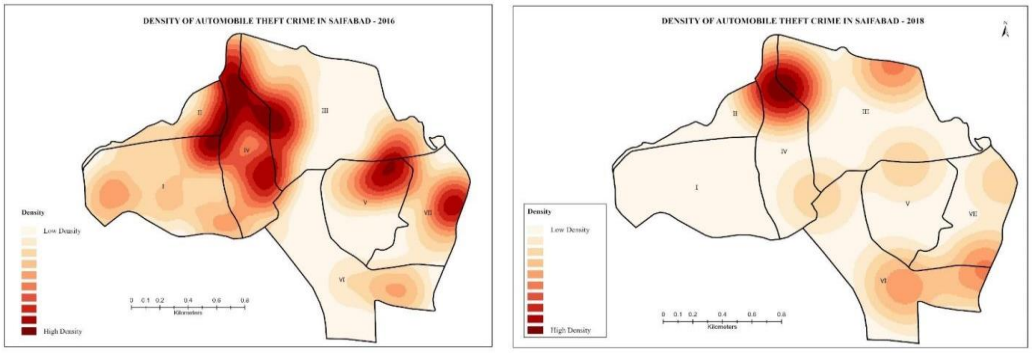


Fig. 8: Density of Automobile Theft Crime in Study Area – 2016 & 2018

In 2016, automobile theft (Fig.08) accounted for a significant 34% of total property crimes, with high-density areas concentrated in Sectors II, III, IV, V, and VII. This crime pattern indicates widespread vulnerability across multiple sectors, particularly those with high traffic or vehicle presence. By 2017 and 2018, the proportion of automobile theft declined to 23.6% and 15.85%, respectively, though Sectors II, III, and IV remained hotspots. Overall, the trend shows a gradual decline in automobile theft, but with clear spatial recurrence in selected sectors requiring targeted interventions.

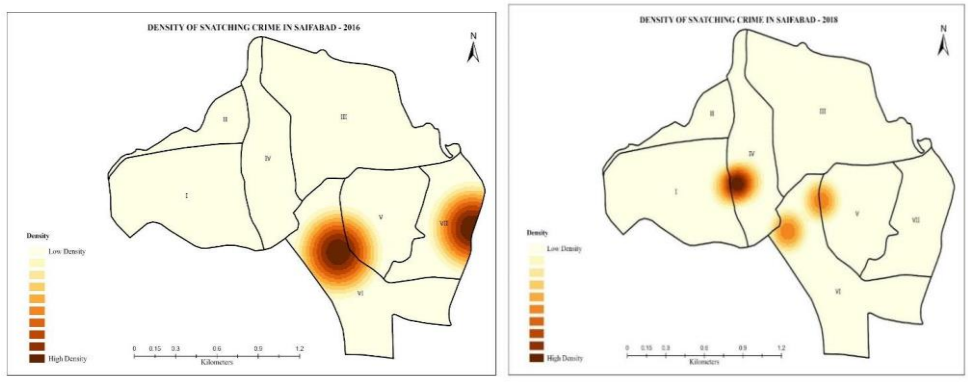


Fig. 9: Density of Snatching Crime in Study Area – 2016 & 2018

In 2016, snatching crimes (Fig. 9), such as theft of chains, mobiles, and purses, accounted for 1.33% of total property offences in the Study Area. These incidents were

primarily concentrated in Sectors VI and VII. By 2018, the proportion of snatching crimes increased significantly to 4.88%. The spatial pattern shifted to Sectors I and IV, emerged as the new high-crime zones. The shift indicates a redistribution of snatching crime across the jurisdiction, likely influenced by changing public movement patterns and surveillance measures.

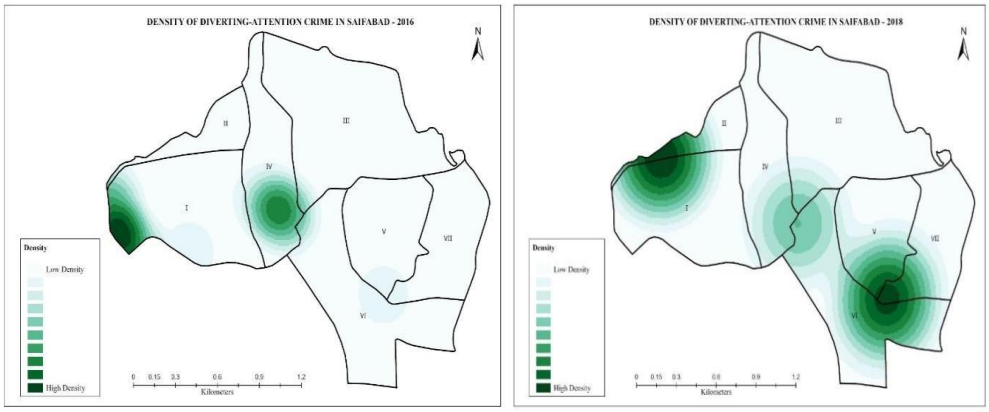


Fig. 10: Density of Diverting-Attention Crime in Study Area – 2016 & 2018

In 2016, attention-diverting crimes (Fig. 10), typically involving theft through distraction, accounted for 10% of total property offences. High-density areas were concentrated primarily in Sectors I and IV. By 2017 and 2018, the proportion of these crimes declined to 4.49%, though the spatial pattern became more dispersed. Sector I remained a recurring hotspot, particularly in its southwest and northwest areas. In 2018, attention-diverting crimes shifted to Sectors V, VI, and VII.

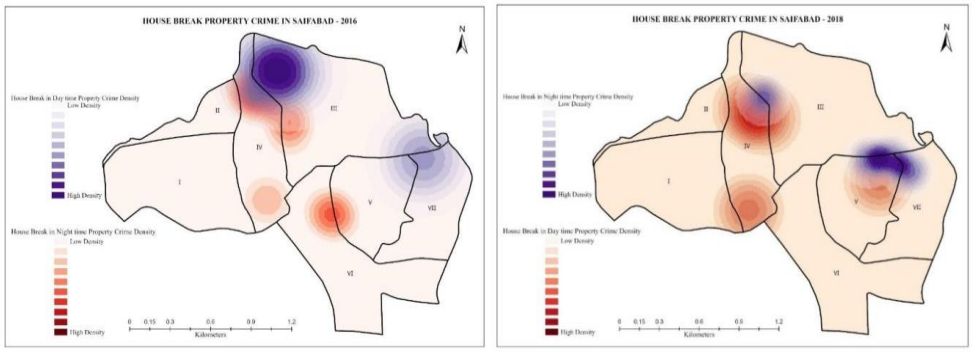


Fig. 11: House Break Property Crime in Study Area – 2016 & 2018

Between 2016 and 2018, the distribution of house break-in offences became more dispersed across the study area (Fig. 11), despite fluctuations in their overall share. In 2016, such crimes accounted for 8% of total offences, concentrated mainly in Sectors III, IV, VI, and VII. Night-time incidents prevailed in the northern parts, whereas day-time

crimes occurred more often in the southern sectors. Sector IV exhibited dense clusters along its eastern and western edges, while Sector I consistently recorded low activity. In 2018, house break-ins rose sharply to 9.76%, with hotspots shifting to Sectors III, IV, V, and VII. Activity was concentrated in the eastern and northern parts of Sector IV and the western and southeastern areas of Sector III

Day-time and night-time offences were equally distributed at 4.88% each, with both displaying similar spatial patterns. Sectors I, II, and VI continued to show low crime densities, reinforcing their position as relatively safer zones over the three years. Overall, the spatial analysis suggests a recurring concentration of house break crimes in specific pockets, particularly in Sectors III and IV.

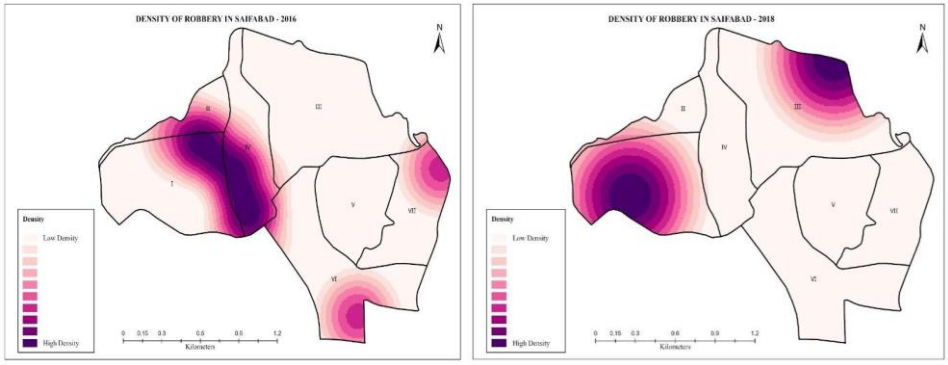


Fig. 12: Density of Robbery in Study Area – 2016 & 2018

In 2016, robbery (Fig. 12) constituted 4% of total property offences in the study area, with higher crime densities concentrated in Sectors I, II, and IV. By 2017 and 2018, the incidence of robbery declined slightly to 2.25% and 2.44%, respectively. In 2017, Sector VI was the only area with high-density robbery activity, particularly in its northeast side, while all other sectors showed low levels. However, in 2018, robbery hotspots shifted to Sectors I and III, with Sector I's southern part and Sector III's north-eastern side recording the highest densities. Despite the overall drop in robbery cases, localised surges in different sectors point to dynamic spatial variations over time.

4.3 Crime Frequency Variations through Standard Deviation:

In this study, Standard deviation was applied to evaluate the spatial variation in crime frequency across different sectors in the study area from 2016 to 2018, across various crime categories. This method enables the identification of sectors that significantly deviate from the average, thereby revealing spatial concentrations and fluctuations in crime incidence.

Fig. 13 represents the distribution of sectors across these categories, highlighting both the frequency and percentage of crime occurrences over the study period. The graph compares the number of high-frequency and low-frequency sectors for each crime type.

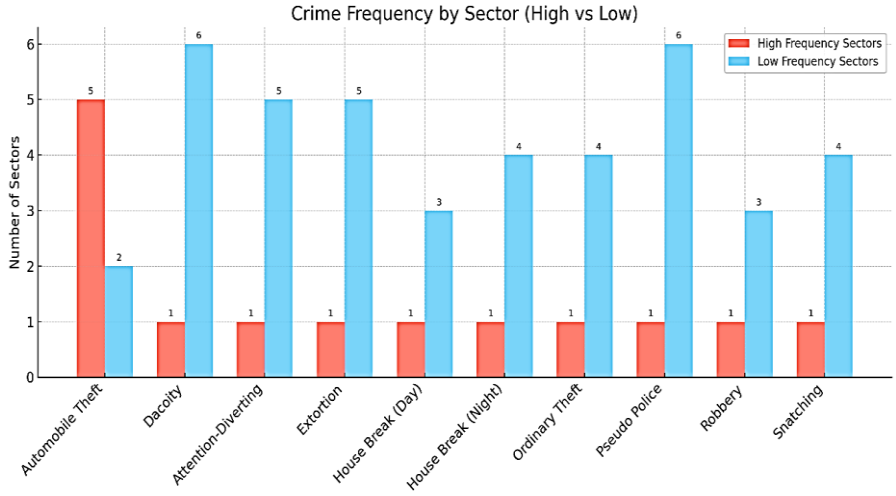


Fig. 13: Crime Frequency by Sector (High vs Low)

The spatial analysis of crime frequency revealed significant variation across sectors in the study area between 2016 and 2018. Automobile theft emerged as the most spatially dispersed crime, with five sectors exceeding the high-frequency threshold (Mean + 1σ), highlighting its widespread nature and suggesting the need for broader urban surveillance measures. In contrast, crimes such as Dacoity, Extortion, Attention-Diverting Thefts, and House Break-ins (Day and Night) showed highly localised patterns, with only one sector each registering high frequency. This points to the existence of discrete high-risk pockets requiring targeted interventions rather than city-wide policing strategies. Additionally, a notable number of sectors recorded frequencies below the mean for less prevalent crimes such as Dacoity and Pseudo Police offences, indicating rare but spatially concentrated criminal activities.

While Ordinary Theft and Robbery are relatively more common, their spatial distribution was uneven, with only one sector falling under the high-concentration category and four under the low-frequency bracket. These findings underscore the value of using standard deviation-based classifications and spatial statistics to detect both persistent and emerging crime hotspots.

4.4 Predictive Analysis

Predictive policing technologies have gained traction worldwide, with agencies in cities like Los Angeles and London using statistical models to forecast crime patterns and allocate resources effectively. While such models hold promise, scholars like Lum and Isaac (2016) caution that these systems may inadvertently perpetuate bias, particularly in areas with historically disproportionate policing. Similarly, Williams et al. (2017) explore the potential of big data and social media in crime detection. These new tools provide real-time insights but require careful consideration to avoid reinforcing existing socio-economic disparities.

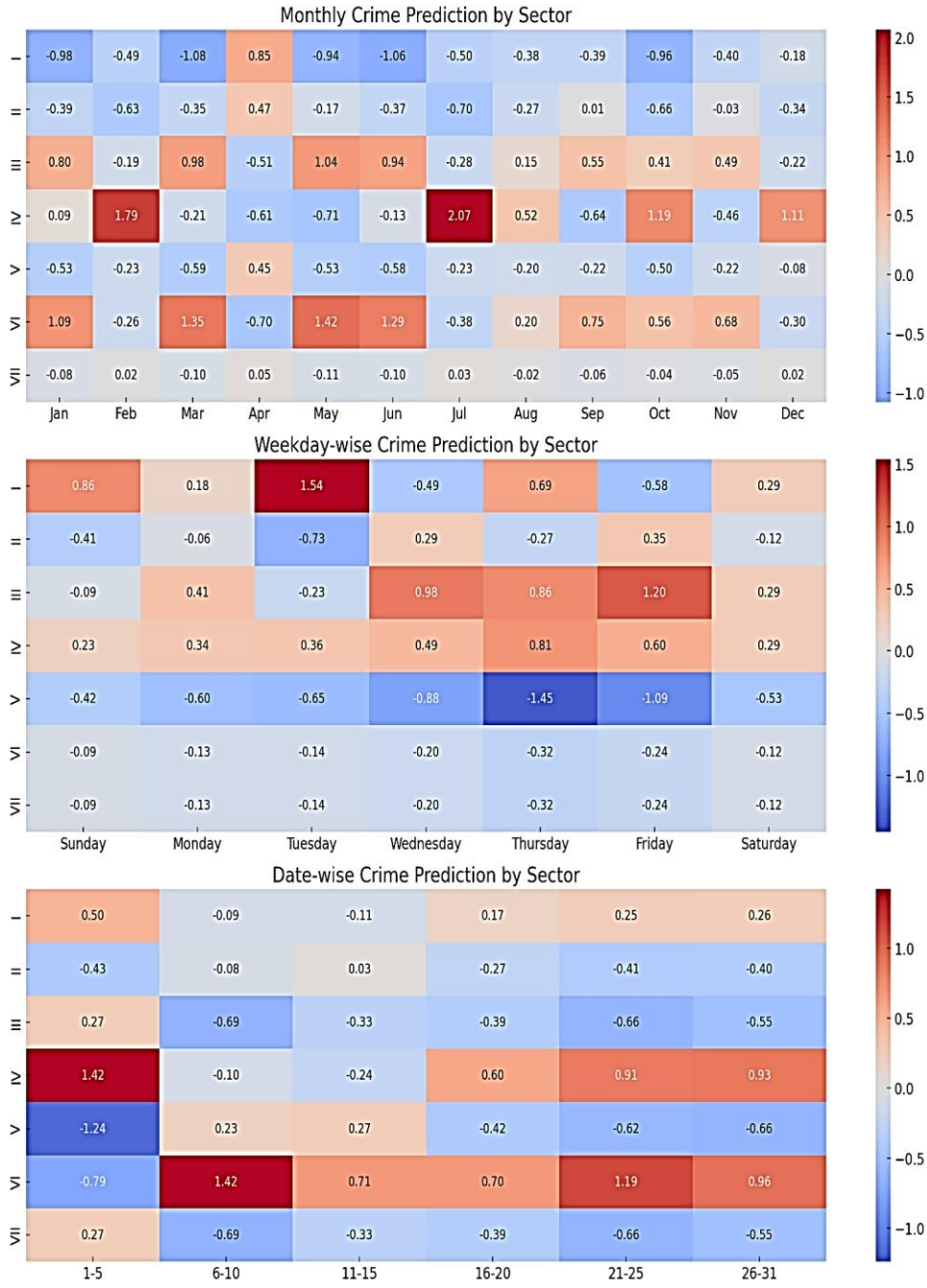


Fig.14: Monthly, Weekday-wise and Date-wise Crime Prediction by Sector

Based on the predictive heatmaps for monthly, weekday-wise, and date-wise crime predictions across the seven sectors of the Study Area, notable temporal and spatial patterns emerged (Fig. 14). Sector IV consistently demonstrates elevated predicted crime

intensity, particularly in March, July, and October, as well as on Tuesdays and during the first and last weeks of each month. This indicates a potential correlation between public activity cycles and crime incidence, likely tied to administrative movements and crowd flows within Sector IV's transit and institutional zones. Sector VI also shows high monthly crime projections in May, June, and September, with peaks during mid-to-late month periods (21st–31st), possibly reflecting patterns of financial activity, footfall around institutional complexes, or salary-related street crimes.

Conversely, Sectors II, III, and VII show consistently lower predictive scores across most timeframes, suggesting relatively subdued crime risks. Notably, Sector III sees slight increases during summer months (April–July) and on Wednesdays and Thursdays, aligning with its mixed-use entertainment profile, which might see more crowd interaction midweek. Meanwhile, Sector I, the dense urban core, reveals intermittent but notable spikes in April and October and during weekends, pointing to leisure-linked vulnerabilities. These insights underscore the importance of targeted policing strategies, with higher alertness during temporal hotspots (late months, mid-week) and sector-specific interventions that factor in both land use and socio-economic dynamics.

4.5 Crime Intensity Heat Map

To analyse the spatial distribution of crimes, a Crime Heat Intensity Map was generated using Kernel Density Estimation (KDE). Each crime incident was treated as a point feature, and KDE was applied to estimate the density of crime events across space.

The crime intensity heat map (Fig.15) provides a visual representation of sector-wise distribution and severity of different property and theft-related crimes. By categorising crime occurrences into three statistical thresholds, Above Average (1σ), High Concentration (2σ), and Very High Concentration (3σ), the map reveals distinct spatial patterns of crime clustering within urban sectors.

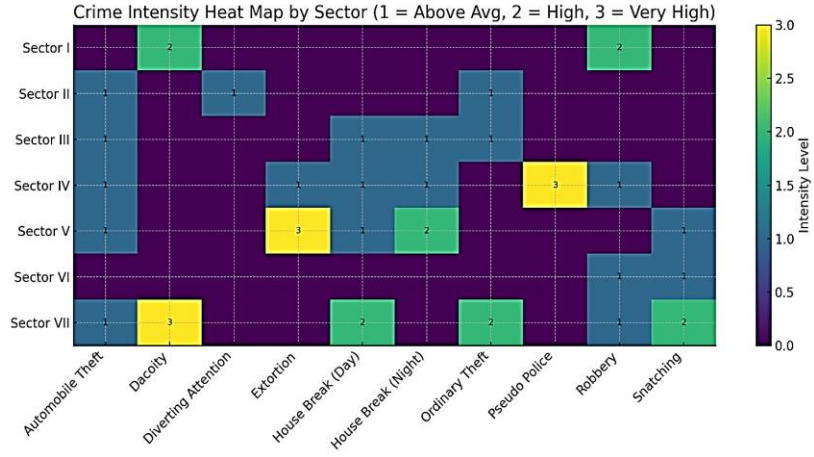


Fig.15: Crime Intensity Heat Map by sector

The areas with high foot traffic, such as markets, transport corridors, and commercial-residential zones like Sectors I, IV, V, and VII, recorded more thefts, snatchings, and property-related crimes. On the other hand, sectors with stable land use, such as Sector VI with more institutional presence, experienced fewer but more targeted crimes like nighttime house break-ins. The overall risk parameters for the study area in the context of time stamp and locational influence are projected below in Table 2, while highlighting sectoral differences.

Table 2: Property Crime in Study Area for the period 2016 – 2018 and Risk Patterns

Dimension	High-Risk Sectors	Low-Risk Sectors	Notable Temporal Peaks
Monthly Trends	Sector IV (Feb, Jul, Oct, Nov) Sector II, VI, III, V	Sectors I, II, V (most months)	Festivals, Salary Cycles
Weekday Patterns	Sector IV (All days) Sector I (Wed–Sat)	Sectors V, VI, (majority of blocks)	Start & End of Month
Date-wise Trends	Sectors IV & VI (1–5 & 21–31)	Sectors II, III, V, VII (majority blocks)	Relatively Stable

Sector IV is recorded consistently high-risk across time scales, needs sustained attention. Sector VI is recorded with crime peaks linked to economic cycles such as festivals, salary cycles of employees, indicating the relevance of the flow of cash/money and density of population. Sectors I and III is recorded high-risk during mid-week (Wed–Sat), requires additional enforcement. These sectors are identified as high-risk sectors due to increased incidence of crime, denoting the necessity of deploying resources during the mid-week in addition to temporal peaks and seasons. Sectors V, VI, and VII are generally stable but should be monitored for emerging shifts. These sectors are classified as low-risk sectors with possible shift due to dynamism in the spatial trends over time.

5. Spatial Interplay between Sectors and Crime Incidence

The crime intensity heat map, when examined in conjunction with the socio-economic and land-use characteristics of the study area's sectors, reveals significant spatial disparities in crime occurrence. These disparities underscore the role of urban morphology, socio-economic stratification, and functional land use in shaping crime patterns. The following discussion presents a sector-wise interpretation of crime intensity in relation to local demographic and socio-spatial dynamics.

Sector I, categorised as a Central Business District (CBD) with dense residential and administrative functions, demonstrates high intensity in Robbery and Snatching. The co-existence of lower- and middle-income populations, slum settlements such as Chintal Basti, and significant footfall due to government offices and religious institutions, creates a

conducive environment for crimes of opportunity. High pedestrian movement and limited surveillance in crowded and informal spaces may facilitate such criminal activities.

Sector II, characterised as a transitional residential zone with growing commercial activity, records moderate levels of Extortion and Ordinary Theft. The ongoing gentrification and demographic transformation may contribute to socio-spatial tensions and limited neighbourhood cohesion. The coexistence of students, working-class populations, and informal settlers in this triangularly configured zone presents challenges in consistent monitoring and law enforcement coverage.

Sector III, representing a mixed-use entertainment and residential district, exhibits moderate crime intensity in House Break (Night) and Ordinary Theft. The sector's socio-economic diversity and functional heterogeneity, ranging from institutional areas to lower-income housing, may lead to uneven levels of vulnerability and security. Areas with high visitor turnover, such as NTR Gardens and IMAX, likely contribute to transient crimes that are difficult to predict and control.

Sector IV, defined as a service-oriented transit corridor, shows high intensity in Pseudo Police offences and Robbery. The presence of major transport nodes (e.g., Lakdikapool railway station) and hotels, along with a predominantly working-class and rental demographic, increases exposure to crimes that target transient populations. The fluidity of movement and anonymity in such environments are often exploited by offenders.

Sector V, a high-activity mixed-use zone with religious and cultural significance, registers very high levels of Diverting Attention crimes and moderate intensities of House Break (Night) and Ordinary Theft. The convergence of large public gatherings at sites such as Birla Temple and Birla Science Museum, coupled with residential informality and administrative offices, generates conditions for distraction-based thefts and break-ins.

Sector VI, comprising low-density institutional and recreational zones, indicates elevated levels of House Break (Night) and moderate intensity in Snatching and Robbery. Despite the presence of high-security institutions (e.g., Assembly, DGP Office, RBI), the spatial dispersion and low residential density, particularly in the southern areas may limit natural surveillance, thereby increasing susceptibility to property crimes.

Sector VII, situated on the peripheral fringe with a blend of government offices and slum clusters, reveals very high intensities in Automobile Theft and Diverting Attention, with moderate levels of Snatching and House Break (Night). The juxtaposition of informal settlements and commercial strips in this sector appears to create crime-prone interfaces. The fragmented socio-economic fabric, combined with open spaces and lower levels of formal policing, may further exacerbate vulnerability to theft-related offences.

The variations in time of occurrence, place of occurrence, day of occurrence and even month in the incidence of different criminal offences are not coincidental. There is a definite relation with the kind and width of roads, literacy-education-occupation-income of

perpetrators, location of the PS and CCTV cameras, areas and time of police patrolling, etc. The superimposition of these factors on incidence can yield significant results for policy and better administration.

6. Conclusion:

The study identified hotspots and examines how crime intensity varies from one sector to another. Over the three years, notable improvements were observed in reducing certain crimes, mainly attributed to data-driven policing, better surveillance systems, improved patrol coordination, and community involvement. The analysis suggests that understanding crime through the lens of spatial patterns combined with urban planning and social awareness can help design better prevention strategies. Rather than treating crimes as isolated events, the spatial approach sees them as also the outcomes of everyday activities and urban design. A well-informed and sector-specific strategy, based on real patterns, can help cities become safer and more inclusive. As Indian cities continue to grow, these methods can offer practical tools for future urban crime prevention.

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