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Exploring the Spatial Synergy Between Urban Crime and Public Service Facilities: A Case Study of Los Angeles, USA

Furong Wang

School of Architecture, Xi'an University of Architecture and Technology, Xi'an, China
1224790485@qq.com

Abstract. Crime incidents represent a critical challenge in urban governance, with their spatial distribution shaped by the urban physical environment and often exhibiting predictable patterns of concentration in specific locales. This study employs the Local Co-location Quotient (LCLQ) and Deep Gravity Model to analyze the spatial relationships between crime incidents and six categories of public service facilities. By identifying zones of high synergy intensity, this research elucidates the underlying mechanisms and establishes definitive correlations between criminal activities and typological public service infrastructure. Through a case study of Los Angeles, key findings include: (1) Facility types have divergent impacts on crime, with transportation arteries and nodes becoming crime hotspots due to the dense passenger flows, while marginal green spaces suffer from safety vulnerabilities caused by insufficient surveillance and environmental concealment, and enclosed spaces with high-frequency activities, like urban CBDs and office districts, also face elevated crime risks. (2) Two distinct distance-decay patterns were identified: a uniform attenuation pattern, which governs the relationships between Crime & Event, Crime & Health and Medicine, and Crime & Community and Government; and a gradually slowing attenuation pattern, which characterizes the interactions between Crime & Travel and Transportation, Crime & Sports and Recreation, and Crime & Arts and Entertainment.（3）In response to the identified patterns, several spatial strategies are proposed to mitigate crime risks. These include: the strategic installation of surveillance cameras in green spaces and transportation hubs; the decentralized planning of green banks; and the avoidance of high-crime zones when designating sites for large-scale gatherings. This study confirms the spatial interdependence between crime and public service facilities, revealing the systematic logic behind crime rate distributions through functional interaction analysis, thereby providing a robust framework for risk assessment and police resource allocation.

Keywords: Crime, Public Service Facilities, Local Co-location Quotient (LCLQ), Deep Gravity Model, Spatial Synergy

1. Introduction

Urban crime, manifesting in public thoroughfares, central business districts, or residential precincts, poses substantial threats to community safety and urban sustainability (NCVS, 2023). Current scholarship in this domain predominantly focuses on the relationship between the urban built

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environment and crime hotspots, with regression-based methodologies—such as Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), the negative binomial regression model and Logistic Regression (LA)—being widely employed [1-5].

For instance, There are researchers utilized OLS regression to demonstrate that intensified nocturnal illumination and complex human activity patterns correlate with elevated theft rates, underscoring the criminogenic implications of nighttime environment [6]. Similarly, there are researchers integrated LA modeling with kernel density analysis to evaluate police station service coverage in crime-prone areas, informing optimal site selection strategies [7]. There are researchers employed negative binomial regression to identify significant positive associations between burglary rates and the presence of banks, bus stops, and entertainment venues [8].

However, these approaches often treat data points as independent entities, overlooking the critical dimension of spatial autocorrelation and potentially leading to biased parameter estimates. Spatial co-location pattern analysis, a rapidly evolving methodology, offers a solution by examining the proximity of heterogeneous point datasets across multiple spatial scales. Notable applications include Leslie and Kronenfeld's [9] analysis of public institutions and tree distributions, which revealed significant intra-type autocorrelation and inter-type co-location, and there are researchers investigation into the spatial associations between crime types and land use characteristics.

This study advances the field by applying LCLQ to quantify spatial associations between crime events and ten public service facility categories, supplemented by rigorous statistical hypothesis testing (permutation tests) to identify significant co-location patterns. Recognizing the road network's influence on urban mobility, network distances are utilized to define spatial neighborhoods. Although LCLQ can effectively identify relevant regions, the causal mechanisms underlying these relationships have not been fully studied. We addressed this by using the gravity model.

Complementing spatial analysis, human mobility exhibits strong spatiotemporal regularities, yet real-world OD flow data often remain scarce [10-16]. Traditional spatial interaction models (e.g., gravity models) oversimplify dynamics by focusing solely on population size and Euclidean distance while neglecting socioeconomic and built environment factors, leading to overestimated flow predictions. Most studies operate at a single spatial scale, disregarding the critical issue of scale sensitivity—a limitation addressed here through the Deep Gravity Model. By integrating deep learning with gravity model frameworks, this approach mitigates data dependency and captures nonlinear mobility patterns. The Shapley value method is further employed to quantify scale-specific impacts, enabling multi-scale OD flow prediction and offering novel insights into urban mobility modeling.

In summary, this research addresses three key gaps: (1) The neglect of spatial autocorrelation in crime-facility studies; (2) The lack of mechanistic explanations for observed co-location patterns. By combining LCLQ and Deep Gravity Model, this study aims to provide a theoretically robust and empirically grounded framework for understanding crime-facility synergies, with direct implications for urban planning, crime prevention, and police resource optimization.

2. Methodology

2.1 Local co-location quotient (LCLQ)

Spatial co-location analysis investigates the distribution patterns of events across multiple scales, particularly useful for identifying clustering tendencies in point datasets. This study employs the Local Co-location Quotient (LCLQ), 1of the Global Co-location Quotient (GCLQ), to measure

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localized spatial associations between crime events (point set A) and public service facilities (point set B). Unlike global metrics, LCLQ captures intra-regional variability, quantifying spatial correlation at specific distance thresholds. The formula is defined as:

$$LCLQ_{A_i \to B} = \frac{N_{A_i \to B}}{\frac{N_B}{N-1}} \tag{1}$$

Where $N_{A_i \to B}$ represents the weighted average of facility points (B) within the neighborhood of crime point A_i, calculated as:

$$N_{A_i \to B} = \sum_{j=1}^{N} \left(\frac{w_{ij} f_{ij}}{\sum_{j=1(j \neq i)}^{N} w_{ij}} \right), (j \neq 1) \tag{2}$$

Here, f_{ij} indicates whether j belongs to feature point B (1 for yes and 0 for no).and w_{ij} denotes a Gaussian weight function:

$$w_{ij} = exp(-0.5 \times \frac{d_{ij}^2}{d_{ib}^2}) \tag{3}$$

This function assigns exponentially decreasing weights to facilities based on their Euclidean distance d_{ij} from A_i, with d_{ib} defining the bandwidth. An LCLQ value > 1 signifies significant spatial co-location, < 1 indicates spatial isolation, and = 1 implies random distribution. Permutation tests ($p < 0.05$) were conducted to validate statistical significance.

2.2 Deep gravity model

Supervised origin-destination (OD) flow prediction models often require extensive historical data, limiting their applicability in data-scarce urban contexts. The Deep Gravity Model [17] addresses this challenge by integrating deep learning with traditional gravity model frameworks, enabling robust predictions of mobility patterns even with limited training samples. Building on the single-constraint gravity model:

$$\overline{y}(l_i, l_j) = O_i P_{ij} = O_i \frac{m_j^{\beta} f(r_{ij})}{\sum_k m_k^{\beta_1} f(r_{ik})} \tag{4}$$

where O_i is the total outflow from origin l_i, m_j is the population at destination l_j, r_{ij} is the network distance measured along the road network, and $f(r_{ik})$ is a distance-decay function. The Deep Gravity Model enhances this framework by incorporating 19 input features: population size, eight POI categories at both origin and destination, and inter-location distance. These features are normalized by area to ensure dimensional consistency.

1. Concatenate the input features index baseline x_i end baseline (feature vector l_i at the starting position), x_j (feature vector l_j at the target position), r_{ij} (distance from the starting position to the target position) to obtain the input vector $x(l_i, l_j) = concat[x_i, x_j, r_{i,j}]$, where j represents the index of the target position and n represents the total number of target positions.

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2. Passing these vectors through the neural network to generate flow scores $s(l_i, l_j)$.

3. Converting scores to probabilities via the softmax function and multiplying by total outflow to obtain OD flow predictions.

The cross-entropy loss function is used to optimize model parameters:

$$H = -\sum_i \sum_j \frac{y(l_i,l_j)}{O_i} lnP_{i,j} \tag{5}$$

3. Case study

3.1 Crime data

Crime incident records were obtained from the Los Angeles County Department of Public Health, with preprocessing procedures excluding incomplete and duplicate entries. Each record includes geospatial coordinates (latitude/longitude), temporal stamps, crime classification, and contextual descriptions, forming a robust dataset for spatial-temporal analysis.

3.2 Public service facility data

Facility data were sourced from CAMS Export (November 2022), containing ten categorized POI layers with precise geographic coordinates (Table 1). Reclassification into functional categories—including Travel & Transportation, Retail, and Health & Medicine—facilitated systematic co-location analysis. Road network and administrative boundary datasets were integrated to define spatial neighborhoods consistent with urban mobility patterns.

Table 1: Classification of public service facilities and proportion of POI

Facility category	POI percentage of volume
Travel And Transportation	10.27%
Sports And Recreation	8.24%
Landmarks And Outdoors	11.13%
Health And Medicine	8.42%
Event	4.61%
Retail	15.79%
Business And Professional Services	12.67%
Dining And Drinking	15.34%
Community and Government	3.21%
Arts And Entertainment	10.13%

4.Result

4.1 LCLQ

We apply LCLQ to investigate the patterns between crime events at specific locations and ten types of public service facilities. Generally speaking, an LCLQ value significantly greater than 1 indicates that there is a colocation relationship between a given crime event and a specific public service facility. Conversely, an LCLQ value less than 1 indicates a possible separation relationship.

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Permutation tests are used to calculate the p-value of each input element of interest to determine whether the observed co-location quotient value is statistically significant. If the p-value is small (less than 0.05), then the actual co-location quotient of this element is statistically significant. Based on the above, it is divided into three patterns and the LCLQ of ten public service facilities is obtained: (1) Co-location - significant: local co-location quotient > 1 and p-value < 0.05; (2) Co-location - not significant: local co-location quotient > 1 and p-value greater than 0.05; (3) Isolation - significant: local co-location quotient is equal to or < 1 and p-value < 0.05.

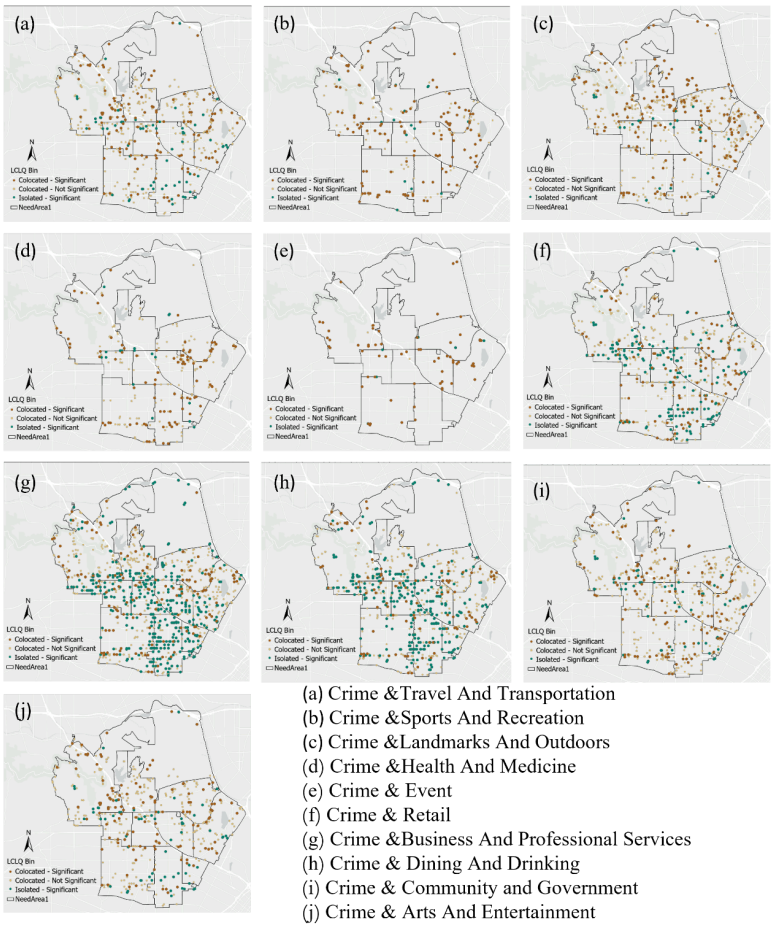

Figure 1: LCLQ of crime and public service facility categories

In the Los Angeles crime events under the research scope, almost all crime events have a synergistic relationship with various public service facilities, as shown in Figure 1. These similar synergy patterns may be influenced by the distribution characteristics of public service facility types. As can be seen from the results where LCLQ > 1 and the p-value is less than 0.05. Travel And Transportation is the most widely distributed among all types of public service facilities at various locations. This indicates that Travel And Transportation, as a relatively common or basic attribute, is involved in various location-related situations. Public service facilities such as Event and Retail appear less frequently, indicating that the results after their synergy only exist in specific locations. As can be seen from the results where LCLQ > 1 and the p-value is less than 0.05, there is a large difference in the number of types of public service facilities at different locations. For example, intersection has distributions of all types, while college and hospital are significantly different from other locations, and they have fewer types of facilities with LCLQ > 1 and p-value less than 0.05. It

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is also found that the areas around college are mainly dominated by three types of public service facilities: Sports And Recreation, Event, and Arts And Entertainment. Hospital is mainly dominated by two types: Travel And Transportation and Health And Medicine. Specifically, green spaces such as Griffith Park and Runyon Canyon Park are located at the edge of Los Angeles. Due to their special geographical location, these places are usually insulated from urban supervision. This situation may provide convenience for crimes in the adjacent environment and pose many potential threats to safety (such as imperfect supervision facilities and green spaces that provide cover for crimes). Another important synergy pattern exists between crime and street intersections. The spatial correlation between crime and roads is spatially heterogeneous and mainly concentrated at major transportation nodes such as Wilshire Blvd and S Wilton Pl, Wilshire Blvd and S Highland Ave, and Silver Lake Blvd and W Temple St. Specifically, Wilshire Blvd is one of the main east-west arteries in Los Angeles, California, USA. The intersection of Wilshire Blvd and S Wilton Pl is an important transportation node with more than several bus lines and multiple subway transfer stations. The busy traffic and expanding travel demand make this area extremely vulnerable to crime. Similarly, the synergy patterns of education, office, school and other places exist in relatively central areas of the city (such as UCLA Community School, Paramount Studios, Los Angeles City College), because such areas are associated with citizens' frequent leisure and entertainment activities. In addition, due to the relatively closed and narrow space in these areas, once a crime occurs, a large number of buildings and shelters are more convenient for hiding crimes.

Table 2: Comparison of LCLQ among 7 different types of locations and 10 types of public service facilities

Regional scope / Facility category	High school	Office	College	Intersection	Hospital	Runyon canyon park	Griffith park
Travel And Transportation	√	√		√	√	√	√
Sports And Recreation			√	√		√	√
Landmarks And Outdoors				√		√	√
Health And Medicine	√	√		√	√		
Event			√	√		√	
Retail	√			√			√
Business And Professional Services		√		√		√	√
Dining And Drinking		√		√			
Community and Government	√	√		√			√
Arts And Entertainment	√	√	√	√		√	√

4.2 Decay relationship between public services and crime distance

In the analysis of the relationship between crime rates and public service facilities, the geometric mean distance is used to examine the relative spatial distribution between supply and demand. To better understand the function model and parameters that capture the spatial distance decay between public service facilities and areas with different levels of criminal activity, three key aspects were considered: widely accepted spatial decay models in related studies, the analysis of distribution mechanisms, and the effectiveness of the fitting results. For spatial decay, we employ an elliptical decay model, dividing by πr^2 based on the sample points. Regarding the distribution mechanism, we randomly select 50 sample points multiple times, compute their average, and then calculate the average of the results as the outcome for the same distance. To assess the validity of the fitting results, we perform an R-squared test and exclude categories with an R-squared value below 0.7, For the geometric mean of the data points with LCLQ > 1 of the above ten types of public service facilities, perform function fitting to obtain the following fitting curves. The fitted function is:

$$y = y_0 + A_1 e^{-(x-x_0)/t_1}$$

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Fitting curves of ten types of public service facilities obtained after fitting. Further integration yields six public service facilities with high correlation. including retail, dining and drinking, business and professional services, and landmarks and outdoor categories. Based on this, 10 function prototypes were selected for trial fitting, and the results of the fittings are shown in Figure 2.

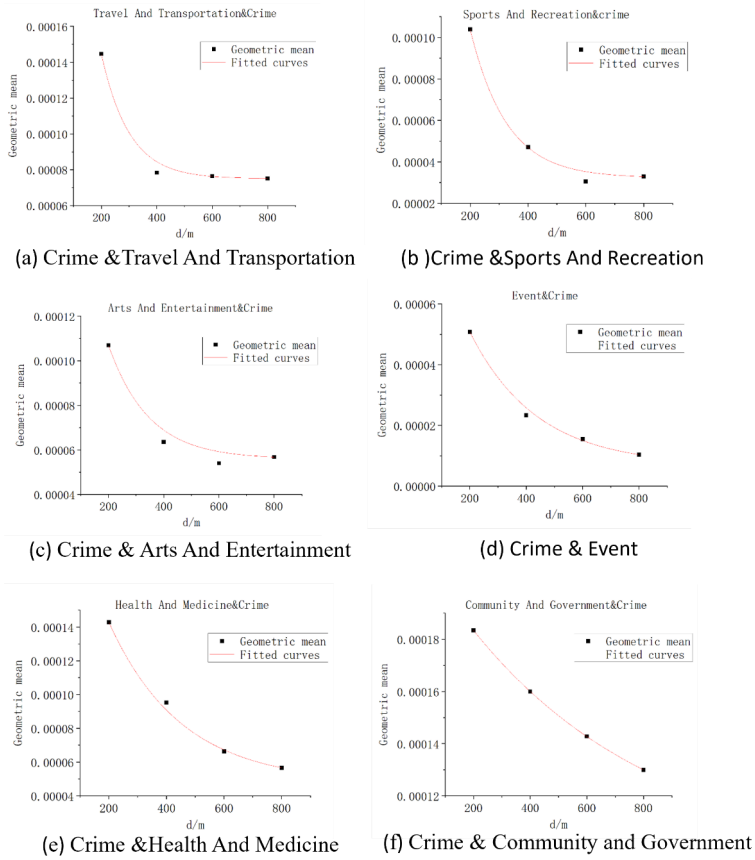

Figure 2: LCLQ fitting curves of six types of public service facilities

The fitted curves for all the crime types show a clear decay trend, meaning that as the distance from the service facility increases, the crime rate decreases. This is a typical spatial decay, where public service facilities (like transportation hubs, recreational centers, health services, etc.) have a more pronounced effect on crime in the nearby areas, and their influence diminishes with greater distance. The geometric mean data points (represented by black squares) are scattered across the x-axis, while the fitted curves show the model of how the crime rates decay with distance. The fitted curves appear to follow a typical exponential or similar decay function, which aligns with the general decay models discussed in your previous analysis.

Graph(a) shows how crimes related to transportation systems decrease with distance from transportation hubs. The decay is quite steep initially, suggesting a significant influence close to these hubs. Similarly, the curve of graph(b) for sports and recreation crime reflects a decay that likely indicates that areas closer to sports complexes or recreational facilities experience a higher rate of crime, with the effect tapering off as the distance increases. Curve of health and medicine crime reflect crimes in proximity to healthcare facilities, where the closer the proximity to hospitals or clinics, the higher the crime rate, especially for specific types of crimes like theft or assault. Event

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Crime represents crimes around large event venues such as stadiums or concert halls, where the immediate area experiences higher crime rates during events, but the effect decays as you move further away. Community and Government Crime: This curve might represent crimes related to government offices or community service centers, showing a more gradual decay in crime rates with distance. Graph(e) shows the decay of crime rates in relation to cultural or entertainment venues, where again, the crime rates are higher near these areas and diminish with greater distance.

The fitted curves in all graphs confirm that the effect of public service facilities on crime is spatially decaying. The closer a crime is to a facility, the higher the rate, and this diminishes over distance.

4.3 Short-range and long-range effects of public services

In further analysis, we can examine the differences in the spatial influence of public service facilities on crime based on the behavior of the geometric mean values and their relationship with the fitted decay curves. Specifically, we can distinguish between short-range and long-range effects by analyzing how the geometric mean values change with distance, and the patterns observed in the travel, art, and sport crime curves versus other categories like health, community, and event crimes.

Table 3: Relationship between variables in the exponential decay function

Contents	Series					
$y = y_0 + A_1 e^{-(x-x_0)/t_1}$	Travel And Transportation	Sports And Recreation	Event	Health And Medicine	Community And Government	Arts And Entertainment
A_1	6.96	7.16	4.39	9.5	8.95	5.1
t	100.57	126.1	237.56	252.01	660.19	145.83

The geometric mean values in the Travel, Art, and Sport crime categories show a sharp decline as the distance from the respective public service facility increases. This sharp decline indicates that these facilities have a short-range impact on crime. A closer proximity to these facilities leads to a significant reduction in crime rates, but as the distance increases, the effect quickly diminishes. This pattern suggests that the influence of public service facilities in these categories is most pronounced within a relatively small geographic area, and the crime rate reaches a stable lower level at a shorter distance. Crime near transportation hubs such as airports, train stations, or bus terminals tends to diminish rapidly as you move away from these areas. The facilities have a powerful but localized impact on crime, with a rapid decay in crime rates as you move away from these hubs. Public art and entertainment venues (e.g., theaters, galleries, or concert halls) also demonstrate a sharp drop in crime rates with increasing distance. These locations tend to have a strong influence on crime rates in their immediate vicinity, but as distance grows, the impact decreases dramatically. Sports facilities such as stadiums or arenas also show a rapid decline in crime rates as the distance from the facility increases. The immediate vicinity of such venues often has high crime rates due to crowds, but the influence of these facilities diminishes rapidly as you move further away.

In contrast, the Health, Community, and Event crime categories show a more gradual and consistent decrease in the geometric mean values as the distance from the facility increases. This gradual decrease suggests a long-range impact, where the effect of public service facilities extends over a larger geographic area, and the crime rate continues to decrease at a more even rate. The facilities in these categories influence a larger portion of the area, and their effect on crime diminishes more slowly. Crime near healthcare facilities (e.g., hospitals and clinics) tends to decrease more gradually with distance. These facilities have a broader influence, affecting a wider area, and their impact on crime is more evenly distributed. Government offices, community centers,

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and similar facilities exhibit a steady decline in crime rates over greater distances. These types of facilities likely serve larger populations, and their impact is not limited to a small area but extends further. Events, such as festivals or public gatherings, exhibit a more evenly distributed impact on crime. Even though these events might cause spikes in crime near the venue, their influence tends to decrease more gradually as you move away from the event space, indicating a long-range effect.

5. Discussion

This study contributes to urban criminology by empirically demonstrating the spatial interdependence between crime and public service infrastructure. Key insights include:

Facility-Typology Impacts: Transportation hubs and CBDs act as crime generators due to high foot traffic, architectural enclosure, and temporal activity peaks, while marginal green spaces suffer from surveillance deficits and environmental design vulnerabilities.

Scale Sensitivity: Multi-scale analysis via LCLQ and Deep Gravity Model reveals that crime-facility relationships are highly context-dependent, varying with distance and urban function. This underscores the need for scale-specific interventions in urban planning and policing.

Policy Implications: Urban planners should prioritize enhanced surveillance systems in transportation nodes and green spaces, while implementing architectural modifications to reduce concealment opportunities. Police departments can leverage LCLQ-derived hotspots for adaptive patrol strategies, optimizing resource allocation to high-risk zones.

Notable limitations include the use of aggregated facility data, which may obscure neighborhood-level nuances, and the absence of temporal dynamics (e.g., daily/weekly crime patterns). The study also relies on correlational analysis, precluding causal inference. Future research should incorporate fine-grained socioeconomic variables (e.g., income inequality, education levels), temporal crime datasets, and qualitative safety perception surveys to deepen mechanistic understanding. Cross-cultural validation in diverse urban contexts and policy impact assessments would further enhance the generalizability of these findings.

6. Conclusion

This study uses the LCLQ and the deep gravity model to analyze the spatial relationship between crime and specific public service facilities, identify the core mechanisms associated with it, and thus provide reference suggestions for urban public safety governance. The identification of distinct decay patterns and facility-specific crime correlations offers actionable insights for evidence-based urban planning, crime prevention, and police governance. These findings advance the field toward more sophisticated, data-driven strategies for creating sustainable and secure urban landscapes.

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