Applied Spatial Analysis and Policy (2025) 18:104
https://doi.org/10.1007/s12061-025-09710-1

Exploring the Impact of Park and Surrounding Environments on Violent Crime in Wuhan: An XGBoost-SHAP Approach

Sainan Lin[1] · Shudi Chen[1] · Kaidi Liu[1] · Yao Yao[2]

Received: 18 November 2024 / Accepted: 3 August 2025

Abstract

Violent crime poses a significant barrier to the equitable use of urban park amenities and access to their associated benefits. While machine learning has emerged as a promising tool for exploring the relationship between park environments and crime, the opaque nature of many models has hindered insights into underlying mechanisms. Moreover, most existing studies have concentrated on parks in central urban areas, overlooking peri-urban parks that increasingly serve expanding metropolitan populations. To address these gaps, this study employs an interpretable machine learning approach, XGBoost with SHAP values, to examine how the environments of both urban and peri-urban parks in Wuhan, China, influence violent crime. We assess four domains of contextual variables: accessibility, built environment, land use, and socioeconomic conditions. Results indicate that while violent crime rates are generally higher in urban parks, park location itself is not a significant standalone predictor. Both accessibility and built environment factors demonstrate nonlinear and context-sensitive associations with violent crime. Despite the potential of environmental design in crime prevention, disadvantaged neighborhoods remain disproportionately affected by unsafe park conditions. These findings highlight the need for place-sensitive planning strategies and demonstrate the value of interpretable machine learning in advancing spatial crime analysis.

Keywords Urban park · Park environment · Violent crime · XGBoost-SHAP method · Wuhan

Extended author information available on the last page of the article

Published online: 11 August 2025

Introduction

Crime in and around parks is a major threat to residents' access to urban amenities, and assessing the relationship between environments around parks and crime has become a prominent topic in the fields of urban planning, geography, and environmental criminology (Maruthaveeran & van den Bosh, 2015; McCord & Houser, 2017; Schusler et al., 2018). In addition to the direct damage to the user's life, it can also cause long-term effects on physical and mental health (Jennings et al., 2017; Lan et al., 2022). Among various types of crime, violent crime is of particular concern due to its severity and broader social consequences. Violent crime poses a serious threat to public safety and undermines the normal use of urban parks. It significantly reduces residents' willingness to participate in outdoor physical activities (Han et al., 2018). Such incidents also foster a sense of insecurity, inhibit the use of public spaces, and weaken neighborhood ties by diminishing community cohesion and trust (Cohen et al., 2014; Valente et al., 2020; Wang & Liu, 2017). Moreover, violent crime often clusters in areas where park design lacks adequate consideration of crime prevention, highlighting the importance of integrating safety principles into environmental planning (Chen et al., 2021). Therefore, understanding how park environments influence violent crime is critical for developing safe, inclusive, and well-used public green spaces.

The relationship between green space and crime is complex and context-dependent. On the one hand, green space is often associated with lower crime rates through mechanisms such as Crime Prevention through Environmental Design (CPTED), which emphasizes visibility, accessibility, and territoriality. Physical features like fences and barriers have been shown to deter crime in some settings (Hajna & Cummins, 2023). In addition, exposure to natural environments may help restore mental health and reduce aggression, thereby lowering the likelihood of violent crime (Burley, 2018; Donovan & Prestemon, 2012). On the other hand, the presence of green space, especially in the form of dense vegetation or poorly monitored areas, may also create opportunities for concealment and reduce informal surveillance, which could facilitate certain types of crime (Kuo & Sullivan, 2001). Moreover, when parks become underutilized due to excessive restrictions or poor design, they may attract antisocial behavior and become localized crime hotspots (Hajna & Cummins, 2023). Thus, the general association between green space and crime is not inherently positive or negative; it depends on how the space is designed, maintained, and integrated into the urban context. Although the understanding of the impact of environmental design methods on park crime is controversial, few studies have analyzed the relationship between surrounding environment characteristics and crime quantitatively, likely due to the absence of a robust system for measuring park-specific environmental features. Compared with general green space, urban parks differ significantly in form and function—they typically feature more deliberate design, greater accessibility, higher visitor density, and are embedded within more complex built and social environments. These distinctive attributes may not only amplify both the protective and risk factors associated with environmental design, but also alter how space is used and surveilled. Consequently, urban parks may exhibit different crime dynamics than other types of green space, making it necessary to systematically investigate their surrounding environments to improve both theoretical understanding and practical approaches to park safety management.

Previous park safety studies have mostly focused on central urban parks, while peri-urban parks have received relatively little attention. Since urban development typically expands outward from the city center, central parks have longer histories and richer datasets available for safety research (Rigolon, 2016; Taylor, Haberman, & Groff, 2019). In contrast, improved transportation infrastructure has increased the accessibility and frequency of use of peri-urban parks (Charney, 2005; Wang et al., 2023). In China, peri-urban and urban parks differ substantially in both landscape characteristics and functional orientation. Peri-urban parks tend to preserve natural features with limited artificial modification, and are primarily designed to provide ecological services. Urban parks, by contrast, are more integrated into the built environment, featuring numerous man-made landscapes and recreational facilities that serve leisure and cultural functions. These differences may lead to distinct patterns of space use, population density, and surveillance, which in turn affect crime dynamics. While studies in the U.S. and Europe have reported higher crime rates in peri-urban parks (Boessen & Hipp, 2018 ; Taylor et al., 2019), such patterns remain underexplored in the Chinese context. Therefore, comparative research is necessary to understand the differentiated safety mechanisms across urban and peri-urban park types.

Existing research on parks and crime has mostly relied on qualitative approaches or traditional statistical techniques, which face notable limitations in both data collection and analytical precision. For instance, the least squares method has been used to assess the relationship between vegetation and different types of crime (Troy et al., 2012; Wolfe & Mennis, 2012), but the findings are often inconsistent due to issues such as scale mismatches and incomplete surveys (Burley, 2018; Donovan & Prestemon, 2012). With the development of machine learning techniques, researchers now have tools to model complex spatial and environmental relationships more effectively (Venter et al., 2022; Liu et al., 2019).

Machine learning has also demonstrated growing advantages in environmental crime prevention (Chen et al., 2024; Su et al., 2023; Yue et al., 2024). Techniques such as the random forest classification algorithm have been used to detect illegal logging (Mujetahid et al., 2023) and predict spatial variations in crime risk (Kadar & Pletikosa, 2018). However, despite its modeling strength, machine learning often suffers from a lack of interpretability due to its "black-box" nature. To address this challenge, interpretability tools have been developed to explain model decision-making processes (Li et al., 2022). Among them, the XGBoost model has been used to construct violent crime classifiers, and SHAP values have been applied to interpret the relative influence of input features on prediction outcomes (Feng et al., 2021; Parsa et al., 2020). These advances offer new possibilities for systematically investigating how different park environments affect violent crime, with stronger explanatory power than traditional models.

This study investigated the relationship between parks and violent crime in urban Wuhan considering four dimensions, namely accessibility, built environment, land use, and socioeconomic factors. The XGBoost-SHAP method was applied to verify the heterogeneous impact of peri-urban parks and urban parks on violent crime under mixed conditions and quantify the impact of specific characteristics on the model.

Literature Review

Park and Crime

The relationship between parks and crime is controversial with some studies confirming that park elements such as tree canopy coverage and green space may be negatively correlated with crime rates (Schusler et al., 2018; Troy et al., 2012). Proponents argue that urban parks can reduce crime by promoting natural surveillance and increasing community cohesion, whilst opponents argue that parks do not always have a positive effect on crime. Studies have found that parks, if not properly designed or maintained, can become accelerators of crime (Li et al., 2024). According to the Broken Windows Theory, environmental phenomena such as overgrown plants, broken facilities, and waste that obstructs the view can signal neglect, thereby encouraging criminal behavior (Beckett & Herbert, 2008; Garcia-Tejeda & Fondevila, 2023). Also, urban parks located on the urban fringe or surrounded by sparsely populated areas may hide crime due to ignorance.

Urban parks are often located in densely populated areas, serving as centers for social interaction and community activities whereas peri-urban parks are often located on the city outskirts, attracting users for hiking and sightseeing (Cornelis & Hermy, 2004; Li et al., 2020). These locational and functional differences can lead to different criminal mechanisms, which means customized management and security strategies are essential. In addition, the surrounding environment of the park affects accessibility by influencing users' subjective sense of security, which is a key area affecting crime in the park, but there is a lack of research on this area.

Park Violent Crime and Park Surrounding Environment Characteristics

There are many types of crime with violent crime being of particular concern. Addressing park violent crime requires a comprehensive understanding of the relative factors including park design, management, and the socioeconomic conditions of the surrounding areas (Sachs et al., 2023). Consequently, this study focused on the heterogeneous effects of urban and peri-urban parks on violent crime rates, specifically, accessibility, built environment, land use, and socioeconomic factors.

Park Accessibility

Parks promote a healthy, vibrant, and resilient community, and as such should be accessible and equitably distributed (Wu et al., 2023a, b). Most Western studies have shown that the distribution of urban parks tends to disproportionately benefit affluent peri-urban communities (Cole et al., 2019; Rigolon & Németh, 2020), and the concentration of wealth helps prevent crime. However, whether park accessibility varies across different socioeconomic groups in Chinese cities is controversial (Wu et al., 2023a, b). In some research, deprived communities, especially those in socioeconomically disadvantaged districts, may have restricted accessibility to parks of higher quality level via walking and public transit (Cheng et al., 2021), while park access in Hangzhou does not reveal significant differences among socioeconomic groups (Wei, 2017). Therefore it is necessary to consider the impact of spatial accessibility on park crime in China.

Parks with high accessibility have a wide range of services that can attract more users, improve the frequency of park use, and promote social and economic benefits. The "eyes on the street" theory (Jacobs, 1961) supports the idea that more park users can serve as an informal surveillance force helping to prevent and reduce criminal behavior (McMillen et al., 2019) because perpetrators may avoid committing crimes in crowded areas for fear of being discovered. However, if the park is highly accessible, it is also more likely to decline the users' sense of privacy which may lead to less access and surveillance (Lis et al., 2019). Therefore, previous studies have suggested strategies to pursue a balance between accessibility and security (Lis et al., 2024). But at present, there is a lack of specific balance point indicators.

Built Environment

CPTED is an effective method to reduce crime with soft design strategies (Cozens & Love, 2015). This approach highlights the combination of safety design and environmental behavior guidance, which includes five key dimensions: natural surveillance, image management, territorial reinforcement, natural access control, and legitimate activity support.

Good green space design can meet all five principles at once, namely, transparent vision (Bhatia & Jason, 2022; Kuo & Sullivan, 2001), clear place functions (Kuo & Sullivan, 2001), physical isolation of offenders (Cozens, 2008; Wu et al., 2023a, b), and legal activities (Liu et al., 2021). Previous studies have extensively discussed the influence of the park's built environment on crime but without a comprehensive insight and a comparative perspective on different kinds of parks (Zhang & Park, 2023). This study developed a built environment indicator system based on the five key dimensions of CPTED.

Land Use

Urban land use ha significantly affects the amount of crime (Wu et al., 2022; Sadeek et al., 2019). Some non-residential land is associated with high crime rates (Stucky & Ottensmann, 2009) with the surrounding land use affecting crime rates in or near parks (Boessen & Hipp, 2018). For instance, parks in areas close to industry are prone to crime, especially at night, and they are associated with a low user density (Gargiulo et al., 2020). The relationship between mixed land use and park crime is controversial. Some studies have shown that parks in mixed-land environments may have lower crime rates (Knorre & MacDonald, 2023), yet Folharini et al. (2023) found that green crime is spatially related to the rural-urban fringe.

Socioeconomic Factors

Social and economic conditions affect park crime in many ways. Studies in developed countries have found that violent crimes are more frequent in urban centers, ethnic minorities, and low-income communities because developed countries are often in a period of maturity or decline in urbanization with young, upper-middle-income populations moving to urban suburbs, also known as the gentrification of the suburbs (Brueckner & Rosenthal, 2009). In these countries, peri-urban parks are seen as a positive investment, well-designed and maintained. In contrast, central parks are mainly used by crowded minorities, low-income people, and transient populations, which may exceed the reasonable park capacity (Wu et al., 2023a, b). Besides, there is a lack of community identity which inspires a sense of fear among park users. Some small community parks also suffer from poor management and may have higher crime rates (Agrawal & Gibson, 1999).

It is important to note that since most of the population of developing countries lives in urban central areas, the function and importance of parks is different from that of developed countries. This has also caused park crime to show socioeconomic characteristics in the process of urbanization in developing countries. China's suburbs, most of which have been converted from rural areas or industrial land, tend to be sparsely populated with low-income communities and a large number of new or poorly managed parks, which can breed crime (Liu et al., 2021). Therefore, it is necessary to consider the particularity of China's peri-urban social economy to study park crime.

Methodology

Study Area and Data

Study Area

Wuhan is the capital of Hubei Province, the largest city in central China, and one of the top 10 largest cities in China, with a population of 13.77 million in 2023. Parks are highly valued by the government as an important public space for people to obtain urban well-being such as health and leisure. Although Wuhan has implemented green space system planning, there are significant differences in the spatial distribution of parks, with the impact of parks on violent crime varying greatly depending on location, affecting crime rates in and around parks. The study area was the main urban zone of Wuhan according to *Wuhan Territorial Spatial Master Plan (2021–2035)*. The study area was divided based on Wuhan's ring roads, that is, the parks within the third ring road are defined as urban parks, and the parks outside the third ring road are defined as peri-urban parks (Fig. 1).

The park data was sourced from Liao et al. (2023), focusing on parks within the urban area, resulting in a total of 134 parks. The original park data was based on the *Wuhan Greening Status Bulletin for 2021*, therefore, it excludes green spaces, small gardens, sports fields, and community parks.

The unit of analysis in this study was each neighborhood park combined with a 500-meter buffer zone, representing the area potentially influenced by the park within a 5-minute walking distance. This buffer accounts for possible spatial errors in geocoding, as crimes associated with parks are sometimes recorded at nearby addresses rather than inside the park itself. Therefore, including the buffer ensures that all vio-

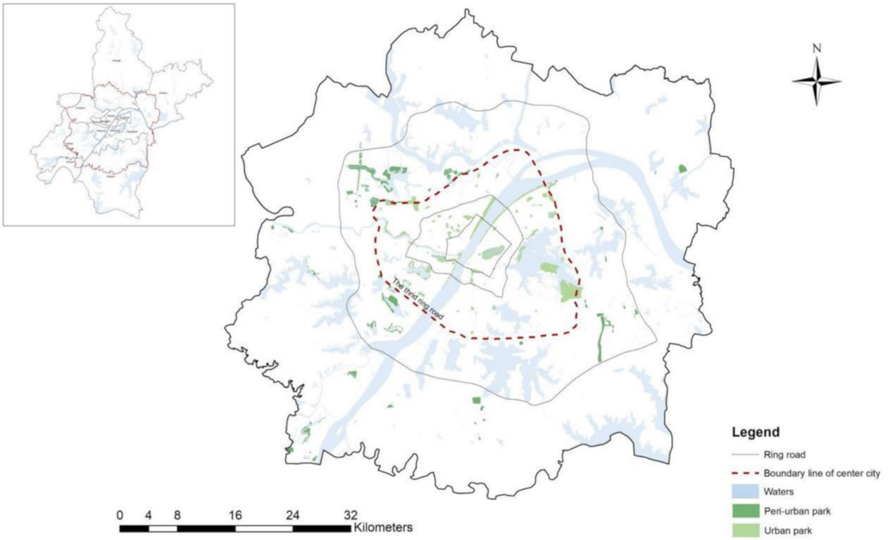


Fig. 1 Study area: The main urban zone of Wuhan, China

lent crime incidents likely related to the park's presence are captured. Violent crime counts within these buffered areas were used as the dependent variable. To further refine the spatial analysis, the study area was divided into 1000 × 1000-meter grid cells using the fishnet tool in ArcGIS 10.4, allowing for the assessment of crime-environment relationships at a consistent spatial resolution.

Dependent Variables

Crime data spanning from 2015 to 2020 were acquired for Wuhan from the China Judgment Literature website (https://wenshu.court.gov.cn/). However, the crime information only included cases to be decided upon, thus excluding other criminal activities that were not reported and uploaded. We selected violent crimes as dependent variable of park crime count, for residents are more susceptible to factors related to violent around environment and tend to avoid areas where they feel unsafe. Violent crime data were filtered based on geographic coordinates in the study area resulting in 2,665 instances of violent crimes. The category of violent crime data encompasses extortion, violence against persons, human trafficking, robbery, endangering public safety, and sexual crime. As shown in Table 1, interpersonal violence is the dominant crime type, comprising 72.68% of all cases, followed by robbery (14.93%) and sexual crimes (7.05%). Less frequent are crimes endangering public safety (3.11%), extortion (2.18%), and human trafficking (0.04%). Urban park areas account for the majority of incidents (90.4%), with a broader crime spectrum, while peri-urban park areas show a higher share of robberies (17.97%) but fewer sexual and safety-related crimes. These differences reflect underlying spatial dynamics: dense urban areas facilitate diverse criminal opportunities, while peri-urban zones face security gaps that make them more susceptible to targeted crimes such as robbery.

Table 1 Descriptive statistics of violent crime

	Total		Urban park areas		Peri-urban park areas	
	Quantity	Proportion(%)	Quantity	Proportion(%)	Quantity	Proportion(%)
Robbery	398	14.93	352	14.61	46	17.97
Interpersonal Violence	1937	72.68	1747	72.52	190	74.22
Endangering public safety	83	3.11	81	3.36	2	0.78
Sexual crimes	188	7.05	172	7.14	16	6.25
Extortion	58	2.18	56	2.32	2	0.78
Human trafficking	1	0.04	1	0.04	0	0.00
Total	2665	100.00	2409	100.00	256	100.00

The crime rate per thousand residents was the dependent variable, which was divided into six levels (0–5) using the Natural Breaks method to facilitate the constructing of crime classification model, with 0 indicating the lowest crime rate and 5 denoting the highest violent crime rate.

Independent Variables

Road data were obtained from the Open Street Map (OSM) website (https://www.openstreetmap.org/) to evaluate the *accessibility* of each block and remove roads that do not connect to the road network. DepthMap software, based on Space Syntax analysis, was used to determine the accessibility of each road using four indices, connectivity, choice, depth, and integration (Rashid, 2017). The connectivity of a line is the number of other lines it intersects, representing spatial permeability or the number of connecting roads. Choice indicates the potential for through-movement of the lines in a map, reflecting the ability of space across it. Depth measures the evenness in the frequency of distribution of nodes from each other in terms of distance. High Integration indicates great accessibility of a node to the other nodes in the entire graph, representing the ability of space to attract people or the usage rate of space.

Based on the Broken Windows Theory, signs of environmental disorder—such as unmanaged green areas or unclear functional zones—can contribute to increased crime by signaling neglect and weakening territorial control. In this context, high functional diversity may lead to “functional chaos” if not properly organized. Accordingly, this study includes the number and diversity of POIs as indicators of built environment activity intensity and spatial order. Meanwhile, the Eyes on the Street theory (Jacobs, 1961) emphasizes the role of informal surveillance and pedestrian presence in preventing crime; this concept is operationalized through accessibility-related variables and the natural surveillance capacity implied by POI density and land use diversity. Additionally, high vegetation coverage may reduce visibility and hinder informal surveillance, weakening the crime deterrence effect. Combined with the principles of CPTED, six variables were selected: road density, building view index (BVI), green view index (GVI), point of interest (POI) diversity, POI quantity, and land use. The BVI and GVI reflect the surface-level proportions of built-up and green areas, respectively, based on land cover classification rather than street view imagery. Vegetation data were obtained from Shi et al. (2023), and rooftop building data were sourced from vectorized building footprints in Zhang et al. (2022). Both indices were calculated for the entire spatial unit of analysis, which includes each park and its surrounding 500-meter buffer zone. The GVI and BVI were calculated as follows:

$$GVI\left(i\right) = \frac{V_i}{T_i} \tag{1}$$

$$BVI\left(i\right) = \frac{R_i}{T_i} \tag{2}$$

Where T is the area of the block, V is the area of vegetation, R is the area of rooftop, i is i th block.

Each POI for 2018 sourced from Autonavi Map was allocated to the corresponding block boundary to quantify the number of amenities in each block. Autonavi Map's POI dataset contains the names, geographic coordinates, and categories for 14 types of service amenities within our study area including catering services, scenic spots, corporate enterprises, shopping services, transportation facilities, finance and insurance services, science and education services, automobile services, commercial housing, life services, sports and leisure services, medical and healthcare services, government agencies and social organizations, accommodation services. The diversity index was calculated using entropy among the 14 POIs to gauge their diversity (Zhang et al., 2022):

$$Diversity_{x,i} = -\sum {}_{i=1}^{n}(P\left(x_i\right)\log(P\left(x_i\right)) \tag{3}$$

Where x_i represents one type of POI that occurs in each block with probability $P\left(x_i\right)$. Here $P\left(x_i\right) = N_x/N_{total}$, where N_x indicates the number of POI type *x* in a block and $P\left(x_i\right)$ represents the proportion of POI type x in comparison to the total count of all POIs in block *i*.

The *land use* dataset was obtained from Gong et al. (2019) covering various types of land use data such as residential land, business office land, commercial service land, industrial land, transportation stations land, administrative land, educational land, medical land and sport and cultural land. Housing prices were used to indicate the *socioeconomic* characteristics of each park block (Feng et al., 2024). A binary variable was created with 1 indicating an urban park and 0 indicating a peri-urban park to compare urban and peri-urban parks.

Analytical Procedure

The research framework in Fig. 2 was proposed to illuminate a diverse set of park environment characteristics influencing the occurrence of violent crime in the park. First, an index system of park environment characteristics was constructed and then, a violent crime level classifier was developed utilizing the XGBoost model. The SHAP algorithm was employed to explain the violent crime level classifier to examine the relationship between the park environment characteristics and the violent crime level.

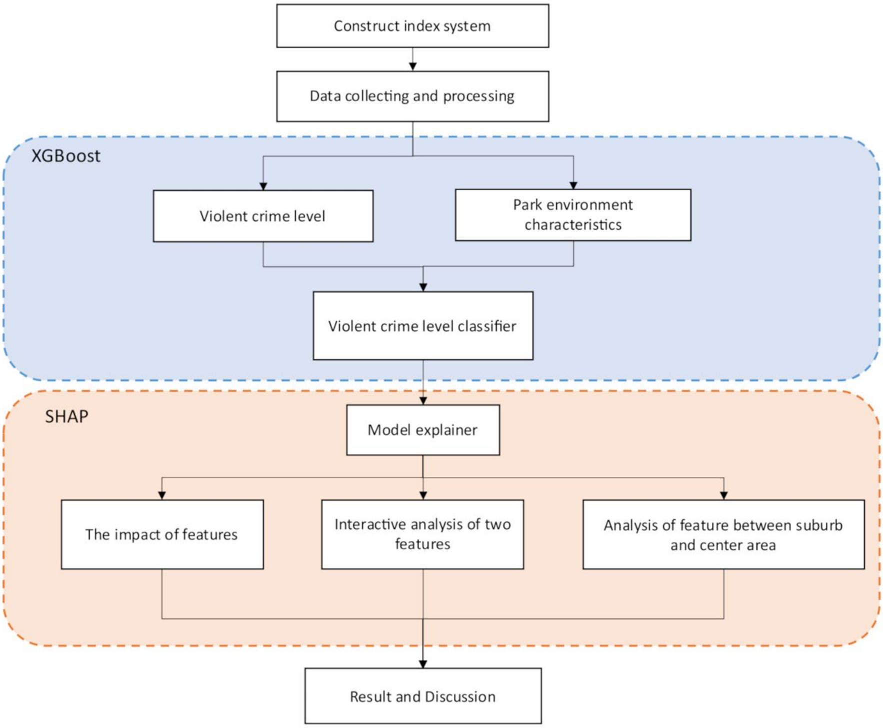


Fig. 2 Analytical procedure

Construction of the Violent Crime Rate Classification Model

The XGBoost model operates within the gradient boosting decision tree (GBDT) framework and is an optimized ensemble tree model that employs an ensemble of weak classifiers to build a strong boosted classifier. XGBoost was developed by Chen and Guestrin (2016) and is renowned for its efficacy in classification tasks and modeling nonlinear relationships. The core concept of the boosting algorithm entails iteratively adding trees and performing feature splits to enhance the model's predictive capacity (Wan et al., 2024). Predicting the violent crime rate level in urban space poses a formidable challenge due to the intricate, non-linear interplay between various park environment characteristics influencing crime occurrences. Linear regression or logistic regression, commonly employed in simpler modeling tasks, may fail to capture these complex relationships effectively, potentially resulting in sub-optimal prediction performance (Wan et al., 2024). Thus, the violent crime rate classification model was constructed using XGBoost by making park environment characteristics features.

To calibrate the XGBoost classification model, we performed parameter tuning based on iterative optimization and validation. The final parameters were set as follows: the learning rate was 0.002, the maximum tree depth was 3, the number of boosting rounds was 20,000, and the subsample ratio was set to 0.5 to balance model diversity and training stability. These parameters were chosen to prevent overfitting while ensuring robust classification performance. Model accuracy was assessed using the concordance index (C-statistic), which quantifies the proportion of correctly ranked pairs across all observations. A C-statistic value of 0.5 indicates random prediction, while a value close to 1.0 denotes strong predictive capability. The final model achieved a C-statistic of 0.8796, demonstrating a high level of prediction accuracy and confirming the model's suitability for exploring the relationships between park environment features and violent crime levels.

Verification of the Violent Crime Rate Classification Using SHAP Value Analysis

The Shapley additive explanations (SHAP) tool offers a unified framework for interpreting predictions, drawing from the principles of Shapley values in cooperative game theory (Lundberg & Lee, 2017). SHAP assigns importance values to each feature for a particular prediction and elucidates both the positive and negative effects of each feature through SHAP values. In this study, park environment characteristics were assigned Shapley values based on their impact on the violent crime rate.

$$g\left(z'\right) = \varphi_0 + \sum_{i=1}^{M} \varphi_i z\prime_i \tag{4}$$

Where $g\left(z'\right)$ signifies the predicted value of violent crime level for x', φ_0 represents the average value of violent crime level; M denotes the total number of the input variable; φ_i represents the attribution value of the i th sample of the neighborhood characteristic and $z\prime_i \in \{0,1\}^M$ indicates whether the i th sample of the neighborhood characteristic is involved in the prediction processing.

According to Eq. 4, the output of the objective function for a sample can be viewed as the summation of all SHAP input variables in that sample and the baseline value, therefore, the SHAP values are computed to explain the model as follows:

$$\varphi_i = \sum_{z' \subseteq f \setminus \{i\}} \frac{\left|z'\right|!\left(M - \left|z'\right| - 1\right)!}{M!}\left[f_x\left(z'\right) - f_x\left(z' \setminus i\right)\right] \tag{5}$$

Where φ_i represents the attribution value of the i th sample of the neighborhood characteristic; $\left|z'\right|$ is the set of all samples in the data set; M represents the total number of input variables; $\left[f_x\left(z'\right) - f_x\left(z' \setminus i\right)\right]$ represents the difference between the model trained with and without the i th input variable.

Results

Differences in Park Environment Characteristics between Urban and Peri-urban Parks

Table 2 reports mean values (with standard deviations in parentheses) for Wuhan urban and peri-urban parks, alongside *p*-values from independent samples t-tests

Table 2 Descriptive statistics of park environment characteristics

	Mean (Standard Deviation)		*P*-value	Mean (Standard Deviation)
	Peri-urban	Urban center		Total area
Accessibility				
Integration	0.0573(0.0094)	0.0616(0.0062)	<0.001	0.0597(0.0081)
Choice	0.0212(0.0428)	0.0174(0.0323)	0.002	0.0191(0.0373)
Connectivity	2.5577(0.8793)	2.6694(0.7852)	0.032	2.6207(0.8289)
Depth	241.4294(41.3896)	220.5008(22.1628)	<0.001	229.6376(33.632)
Built environment features				
Road density	4.6017(11.5483)	6.7691(12.5147)	0.081	5.8229(12.1432)
BVI	9.91% (0.1084642)	11.12%(0.0802)	<0.001	10.59% (0.0937)
GVI	13.89% (0.1437838)	28.14% (0.2083)	<0.001	21.92% (0.1961)
POI diversity	0.5303(0.3083)	0.7236(0.2485)	<0.001	0.6392(0.2922)
POI quantity	180.8377 (358.6796)	604.8073(783.8065)	<0.001	419.7143(667.9703)
Land use features				
Residential	21.38% (0.3178)	39.11% (0.3441)	<0.001	31.37% (0.3441)
Business office	0.17% (0.02)	2.64% (0.097)	<0.001	1.56% (0.075)
Commercial service	1.81% (0.0937)	2.95% (0.1034)	0.005	2.45% (0.0994)
Industrial	21.80% (0.3343)	7.84% (0.2071)	<0.001	13.93% (0.2786)
Transportation stations	0.44% (0.0411)	0.67% (0.0449)	0.161	0.57% (0.0433)
Administrative	2.82% (0.1377)	2.48% (0.0831)	0.164	2.63% (0.1103)
Educational	4.25% (0.1523)	5.54% (0.1706)	0.071	4.98% (0.1629)
Medical	1.16% (0.088)	0.61% (0.0487)	0.017	0.85% (0.0687)
Sport and cultural	1.94% (0.1025)	4.05% (0.1401)	<0.001	3.13% (0.1254)
Socio-economic features				
Housing price	11091.9616 (7448.0511)	17506.7544 (10732.5714)	<0.001	14706.2391 (9957.8367)
Number of Park blocks	382	493		875
Crime				
Violent Crime per Thousand Residents	48.95% (2.6607)	89.70% (4.5266)	0.096	71.91% (3.8291)

examining whether differences between the two groups are statistically significant. The average violent crime rates in urban park blocks are numerically higher than those in peri-urban park blocks (89.70% vs. 48.95%), although this difference does not reach statistical significance ($p = 0.096$). This suggests a potential trend that urban park blocks might face higher crime risks, but the evidence is not strong enough to confirm a significant disparity in security levels between the two types of parks.

In terms of accessibility, urban park blocks exhibit a higher mean value than peri-urban areas (0.0616 vs. 0.0573), with a highly significant difference ($p < 0.001$), suggesting stronger network integration in urban centers. While peri-urban blocks have a slightly higher mean value of choice ($p = 0.002$), urban blocks demonstrate marginally better connectivity, albeit the difference is small but statistically significant. Meanwhile, peri-urban areas show substantially higher mean depth values, reflecting longer average path lengths and lower spatial integration. These spatial characteristics imply that urban park blocks are more centrally positioned within the street network, with higher potential for attracting foot traffic and serving as nodes in shortest-path routes. Such centrality may facilitate criminal movement between locations and reduce opportunities for effective surveillance, compared to the more peripheral and structurally isolated peri-urban park blocks.

In terms of built environment features, urban park blocks scored also exhibit higher than peri-urban areas in BVI (11.12% vs. 9.91%), GVI (28.14% vs. 13.89%), POI diversity (0.72 vs. 0.53), and POI quantity (604.81 vs. 180.84). All differences are highly significant except for road density, which shows a marginal difference ($p=0.081$). These results suggest that urban park blocks are embedded within a more complex, functionally diverse, and visually enriched built environment compared to their peri-urban counterparts.

The proportion of residential land is the highest in urban park blocks, with other functional land showing a relatively balanced distribution, which means urban park blocks have more residents and a more diverse active crowd. In contrast, peri-urban park blocks have the highest proportion of industrial land and a more singular land use pattern. Fewer significant differences are observed in transportation stations, administrative land.

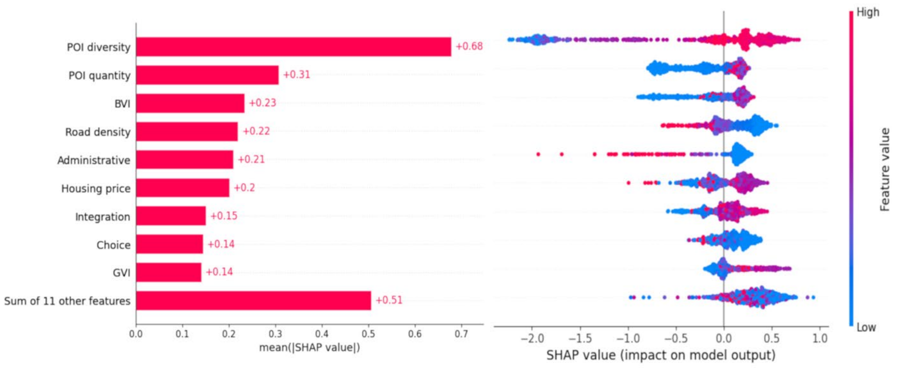
Housing prices tend to be lower in peri-urban park blocks than those in urban park blocks, reflecting the residents' income to a certain extent. Therefore, we can infer those residents living in urban park blocks are likely to include more high-income groups, and there is a greater disparity in social status among residents compared to peri-urban park blocks.

Park Environment Characteristics and Violent Crime

The Impact of Park Environment Characteristics on Violent Crime

Figure 3 shows the overall impact of park environment characteristics on the level of violent crime. Each factor is ranked based on its importance in Fig. 3a showing that nine park environment characteristics significantly impact the violent crime rate, with built environment characteristics, accessibility, and housing prices having particularly noteworthy effects. The horizontal axis in Fig. 3b represents the SHAP value of each factor corresponding to Fig. 3a signifying its impact on the model. Each point on the graph represents a sample with red points representing high feature values, while blue points represent low feature values. For example, red points for POI diversity and POI quantity are concentrated on the right side of the coordinate axis, indicating that high functional diversity and quality of the built environment tend to promote violent crime.

Furthermore, the SHAP dependence plot for GVI (Fig. 4a) and BVI (Fig. 4b) displays an inverted U-shaped pattern. This suggests that moderate green visibility may reduce crime, while excessive vegetation counteracts this effect. For GVI, when the value falls within the range of 23–38%, the SHAP value significantly increases with increasing GVI but as the GVI continues to increase, the SHAP value gradually decreases but remains above 0, suggesting that GVI promotes violent crime when it exceeds 23%. The histogram of blocks suggested that GVI and BVI value within the range of 0 to 20% and 0 to 10%, which means most of blocks have a negative



(a) The ranking of park environment factors on the violent crime rate

(b) Overall impact of park environment factors on the violent crime rate

Fig. 3 (**a**)-(**b**). The relative importance of park environment factors and a summary of local explanations Note: The x-axis values represent the values of the independent variables, the left y-axis denotes SHAP values, and the right y-axis indicates frequency values

influence for violent crime. Research in Portland has demonstrated that green infrastructure has the potential to mitigate negative mental outcomes, such as aggression (Burley, 2018). Conversely, considering other research (Wolfe & Mennis, 2012), which suggests that poorly maintain and overly vegetated trees are positively associated with prevalence violent crime. Similarly, the SHAP value rapidly increases for the BVI values from 0 to 15%, peaking when the BVI equals 23%. Within the range of 10 to 30%, BVI has a positive effect on violent crime. It is speculated that blocks characterized by sparse buildings may exhibit a higher violent crime rate. Additionally, blocks with high road density indicate more dispersed land patterns, with a decrease in violent crime rate observed as road density increases, implying that a well-connected public environment could enhance security.

Furthermore, integration values (Fig. 4c) within the range of 0.052 to 0.06 and 0.062 to 0.07 tend to promote violent crime, suggesting that criminals may gravitate towards areas with higher crime targets but a lower influx of people, as these areas might provide better opportunities for committing crimes without attracting too much attention. The integration results suggest that criminals tend to select areas for crime where they can easily blend in and escape unnoticed. Therefore, if park blocks have convenient transportation conditions, such as easy access to roads or public transit, the violent crime rate in those blocks is likely to be lower.

There was no significant difference in the probability of violent crime among different types of land, except for administrative land, which shows a significant inhibitory effect on crime. Regarding socioeconomic characteristics, housing prices predominantly fall within the range of 8,000 to 20,000 Yuan (Fig. 4d), a pattern that may largely be attributed to the influence of suburban parks, which play a significant role in shaping low-priced housing zones. The SHAP value of housing prices is the highest when the housing price peaks around 20,000 Yuan per square meter, while the SHAP value becomes negative when the housing price exceeds 30,000 Yuan per

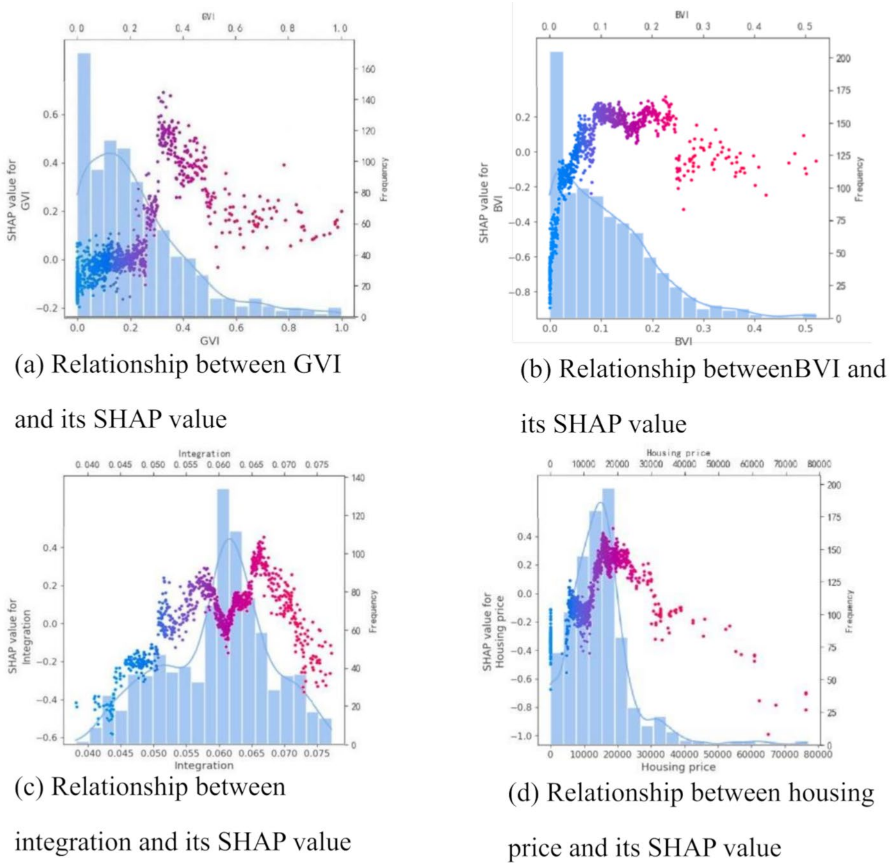
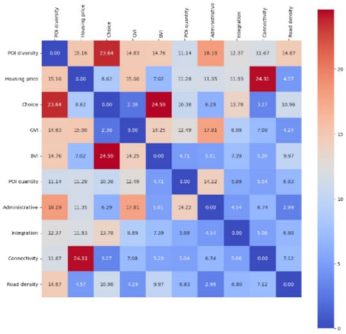


Fig. 4 (**a**)-(**d**) Nonlinear relationships between park environment factors and the violent crime rate. Note: The x-axis values represent the values of the independent variables, the left y-axis denotes SHAP values, and the right y-axis indicates frequency values

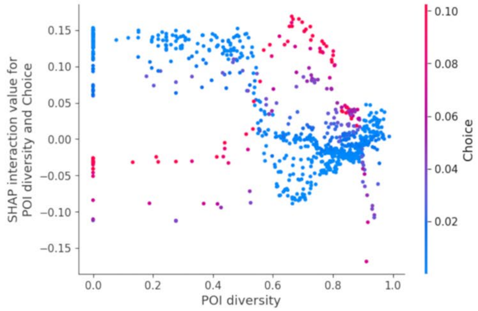
square meter or falls below 8,000 Yuan per square meter (Fig. 4d). This suggests that violent crimes are more likely to occur in neighborhoods where the housing price is close to the average, as the security measures in these areas might be less stringent compared to high-price blocks, making them more attractive to criminals.

Interactive Effects of Two Factors on Park Crime

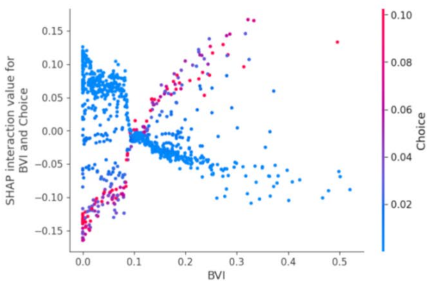
According to the interactive analysis, there are significant mutual influences in the choice-POI diversity, choice-BVI, and connectivity-houses prices. The interaction value of the features matrix is presented in Fig. 5(a), where larger numbers signify more significant interactions. Figures 4(b)-(d) depict the interaction effects of two factors, with the X-axis representing one of the factors and the Y-axis representing the SHAP value of the other factor. In terms of the built environment, when the POI diversity (Fig. 5b) is less than 0.6, blue scatters overtop red scatters, indicating that low POI diversity tends to correlate with lower violent crime rates in low-accessi-



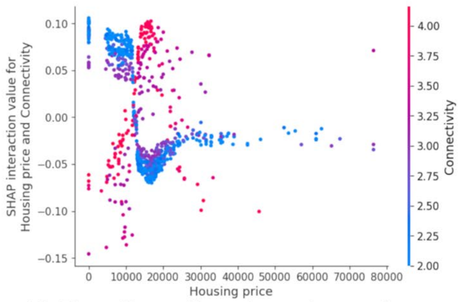
(a) Interactive effects of two factors on SHAP values



(b) The effect of POI diversity and choice on SHAP values



(c) The effect of BVI and choice on SHAP values



(d) The effect of housing prices and connectivity on SHAP values

Fig. 5 (**a**)-(**d**). Interactive analysis of two features. Note: The x-axis denotes the values of one independent variable, the right y-axis represents the values of the other independent variable, and the color of the scatter points indicates the magnitude of the latter

bility blocks. Conversely, when the value of POI diversity exceeds 0.6, the trend reverses. Similarly, when the BVI (Fig. 5c) is less than 10%, blue scatters overtop red scatters indicating that low-accessibility blocks with sparse buildings tend to have a higher violent crime rate than high-accessibility blocks. However, when the BVI surpasses 10%, the SHAP of high-accessibility blocks increases with the rising BVI but the opposite is observed in low-accessibility blocks. The security of high-accessibility blocks tends to decrease as the complexity of the building environment increases, whereas security increases with building complexity in low-accessibility blocks. We speculated that POIs and building density can attract people and increase guardianship in low-accessibility blocks. However, this effect is not as pronounced in high-accessibility blocks where there is no shortage of guardianship but the complex building environment provides more opportunities for criminals to hide or escape. Therefore, increasing the diversity of the built environment in low-accessibility parks can reduce violent crime but it is essential to consider the influence of various factors in high-accessibility parks.

In terms of housing prices, Fig. 5d indicates that blocks with housing prices exceeding 30,000 yuan per square meter typically exhibit low accessibility conditions, while blocks with housing prices below 30,000 yuan have significant fluctuations in accessibility conditions, with low accessibility tending to promote violent crime under similar housing prices. Thus, high accessibility conditions can mitigate violent criminal behavior, and a high-house-price community equipped with superior property management and security facilities can mitigate the negative effects stemming from low accessibility.

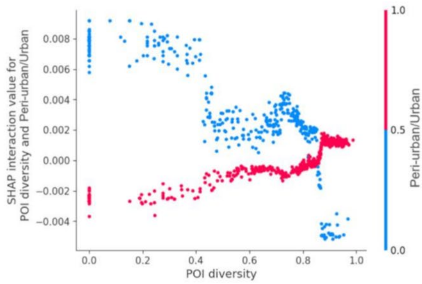
Comparison of Urban and Peri-urban Parks

Figure 6(a)-(f) presents a comparative analysis of the differences between urban and peri-urban parks. In this analysis, red scatters represent samples from urban parks, while blue scatters represent samples from peri-urban parks. There is an obvious difference in built environment characteristics and accessibility. The change in accessibility significantly affects violent crime in peri-urban park blocks, with improved accessibility elevating the SHAP value, thereby promoting violent crime rates. We hypothesize that the number of crime targets in low-accessibility peri-urban parks is fewer than that in high-accessibility counterparts. Additionally, the lower population density in low-accessibility peri-urban parks tends to impede criminals' ability to blend in or escape detection. These results are consistent with Crime and Accessibility Theory, which posits that criminals generally tend to commit crimes in areas with high accessibility.

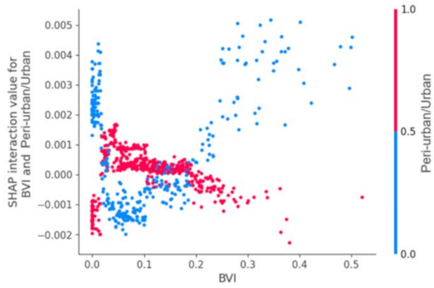
Based on observed characteristics of the built environment, the increasing POI diversity appears to mitigate violent crime while a rise in BVI may exacerbate violent crime in peri-urban park blocks. This is possible because of the extensive industrial land around the peri-urban park and the dominance of factories, therefore, the increasing BVI due to the increasing industrial land could not significantly improve the vitality of peri-urban parks. When the POI is 0, the difference in the SHAP value between peri-urban and urban parks is most pronounced. There tends to be a higher violent crime rate in urban parks when there is no POI facility but this is reversed in peri-urban blocks. Consequently, it is important to maintain vitality in buildings within peri-urban park blocks, while also ensuring that a certain number of service facilities are provided in urban parks.

Conclusions and Discussion

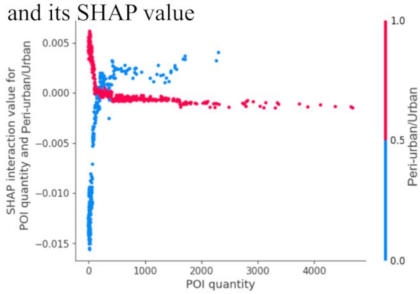
This study employed the XGBoost algorithm modeling method to explore the factors influencing violent crime in urban and peri-urban parks within an integrated framework that jointly considered different types of park environment features, namely accessibility, built environment, land use, and socio-economic characteristics. There were nonlinear variations in GVI, BVI, integration, and housing prices concerning violent crime, exerting different scopes of influence and contributing to varying effects on violent crime rates. Also, the interactions between factors are important in influencing violent crime rates, as demonstrated in the two-factor analysis. This



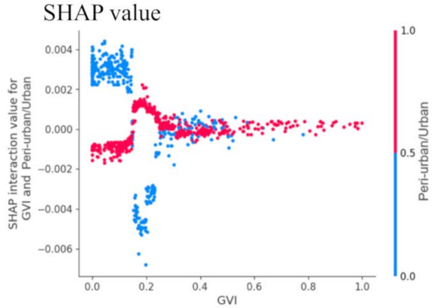
(a) Relationship between POI diversity and its SHAP value



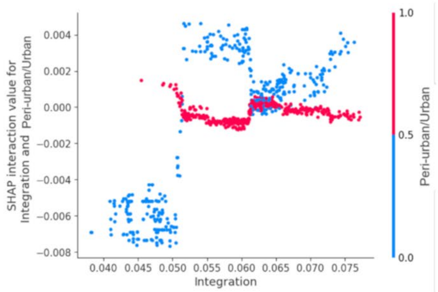
(b) Relationship between BVI and its SHAP value



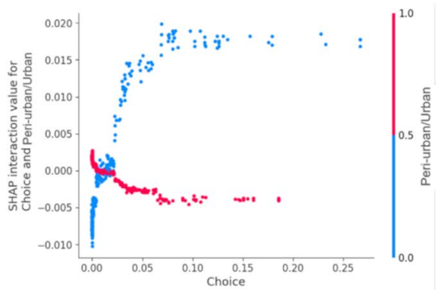
(c) Relationship between POI quantity and its SHAP value



(d) Relationship between GVI and its SHAP value



(e) Relationship between integration and its SHAP value



(f) Relationship between choice and its SHAP value

Fig. 6 (**a**)-(**f**). An interactive analysis of features across urban and peri-urban parks. Note: The x-axis denotes the values of the independent variables, with red scatter points representing urban park blocks and blue scatter points indicating peri-urban blocks

approach recognizes the nonlinear variation factors and avoids a one-size-fits-all planning model in urban planning. In practice, our work provides a new method for turban planners to better understand how the urban environment influences the community's social activities.

Differences between Urban Parks and Peri-urban Parks

Unlike disadvantaged social status groups in the United States, which have limited access to high-quality parks (Rigolon, 2016), there are no significant differences in park accessibility across different socioeconomic groups in China (Wei, 2017). This study finds that the compositional differences of populations in peri-urban parks and parks located in different positions are not significant. Therefore, there are significant differences in park environment characteristics between urban and peri-urban park blocks. Urban park blocks typically boast superior accessibility, a more intricate built environment, and a more diverse land use model than peri-urban park blocks. Furthermore, there is a larger disparity in housing prices surrounding urban parks which means a greater socioeconomic divide within urban park blocks. Consistent with previous studies suggesting that densely populated urban areas tend to experience higher crime rates compared to rural areas, urban park blocks tend to have a higher violent crime rate. Urban parks may become a breeding ground for social and economic conflicts.

Park Environment Characteristics and Violent Crime

The results suggest that surrounding environmental characteristics are strongly associated with violent crime in and around parks, with accessibility, built environment indicators, and housing prices showing the most substantial effects. Accessibility reflects both pedestrian presence and traffic convenience, and its protective effect supports the "Eyes on the Street" theory (Jacobs, 1961): areas with higher foot traffic and user engagement tend to offer stronger informal surveillance. However, in poorly monitored areas, accessibility may also facilitate criminal escape, highlighting the need to balance openness with effective guardianship.

The interaction analysis further indicates that accessibility modifies the influence of POI diversity, BVI, and housing prices on violent crime risk, suggesting that these features do not operate independently but are shaped by broader spatial dynamics. High POI density and functional diversity, while often signaling vibrancy, may also lead to functional disorder if not clearly organized—echoing the Broken Windows Theory, which links environmental neglect or ambiguity to elevated crime risk. Similarly, excessive vegetation (GVI) may reduce visibility and weaken informal surveillance, while low-accessibility buildings may become neglected spaces prone to violence.

Contrary to expectations, the park location was not a significant predictor of the city's violent crime rate, therefore rejecting the "one fits all" model that considers that urban parks would attract more violent crime solely based on differences in their park environment characteristics. Instead, our findings suggest that the influence on violent crime rates is shaped by a more complex interplay of factors. The association of accessibility and complex built environment characteristics with a high violent crime rate is evident. While accessibility and built environment characteristics play an important role in impacting violent crime rates, effective security conditions can mitigate the negative influence caused by inaccessible traffic conditions and a complex built environment. The violent crime rate is obviously suppressed in blocks with high administrative land use rates or high housing prices. Furthermore, high housing price blocks are associated with low violent crime rates even in blocks with inaccessible traffic conditions, suggesting that good security is effective in reducing crime, and residents in upscale neighborhoods have better access to park services. These findings are consistent with studies that reported that economically distressed communities are more susceptible to violent conflicts (O'Brien & Sampson, 2015; Zhang et al., 2022). Furthermore, our research suggests that housing prices of about 17,000 yuan are most conducive to violent crime, as this price point corresponds to the largest proportion of residential areas, making it a prime target for criminal activity. Additionally, the security conditions in these communities are generally lacking, leading criminals to choose a familiar environment with inadequate security conditions for their activities.

Finally, regression analysis has been frequently employed in prior research in urban planning and environmental criminology, with many of these studies seeking to establish connections between urban characteristics and crime to develop urban design strategies. However, this method can only determine the coeffective value of a certain factor on violent crime without providing insight into how its influence on crime may change due to the interactive effects of different factors. Therefore, it is unreasonable to simply categorize a factor as "inhibiting" or "facilitating" crime. Our approach contributes to the growing focus on using machine learning to explain the threshold of environmental change regarding the violent crime rate in and around parks, thereby improving our understanding of how violent crime occurs in park blocks.

Policy Implications

Based on the observed associations between violent crime and park environment characteristics, we propose the following policy strategies: First, compared to large expansive parks, linear parks embedded in residential neighborhoods tend to offer higher visibility, better natural surveillance, and greater integration with pedestrian pathways. These features not only reduce visual obstruction from vegetation but also enhance residents' sense of safety and passive monitoring, potentially lowering the risk of violent crime. Second, in areas with dense commercial functions and high pedestrian flows, residents are often less sensitive to unfamiliar individuals. To address this, regular community activities can strengthen social ties and territorial awareness, making residents more vigilant. Third, urban and peri-urban parks require differentiated safety strategies. While urban parks benefit from active use and diversified functions, peri-urban parks—often more isolated and ecologically oriented—should incorporate more built infrastructure, lighting, and human activity zones to reduce crime vulnerability. Increasing artificial elements in these areas has been shown to significantly reduce safety-related incidents.

Limitation and Future Research Directions

This study has several limitations that warrant further investigation. First, the analytical unit of 1000×1000 m may overlook micro-scale social dynamics and spatial interactions across community boundaries. Second, street view images used to derive built environment indicators were captured only during daylight hours, omitting nighttime conditions such as street lighting—an important factor influencing perceptions of safety. Third, due to data constraints, this study was unable to include direct indicators of formal surveillance or law enforcement presence, such as street-level CCTV coverage or patrol frequency, which are known to affect crime rates. Instead, built environment proxies such as road density, POI diversity, and building visibility were used to approximate levels of surveillance and activity. Future research should incorporate high-resolution administrative or policing data to better assess the role of formal guardianship in park-related crime. Finally, a longitudinal approach that tracks changes in park environments and crime over time would help clarify causal relationships and inform more dynamic and adaptive safety interventions.

Author Contributions Sainan Lin: Writing-original draft preparation, Formal analysis and investigation, Funding acquisition, Conceptualization, Revision; Shudi Chen: Methodology, Formal analysis and investigation, Visualization, Writing - original draft preparation, Revision; Kaidi Liu: Formal analysis and investigation, Writing - original draft preparation, Revision; Yao Yao: Data curation, Conceptualization, Validation, Writing-review & editing, Revision.

Funding This research is supported by National Natural Science Foundation of China (42471276; 42171205).

Data Availability The codes and sample data to reproduce our work are publicly available at https://doi.org/10.6084/m9.figshare.27824571.

Declarations

Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.

References

Agrawal, A., & Gibson, C. C. (1999). Enchantment and disenchantment: The role of community in natural resource conservation. *World Development*, *27*(4), 629–649. https://doi.org/10.1016/s0305-750x(98)00161-2

Beckett, K., & Herbert, S. (2008). Dealing with disorder - Social control in the post-industrial city. *Theoretical Criminology*, *12*(1), 5–30. https://doi.org/10.1177/1362480607085792

Bhatia, S., & Jason, L. (2022). Greenness and crime in the city: An investigation using remote sensing and spatial panel models. *Applied Spatial Analysis and Policy*, *16*, 229–257.

Boessen, A., & Hipp, J. R. (2018). Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Social Science Research*, *76*, 186– 201. https://doi.org/10.1016/j.ssresearch.2018.08.008

Brueckner, J. K., & Rosenthal, S. S. (2009). Gentrification and neighborhood housing cycles: Will america's future downtowns be rich? *Review of Economics and Statistics*, *91*(4), 725–743. https://doi.org/10.1162/rest.91.4.725

Burley, B. A. (2018). Green infrastructure and violence: Do new street trees mitigate violent crime? *Health & Place*, *54*, 43–49. https://doi.org/10.1016/j.healthplace.2018.08.015

Charney, I. (2005). Canadian human landscape examples - Two visions of suburbia: Mississauga City centre and heartland business community. *Canadian Geographer-Geographe Canadien*, *49*(2), 214–220. https://doi.org/10.1111/j.0008-3658.2005.00090.x

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.
Chen, G., Zhang, S., Yan, B., & Miao, S. (2021). Environmental safety evaluation of geopark based on CPTED concept and fuzzy comprehensive analysis. *Plos One*, *16*(11), 22. https://doi.org/10.1371/journal.pone.0260316
Chen, S., Lin, S., Yao, Y., & Zhou, X. (2024). Urban public space safety perception and the influence of the built environment from a female perspective: Combining street view data and deep learning. *Land*, *13*, 2108.
Cheng, S., Liao, Z., & Zhu, Y. (2021). Dynamic changes in community deprivation of access to urban green spaces by multiple transport modes. *Frontiers in Public Health*, *9*, 615432. https://doi.org/10.3389/fpubh.2021.615432
Cohen, D. A., Marsh, T., Williamson, S., Han, B., Derose, K. P., Golinelli, D., & McKenzie, T. L. (2014). The potential for pocket parks to increase physical activity. *American Journal of Health Promotion*, *28*(3), S19–S26. https://doi.org/10.4278/ajhp.130430-QUAN-213
Cole, H. V. S., Triguero-Mas, M., Connolly, J. J. T., & Anguelovski, I. (2019). Determining the health benefits of green space: Does gentrification matter? *Health & Place*, *57*, 1–11. https://doi.org/10.1016/j.healthplace.2019.02.001
Cornelis, J., & Hermy, M. (2004). Biodiversity relationships in urban and suburban parks in Flanders. *Landscape and Urban Planning*, *69*(4), 385–401. https://doi.org/10.1016/j.landurbplan.2003.10.038
Cozens, P. M. (2008). New urbanism, crime and the suburbs: A review of the evidence. *Urban Policy and Research*, *26*(4), 429–444. https://doi.org/10.1080/08111140802084759
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
Donovan, G. H., & Prestemon, J. P. (2012). The effect of trees on crime in Portland, Oregon. *Environment and Behavior*, *44*(1), 3–30. https://doi.org/10.1177/0013916510383238
Feng, D., Wang, W., Mangalathu, S., & Taciroglu, E. (2021). Interpretable XGBoost-SHAP machine-learning model for shear strength prediction of squat RC walls. *Journal of Structural Engineering*, *147*(11), 13. https://doi.org/10.1061/(asce)st.1943-541x.0003115
Feng, Z., Tang, Y., Huang, H., & Liu, Y. (2024). Urbanicity and depression among Chinese youth: A cross-sectional study based on the China Labor-Force Dynamic Survey. *Applied Spatial Analysis and Policy*, *17*, 619–636.
Folharini, S. O., de Melo, S. N., Ramos, R. G., & Brown, J. C. (2023). Land use and green crime: Assessing the edge effect. *Land Use Policy*, *129*, 106636. https://doi.org/10.1016/j.landusepol.2023.106636
Garcia-Tejeda, E., & Fondevila, G. (2023). Policing social disorder and broken windows theory: Spatial evidence from the Franeleros experience. *Isprs International Journal of Geo-Information*, *12*(11), 20. https://doi.org/10.3390/ijgi12110449
Gargiulo, I., Garcia, X., Benages-Albert, M., Martinez, J., Pfeffer, K., & Vall-Casas, P. (2020). Women's safety perception assessment in an urban stream corridor: Developing a safety map based on qualitative GIS. *Landscape and Urban Planning*, *198*, 103779. https://doi.org/10.1016/j.landurbplan.2020.103779
[dataset] Gong, P., Chen, B., Xuecao, L., Liu, H., & Xu, B. (2019). Mapping essential urban land use categories in China (EULUC-China): Preliminary results for 2018. *Science Bulletin, 65*(3), 182–187.
Hajna, S., & Cummins, S. (2023). Effects of the onset of the COVID-19 pandemic restrictions on park crime in london, england: An interrupted time series analysis. *Urban Forestry & Urban Greening*, *84*(6), 127934. https://doi.org/10.1016/j.ufug.2023.127934
Han, B., Cohen, D. A., Derose, K. P., Li, J., & Williamson, S. (2018). Violent crime and park use in low-income urban neighborhoods. *American Journal of Preventive Medicine*, *54*(3), 352–358. https://doi.org/10.1016/j.amepre.2017.10.025
Jacobs, J. (1961). *The death and life of great American cities*. Vintage.
Jennings, V., Floyd, M. F., Shanahan, D., Coutts, C., & Sinykin, A. (2017). Emerging issues in urban ecology: Implications for research, social justice, human health, and well-being. *Population and Environment*, *39*(1), 69–86. https://doi.org/10.1007/s11111-017-0276-0
Kadar, C., & Pletikosa, I. (2018). Mining large-scale human mobility data for long-term crime prediction. *Epj Data Science*, *7*, 27. https://doi.org/10.1140/epjds/s13688-018-0150-z
Knorre, A., & MacDonald, J. (2023). Shootings and land use. *Journal of Criminal Justice*, *86*(16), 102068. https://doi.org/10.1016/j.jcrimjus.2023.102068

Kuo, F. E., & Sullivan, W. C. (2001). Environment and crime in the inner city - Does vegetation reduce crime? *Environment and Behavior*, *33*(3), 343–367. https://doi.org/10.1177/00139160121973025

Lan, T. H., Liu, Y. X., Huang, G. L., Corcoran, J., & Peng, J. (2022). Urban green space and cooling services: Opposing changes of integrated accessibility and social equity along with urbanization. *Sustainable Cities and Society*, *84*(10), 104005. https://doi.org/10.1016/j.scs.2022.104005

Li, F. Z., Guo, S. Y., Li, D., Li, X., Li, J., & Xie, S. (2020). A multi-criteria Spatial approach for mapping urban ecosystem services demand. *Ecological Indicators*, *112*(11), 106119. https://doi.org/10.1016/j.ecolind.2020.106119

Li, X., Xiong, H., Li, X., Wu, X., Zhang, X., Liu, J., Bian, J., & Dou, D. (2022). Interpretable deep learning: Interpretation, interpretability, trustworthiness, and beyond. *Knowledge and Information Systems*, *64*(12), 3197–3234. https://doi.org/10.1007/s10115-022-01756-8

Li, J., Gao, J., Zhang, Z., Fu, J., Shao, G., Zhao, Z., & Yang, P. (2024). Insights into citizens' experiences of cultural ecosystem services in urban green spaces based on social media analytics. *Landscape and Urban Planning*, *244*(9), 104999. https://doi.org/10.1016/j.landurbplan.2023.104999

Liao, Y., Wang, S., Chang, K., Qin, C., Deng, Z., Lv, Z., & Zhou, Q. (2023). A dataset of major urban park of Wuhan in 2021. *China Scientific Data*.

Lis, A., Zalewska, K., & Iwankowski, P. (2019). Why do we choose fear-evoking spots in parks? The role of danger and privacy in the model of dependence between spatial attributes and preference. *Urban Forestry & Urban Greening*, *38*, 193–204. https://doi.org/10.1016/j.ufug.2018.12.012

Lis, A., Zalewska, K., Iwankowski, P., Betkier, K., Bilska, P., Dudar, V., & Lagiewka, A. L. (2024). Evaluation of sense of safety and privacy in parks in relation to the topography, the presence of dense vegetation and other people in the area. *Landscape and Urban Planning*, *242*, 104948. https://doi.org/10.1016/j.landurbplan.2023.104948

Liu, Y., Wang, R., Grekousis, G., Liu, Y., & Li, Z. (2019). Neighbourhood greenness and mental wellbeing in guangzhou, china: What are the pathways? *Landscape and Urban Planning*, *190*, 103602.

Liu, Z. H., Huang, Q. D., & Yang, H. Y. (2021). Supply-demand Spatial patterns of park cultural services in megalopolis area of shenzhen, China. *Ecological Indicators*, *121*(11), 107066. https://doi.org/10.1016/j.ecolind.2020.107066

Lundberg, S. M., & Lee, S. I. (2017). *A unified approach to interpreting model predictions*. Neural Information Processing Systems.

Maruthaveeran, S., & van den Bosh, C. K. (2015). Fear of crime in urban parks - What the residents of Kuala Lumpur have to say? *Urban Forestry & Urban Greening*, *14*(3), 702–713. https://doi.org/10.1016/j.ufug.2015.05.012

McCord, E. S., & Houser, K. A. (2017). Neighborhood parks, evidence of guardianship, and crime in two diverse US cities. *Security Journal*, *30*(3), 807–824. https://doi.org/10.1057/sj.2015.11

McMillen, D., Sarmiento-Barbieri, I., & Singh, R. (2019). Do more eyes on the street reduce crime?? Evidence from chicago's safe passage program. *Journal of Urban Economics*, *110*, 1–25. https://doi.org/10.1016/j.jue.2019.01.001

Mujetahid, A., Nursaputra, M., & Soma, A. S. (2023). Monitoring illegal logging using Google Earth engine in Sulawesi Selatan tropical forest, Indonesia. *Forests*, *14*(3), 14. https://doi.org/10.3390/f14030652

O' Brien, D. T., & Sampson, R. J. (2015). Public and private spheres of neighborhood disorder: Assessing pathways to violence using large-scale digital records. *Journal of Research in Crime and Delinquency*, *52*(4), 486–510.

Parsa, A. B., Movahedi, A., Taghipour, H., Derrible, S., & Mohammadian, A. (2020). Toward safer highways, application of XGBoost and SHAP for real-time accident detection and feature analysis. *Accident Analysis and Prevention*, *136*(8), 105405. https://doi.org/10.1016/j.aap.2019.105405

Rashid, M. (2017). *Studies on the geometry of urban layouts: A review of the literature*. Springer International Publishing.

Rigolon, A. (2016). A complex landscape of inequity in access to urban parks: A literature review. *Landscape and Urban Planning*, *153*, 160–169. https://doi.org/10.1016/j.landurbplan.2016.05.017

Rigolon, A., & Németh, J. (2020). Green gentrification or 'just green enough': Do park location, size and function affect whether a place gentrifies or not? *Urban Studies*, *57*(2), 402–420. https://doi.org/10.1177/0042098019849380

Sachs, A. L., Boag, A. E., & Troy, A. (2023). Valuing urban trees: A hedonic investigation into tree canopy influence on property values across environmental and social contexts in baltimore, Maryland. *Urban Forestry & Urban Greening*, *80*(11), 127829. https://doi.org/10.1016/j.ufug.2022.127829

Sadeek, S. N., Ahmed, A., Hossain, M., & Hanaoka, S. (2019). Effect of land use on crime considering exposure and accessibility. *Habitat International*, *89*(10), 102003. https://doi.org/10.1016/j.habitatint.2019.102003

Schusler, T., Weiss, L., Treering, D., & Balderama, E. (2018). Research note: Examining the association between tree canopy, parks and crime in Chicago. *Landscape and Urban Planning*, *170*, 309–313. https://doi.org/10.1016/j.landurbplan.2017.07.012

Shi, Q., Liu, M., Marinoni, A., & Liu, X. (2023). UGS-1m: Fine-grained urban green space mapping of 31 major cities in China based on the deep learning framework. *Earth Syst Sci Data*, *15*(2), 555–577. https://doi.org/10.5194/essd-15-555-2023

Stucky, T. D., & Ottensmann, J. R. (2009). Land use and violent crime. *Criminology*, *47*, 1223–1264.

Su, N. X., Li, W. J., & Qiu, W. S. (2023). Measuring the associations between eye-level urban design quality and on-street crime density around new York subway entrances. *Habitat International*, *131*(13), 102728. https://doi.org/10.1016/j.habitatint.2022.102728

Taylor, R. B., Haberman, C. P., & Groff, E. R. (2019). Urban park crime: Neighborhood context and park features. *Journal of Criminal Justice* , *64*, 101622. https://doi.org/10.1016/j.jcrimjus.2019.101622

Troy, A., Grove, J. M., & O'Neil-Dunne, J. (2012). The relationship between tree canopy and crime rates across an urban-rural gradient in the greater Baltimore region. *Landscape and Urban Planning*, *106*(3), 262–270. https://doi.org/10.1016/j.landurbplan.2012.03.010

Valente, D., Pasimeni, M. R., & Petrosillo, I. (2020). The role of green infrastructures in Italian cities by linking natural and social capital. *Ecological Indicators*, *108*(8), 105694. https://doi.org/10.1016/j.ecolind.2019.105694

Venter, Z. S., Shackleton, C., Faull, A., Lancaster, L., Breetzke, G., & Edelstein, I. (2022). Is green space associated with reduced crime? A national-scale study from the global South. *Science of the Total Environment*, *825*(8), 154005. https://doi.org/10.1016/j.scitotenv.2022.154005

Wan, A., Gong, Z., Chen, T., & Al-Bukhaiti, K. (2024). Mass flow characteristics prediction of refrigerants through electronic expansion valve based on XGBoost. *International Journal of Refrigeration*, *158*, 345–352. https://doi.org/10.1016/j.ijrefrig.2023.12.011

Wang, K., & Liu, J. J. (2017). The spatiotemporal trend of city parks in Mainland China between 1981 and 2014: Implications for the promotion of leisure time physical activity and planning. *International Journal of Environmental Research and Public Health*, *14*(10), 15. https://doi.org/10.3390/ijerph14101150

Wang, F., Wu, W., & Wang, D. (2023). Emerging evidence on transit-oriented development in the global South. *Transportation Research Part D: Transport and Environment*, *123*, 103898. https://doi.org/10.1016/j.trd.2023.103898

Wei, F. (2017). Greener urbanization? Changing accessibility to parks in China. *Landscape and Urban Planning*, *157*, 542–552. https://doi.org/10.1016/j.landurbplan.2016.09.004

Wolfe, M. K., & Mennis, J. (2012). Does vegetation encourage or suppress urban crime? Evidence from philadelphia, PA. *Landscape and Urban Planning*, *108*(2–4), 112–122. https://doi.org/10.1016/j.landurbplan.2012.08.006

Wu, W., Chen, W., Yun, Y., & Wang, F. (2022). Urban greenness, mixed land use and life satisfaction. *Landscape and Urban Planning*, *224*, 104428.

Wu, W., Tan, W., Wang, R., & Chen, W. (2023a). From quantity to quality: Effects of urban greenness on life satisfaction and social inequality. *Landscape and Urban Planning*, *238*, 104843.

Wu, Y., Wei, Y. D., Liu, M., & García, I. (2023b). Green infrastructure inequality in the context of COVID-19: Taking parks and trails as examples. *Urban Forestry & Urban Greening*, *86*, 128027. https://doi.org/10.1016/j.ufug.2023.128027

Yue, H., Liu, L., Xu, C., Song, G., Chen, J., He, L., & Duan, L. (2024). Investigating the diurnal effects of on-street population and streetscape physical environment on street theft crime: A machine learning and negative binomial regression approach using street view images. *Applied Geography*, *163*, 103194. https://doi.org/10.1016/j.apgeog.2023.103194

Zhang, P., & Park, S. (2023). Investigating spatial heterogeneity of park inequity using three access measures: A case study in Hartford, Connecticut. *Applied Geography*, *151*, 102857. https://doi.org/10.1016/j.apgeog.2022.102857

Zhang, Z., Qian, Z., Zhong, T., Chen, M., Zhang, K., Yang, Y., Zhu, R., Zhang, F., Zhang, H., Zhou, F., Yu, J., Zhang, B., Lü, G., & Yan, J. (2022). Vectorized rooftop area data for 90 cities in China. *Scientific Data*, *9*(1), 66. https://doi.org/10.1038/s41597-022-01168-x

Authors and Affiliations

Sainan Lin[1] · Shudi Chen[1] · Kaidi Liu[1] · Yao Yao[2]

✉ Yao Yao
yaoy@cug.edu.cn

Sainan Lin
sainan.lin@whu.edu.cn

1 School of Urban Design, Wuhan University, Hubei Habitat Environment Research Centre of Engineering and Technology, Wuhan, Hubei Province, China

2 School of Geography and Information Engineering, China University of Geosciences, Wuhan, Hubei Province, China