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Original article

Revealing park visitation under dual environmental threats in a socially stratified city: Evidence from smartphone mobility data in Dallas

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ABSTRACT

Urban parks are pivotal to residents' physical activity and health promotion. Yet, few studies have explored how environmental threats, ranging from the physical (extreme weather) to the social (violent crime), collectively shape park use, nor have they considered the divergent risk exposures of parks situated in diverse socioeconomic contexts. Taking Dallas, USA, as a case study, we integrate large-scale smartphone mobility data, place-based high-resolution extreme weather metrics, and geocoded violent crime records, and apply an interpretable machine learning framework (BO-LightGBM-SHAP) to uncover the differentiated associational patterns of park visitor volume across neighborhoods with varying poverty levels. Results reveal that parks in high-poverty-rate neighborhoods, while bearing the greatest climate-safety risks, exhibit the highest weekly average visitor volumes among all groups, indicating their essential infrastructure role. The determinants of visitation vary markedly along the poverty gradient: parks in high-poverty-rate areas are most sensitive to the dual environmental risks; visitation in medium-poverty-rate areas shows strong threshold effects related to parks' physical attributes and accessibility; and usage in low-poverty-rate communities is governed primarily by internal socioeconomic structure. Furthermore, extreme heat and precipitation exert context-dependent, non-linear effects on visitor volume, while extreme cold acts as a uniform deterrent across all communities. Violent crime shows a threefold heterogeneity in its association with park visitation across crime type, time lag, and poverty context. These findings highlight the need for urban planning to adopt locally tailored strategies that integrate climate adaptation and public-safety considerations, providing actionable guidance for building more equitable and resilient urban park systems.

1. Introduction

In an era of intensifying climate change and public health challenges, the role of urban parks in enhancing resident well-being, fostering social cohesion, and delivering critical ecosystem services has become increasingly important (Yousofpour et al., 2024; Ayala-Azcárraga et al., 2019). Parks provide essential opportunities for physical activity, community engagement, and psychological restoration, directly supporting the health and livability of urban populations (Motomura et al., 2024; Li et al., 2023). Recently, the factors influencing park visitation have been extensively investigated, including park-specific features, the surrounding built environment, and socioeconomic characteristics (Liao et al., 2025; Liu et al., 2023).

The increasing frequency and intensity of extreme climate events have introduced new challenges to park visitation (Song and Wei, 2024; Ye et al., 2025b; Chu and Rotta Loria, 2024). While a growing body of work has investigated the association of routine weather on park use (Jaung and Carrasco, 2021; Zhang et al., 2024), little is known about how extreme climatic conditions (e.g., extreme heat, cold waves, heavy rainfall), typically defined as meteorological events that exceed historical thresholds and constitute environmental risks, shape outdoor recreation behaviors (Tuholske et al., 2021; Gong et al., 2025). Limitations in data availability have further constrained many analyses to the city scale, neglecting the pronounced intra-urban disparities in climate

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exposure and resilience (Qiao et al., 2025). Such gaps hinder our understanding of neighborhood-level vulnerabilities and complicate the design of targeted urban planning and climate adaptation.

Urban residents navigate a complex landscape of environmental risks where, alongside climatic threats, violent crime emerges as a pervasive social hazard capable of undermining public safety and disrupting recreational activities in public spaces like parks (Theall et al., 2022; Marquet et al., 2020). The existing literature has predominantly relied on survey data to capture park visitation intentions under unsafe conditions or has focused on the effects of subjective safety perceptions (Marquet et al., 2019; Han et al., 2018). There is a lack of research that integrates objective crime data with fine-scale park visitation data from mobile devices to inform evidence-based strategies.

Importantly, urban populations are often exposed to concurrent environmental threats, ranging from the physical (extreme weather) to the social (violent crime). Existing research suggests that natural disasters and local crime can be conceptualized as analogous environmental stressors, as they not only share objective characteristics but are also perceived in similar ways, such as safety concerns by the public (Taylor and Shumaker, 1990). Analyzing them in parallel thus offers deeper insights than either perspective could provide alone, yet a significant gap persists in our understanding of the mechanisms through which these dual environmental risks impact the use of urban parks. Moreover, how responses and vulnerabilities to these compounded risks diverge across neighborhoods with different income levels remains understudied. Such responses are unlikely to be uniform; rather, they are shaped by structural inequalities, resource availability, and adaptive capacities that differ by income level (Leap et al., 2024; Lee and Contreras, 2021). Addressing these knowledge gaps requires analytical frameworks capable of revealing underlying disparities in recreational activities and environmental benefits across socioeconomically diverse park neighborhoods.

Therefore, this study focuses on the City of Dallas, an ideal case because it is home to one of the nation's largest municipal park systems (Trust for Public Land, 2025a), while also grappling with violent crime rates well above the national average (Safe and Sound Security, 2025) and increasingly frequent extreme weather conditions. We integrated multi-source data, including smartphone mobility data, high-resolution extreme weather metrics, and geocoded violent crime records for 2019, to examine how key forms of urban disturbance, namely extreme weather and violent crime, are associated with park visitor volume across neighborhoods stratified by poverty level. Recognizing that the relationship between these factors and park visitation can be non-linear (Gao et al., 2025), we employ a Bayesian optimization (BO)–LightGBM framework to model urban park visitation patterns, further utilizing the Shapley Additive Explanations (SHAP) algorithm to uncover key determinants, critical thresholds, and complex nonlinear effects shaping park use behaviors.

This study seeks to address the following research questions: (1) How do patterns of park visitation, extreme weather exposure, and crime risk structurally differ across park neighborhoods with varying poverty levels? (2) How are park visitation patterns across communities differentially associated with the dual risks of extreme weather and violent crime, together with other key contextual factors? (3) Do the relationships between extreme weather, violent crime, and park visitation exhibit non-linear and threshold patterns, and how do these associations vary by neighborhood poverty level? By revealing how the dual environmental risks of extreme weather and violent crime shape park visitation for socially disadvantaged communities, this research aims to offer new insights to support promoting fairer access to parks, strengthening climate resilience, and improving public safety.

2. Literature review

2.1. Determinants and inequalities of urban park visitation

Urban parks, as vital public green spaces, are subject to a complex interplay of factors shaping visitation patterns. Extensive research has highlighted that intrinsic park attributes, such as size, greenness, landscape configuration, and recreational facilities, are key predictors of park usage (Zhang et al., 2019; Kaźmierczak, 2013). External factors such as accessibility and the number of points of interest (POIs) and population within the park's catchment area also play a significant role (Liao et al., 2025; Liu et al., 2023).

Among environmental risks, climatic conditions play a crucial role in modulating park use. While the effects of routine weather, such as temperature and precipitation, on outdoor recreation have been widely studied (Li et al., 2025; Zhang et al., 2023), the impact of extreme weather events, which act as acute environmental shocks, is a less-understood yet increasingly critical area of inquiry. Studies show that extreme summer heat can significantly reduce park visitation in both urban and rural settings. For example, an analysis of mobile phone data in Atlanta by Song and Wei (2024) identified a distinct threshold effect, where higher temperatures positively influenced visitation until approximately 35°C, after which traffic sharply declined. Contrastingly, a survey in German parks on hot summer days reported that while many participants visited parks with the same frequency, some reported visiting more often and others less often, suggesting diverse coping strategies (Kabisch et al., 2021). The complexity of these impacts is further highlighted by a longitudinal study of national parks in California, which found that the effects of extreme drought or wet years on visitation varied significantly depending on the park's geographic location and the recreational activities it offered (Jenkins et al., 2023).

Concerns about crime risks also act as significant barriers to park visitation (Roman et al., 2013). Research indicates that the mere presence of a park does not guarantee its use, as this relationship is heavily mediated by both objective and perceived safety (Kaczynski et al., 2008). A survey-based study in North Carolina by Marquet et al. (2020) found that crime occurring within or near a park was the strongest negative predictor of visitation frequency. Another two-year study of 48 parks in Los Angeles by Han et al. (2018) demonstrated that gun violence significantly reduced the use of outdoor park spaces, with a more pronounced deterrent effect on adults and seniors compared to youth and children. Further evidence on the temporal dynamics of crime's impact comes from Marquet et al. (2019), who correlated police reports with park usage across different time lags. Their findings revealed that violent crimes had a more significant and consistently negative association with park visitation than property crimes, with the effects being more pronounced over one- and three-month periods than one week.

Environmental justice studies have consistently documented disparities in park area, quality, and visitation (Rigolon et al., 2018). For instance, an observational and interview-based study in a major Southern California city found that, although park use was generally lower in high-poverty-rate neighborhoods, those who did visit tended to live closer to the park and visited more frequently (Cohen et al., 2012). In Hong Kong, a survey study by Lo et al. (2022) found that economically disadvantaged households living in small apartments suffered greater heat stress and used urban parks more frequently as essential cooling spaces. Underscoring these disparities, an observational study in Michigan parks revealed that White park users were more likely to meet national physical activity recommendations, whereas other ethnic groups were observed to be less active (Reed et al., 2012).

2.2. Emerging big data in urban park studies

The rapid development of information and communication technologies has catalyzed a paradigm shift in urban park research, moving from a reliance on traditional surveys and interviews toward an analytical model centered on large-scale, spatiotemporally continuous big data. Compared to conventional methods, which are often constrained by low spatial and temporal resolution, emerging data sources such as mobile device data, social media check-ins, GPS trajectories, and population heatmaps have significantly enhanced the capability to monitor the spatiotemporal dynamics of park visitation (Vich et al., 2021; Guo et al., 2019; Lyu and Zhang, 2019).

Among these new sources, smartphone data has been particularly important in enhancing the precision of park visitation research. Studies based on large-scale mobile phone signaling data have revealed a high degree of heterogeneity in the spatiotemporal distribution of visitor volume, even among parks of similar size (Guan et al., 2020; Ren and Guan, 2022). For instance, Curtis et al. (2022) leveraged anonymous location data from Google Mobility Reports to investigate park usage across 620 U.S. counties during the initial phase of the COVID-19 pandemic. Similarly, Liu et al.(2023) utilized mobile phone signaling data from China Unicom to identify the key factors influencing visitor flow and duration across 152 urban parks in Chengdu, China.

In the United States, third-party anonymous mobile data platforms, notably SafeGraph, have become widely adopted for studying urban mobility, commercial vitality, and public health (Fernandez et al., 2023; Leong et al., 2023; Wei et al., 2024; Wu et al., 2025). Within urban park research, scholars have utilized SafeGraph data to uncover relationships between park visitation or duration and attributes of the park, its facilities, and the surrounding built environment (P. Liu et al., 2025; Lu and Song, 2024; Sun et al., 2024). For example, leveraging this dataset, Sun et al. (2024) investigated seasonal variations in park characteristics and access patterns in Atlanta, while Liu et al. (2025) assessed the impacts of climate on pocket park visitation in Austin before and after the COVID-19 pandemic.

Despite the clear advantages of big data methods, including vast sample sizes, broad spatial coverage, and high spatiotemporal resolution, they are not without limitations, such as spatial inaccuracies and issues of representativeness and sampling bias (Jardel and Delamater, 2024; Sanchez and Ye, 2023; Shen and Karimi, 2016; Ye et al., 2025a). Overall, however, urban big data from mobile devices has profoundly advanced the capacity to monitor and model urban park visitation, providing a crucial data foundation for subsequent analyses of spatiotemporal heterogeneity and environmental justice in park visitation.

3. Data and methodology

3.1. Study area

The City of Dallas, Texas, the ninth-largest city in the United States, had an estimated population of 1.3 million and is demographically diverse, with 42 % Hispanic or Latino, 36 % White, 23 % Black, and 4 % Asian residents, and a median household income of $65,400, which is below the national average (City of Dallas, 2024). Dallas operates one of the nation's largest municipal park systems, offering an extensive green space network (Fig. 1), with 81 % of residents living within a 10-minute walk of a park (Trust for Public Land, 2025a). However, the city consistently reports violent crime rates well above national averages; in 2024, Dallas recorded 778 violent crimes per 100,000 residents, nearly twice the U.S. average (Safe and Sound Security, 2025). Such conditions may influence residents' perceptions of safety and reduce their likelihood of utilizing public parks. In parallel, Dallas's humid subtropical climate is increasingly characterized by frequent and intense heat waves, alongside episodes of extreme rainfall that overwhelm infrastructure and exacerbate climate-related hazards (ClimateCheck, 2025). This complex socio-environmental context positions Dallas as a critical case for examining the intersection of park visitation, urban crime, and extreme weather events.

3.2. Research framework

This study employs a five-stage research framework to investigate patterns of park visitation and the associated factors that vary across neighborhood poverty levels in Dallas (Fig. 2). First, we constructed a

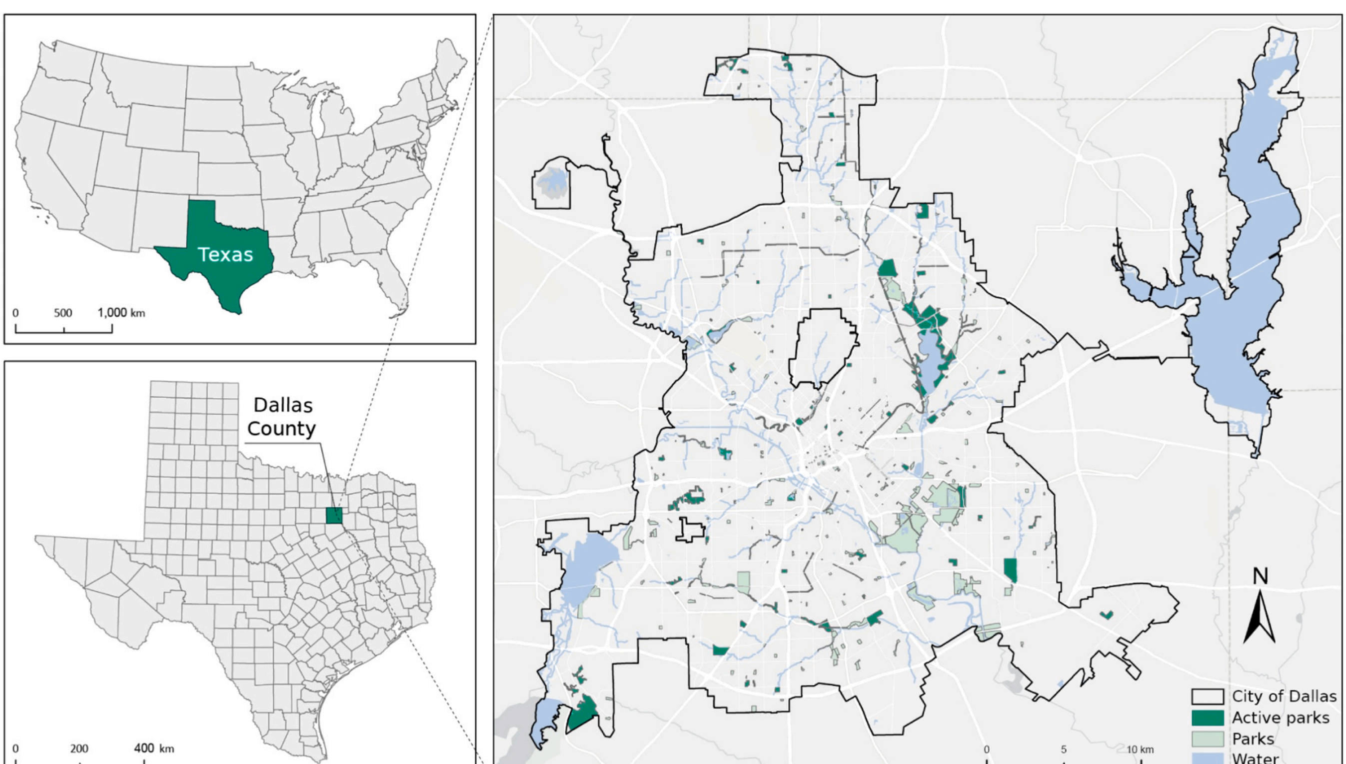

Fig. 1. Study area and parks in the City of Dallas (Active parks are defined as parks with visitation records for over 80 % of the year).

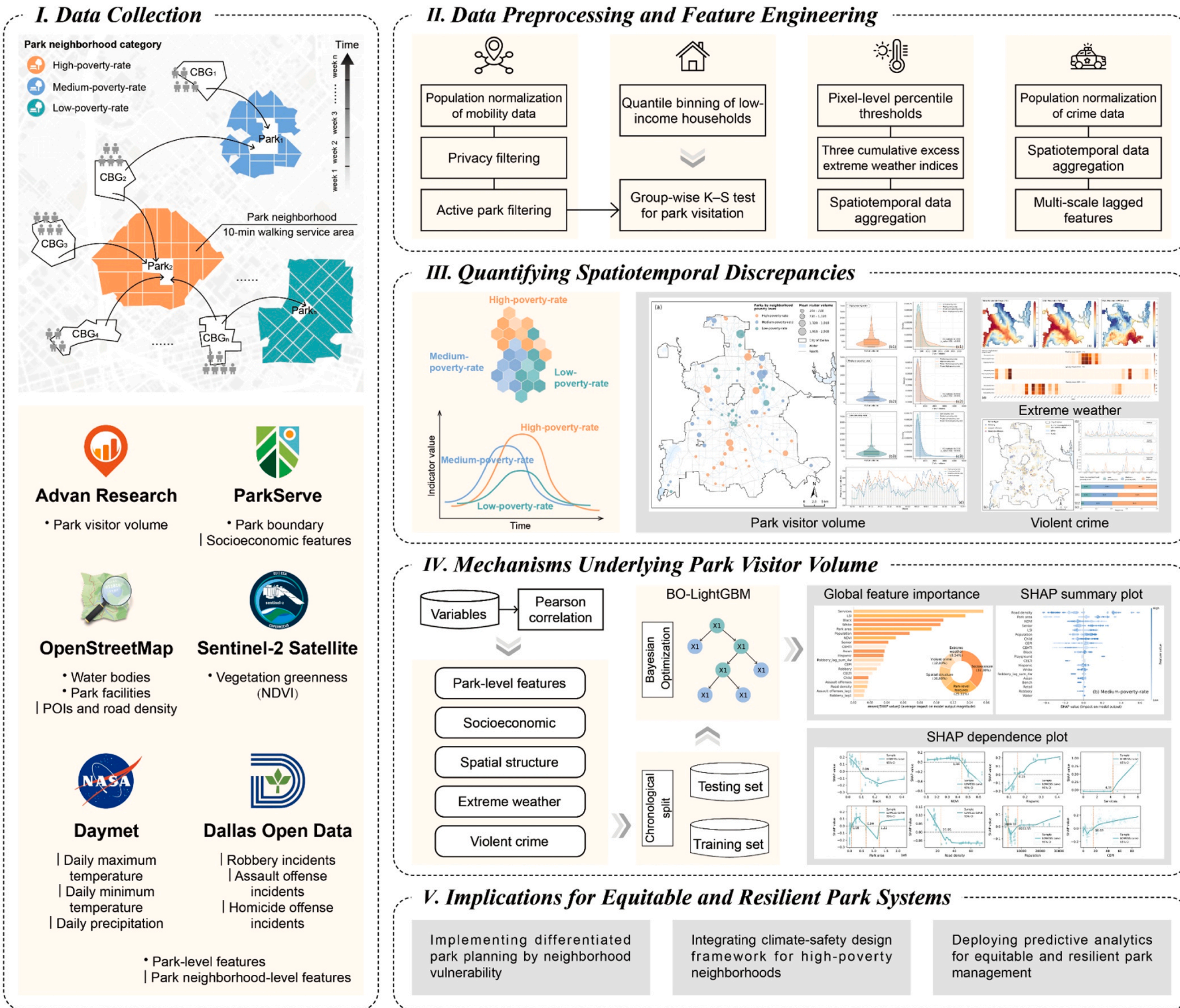

Fig. 2. Research framework.

multi-source dataset that combines smartphone mobility data, park attributes, as well as socioeconomic context, spatial structure, high-resolution gridded meteorological data, and geocoded violent crime incidents at the park neighborhood level. In this paper, a park's neighborhood is defined as its 10-minute walking service area. The 10-minute walk reflects the typical distance residents are willing to travel on foot to access neighborhood parks and is commonly used to evaluate close-to-home park accessibility across U.S. cities; according to the ParkServe® definition, a 10-minute walk corresponds to a half-mile network-based distance from each park's public access points (Trust for Public Land, 2025b).

In the data preprocessing and feature engineering stage, we normalized and filtered the raw data, constructed three cumulative extreme weather indices, and created multi-scale lagged variables for crime. To enable a stratified analysis, parks were also classified into high-, medium-, and low-poverty-rate groups based on the proportion of low-income households in their neighborhoods, determined using the tertile method. We then quantified the spatiotemporal disparities in park visitation, extreme weather, and violent crime across three park groups, highlighting patterns of structural inequality and vulnerability. Moreover, we applied a BO-LightGBM machine-learning approach to examine how extreme weather, violent crime, and other key factors are associated with park visitor volume across neighborhoods stratified by poverty level. SHAP was employed to ensure model interpretability, uncovering the non-linear and threshold effects of key predictors. Finally, we synthesized policy implications to guide equitable and resilient park usage in cities facing combined extreme weather and safety risks.

3.3. Data collection and processing

3.3.1. Park visitation data

Park visitation data for 2019 were obtained from Advan Research (formerly SafeGraph), a commercial provider of anonymized and aggregated mobile device location data (Advan, 2025). The dataset is constructed using machine learning and POI boundary validation, and its accuracy in reflecting population mobility patterns has been validated in previous studies (Lu and Song, 2024; Gu et al., 2024). Specifically, the dataset includes POI-level statistics such as the number of visits (visit_counts), unique visitors (visitor_counts), and the home Census Block Groups (CBGs) of the visitors (visitor_home_cbgs) for each POI. Visitor home CBGs are identified based on users' most frequent device location between 6 p.m. and 7 a.m. over a 6-week observation window.

To account for differences in CBG population sizes and mobility behaviors, we calculated normalized weekly CBG-to-POI visitor volumes, as given in Eqs. (1)–(2), following approaches established in prior research (Song et al., 2022; Sun et al., 2024).

$$\mathrm{VBG}_{i,p,w} = \left(SBGV_{i,p,w} \times POP_i\right)/SGD_{i,w} \tag{1}$$

$$\mathrm{VP}_{p,w} = \sum\nolimits_{i=1}^{n} \mathrm{VBG}_{i,p,w} \tag{2}$$

where $SBGV_{i,p,w}$ is the number of Advan Research visitors from CBG i to park POI p during week w, POP_i is the total population of CBG i based on the American Community Survey (ACS) 5-year data, and $SGD_{i,w}$ is the total number of Advan Research devices observed in CBG i in week w. The total visitation volume $VP_{p,w}$ thus represents the adjusted number of visitors to POI p during week w, accounting for population normalization and sampling bias.

A total of 356 park POIs were initially identified within the City of Dallas in the dataset, which contains 286,612 visit observations spanning 52 full weeks, from January 7 to December 29, 2019. According to the privacy-preserving policy of the dataset, any weekly travel records smaller than or equal to 4 (either from a POI or CBG) are reported as four, which we excluded to ensure data reliability. In addition, following previous park visitation studies (Song et al., 2022; Song and Wei, 2024; Sun et al., 2024), we retained only those parks with visit data available for more than 80 % of the 52-week period, as our focus was on parks with active visitation patterns, which also helped reduce noise from sparsely visited or short-lived POIs. After these filtering steps, the final dataset comprised 89 active parks in the City of Dallas (Fig. 1). Fig. A1 illustrates the distributional differences in park area and landscape shape index (LSI) between active and non-active parks, as well as differences in the proportion of low-income households and total population in their surrounding neighborhoods.

3.3.2. Park-level and neighborhood-level environmental data

To characterize the environmental attributes of parks at both the park and neighborhood levels, we compiled a set of indicators, including each park's landscape and facility features, as well as the spatial structure and socioeconomic context of the surrounding neighborhood.

Park-level landscape and facility features included park area, LSI, vegetation greenness, the presence of water bodies, and the number of playgrounds, fountains, and benches. Park boundary shapefiles were obtained from the ParkServe® dataset (Trust for Public Land, 2025b). The LSI was calculated following prior studies (Chen et al., 2022), as shown in Eq. (3):

$$\mathrm{LSI} = \frac{L}{2\sqrt{\pi} \times A} \tag{3}$$

where L is the perimeter and A is the area of the park. Higher LSI values indicate more irregular and complex park shapes.

Vegetation greenness was assessed using the annual mean Normalized Difference Vegetation Index (NDVI) for 2019, derived from atmospherically corrected Sentinel-2 Surface Reflectance imagery processed in Google Earth Engine at a spatial resolution of 10 m. All available cloud-free scenes from 2019 were used to ensure temporal alignment with the park visitation data period. The NDVI of each park was computed by averaging the values of all pixels intersecting the park polygon. The presence of water bodies (e.g., rivers or lakes) and the number of playgrounds, fountains, and benches were identified using historical OpenStreetMap (OSM) data from 2019.

The environmental attributes of park neighborhoods included spatial structure factors and socioeconomic factors. POIs located within park neighborhoods were extracted from OSM 2019 and categorized into four types—food, education, retail, and services—based on their *fclass* information. The detailed classification criteria are provided in Table A1. Road density was calculated as the total road length per square kilometer within each park's neighborhood, using OSM 2019 road network data. Additionally, socioeconomic characteristics of park neighborhoods were obtained from the ParkServe® dataset, with calculation methods described in the official documentation (Trust for Public Land, 2025b). Variables included the total population and the proportions of children, senior residents, and racial or ethnic subgroups, specifically Black, Asian, Hispanic, and White populations. The proportion of low-income households was also obtained. Based on this variable, we classified parks into high-, medium-, and low-poverty-rate neighborhood groups using the tertile method, which ensures balanced group sizes for statistical analysis and is consistent with previous studies (Wende et al., 2025; Markevych et al., 2017; Parsons et al., 2015). A Kolmogorov–Smirnov (KS) test was then conducted to assess the statistical significance of differences in park visitation across these groups, supporting the validity of this classification.

3.3.3. Extreme weather data and definition

We used daily maximum temperature (TMAX), minimum temperature (TMIN), and precipitation (PRCP) data from the Daymet dataset (Thornton et al., 2022), provided in NetCDF format with a spatial resolution of 1 km and covering the study area from 1989 to 2019, to characterize extreme weather at fine spatial and temporal scales. A percentile-based approach was employed to derive pixel-level fixed thresholds for extreme weather, using a 30-year historical reference period (1989–2018). Following common practices in climate-extreme analyses, the 90th and 10th percentiles were adopted for temperature-based extremes to ensure adequate sample representation, whereas the 95th percentile was applied for precipitation, given its greater variability and intermittency (WMO, Zhang, 2009; Zhang et al., 2022; J. Liu et al. 2025).

To capture the cumulative intensity of exposure rather than binary exceedance events, we employed three composite indices: CEHTI (Cumulative Excess High Temperature Index), CELTI (Cumulative Excess Low Temperature Index), and CEPI (Cumulative Excess Precipitation Index), building upon a prior study (J. Liu et al. 2025) while adapting them to different extreme weather stressors. These indices quantify the weekly cumulative magnitude of threshold exceedance within each park neighborhood. Together, they provide a more continuous and nuanced representation of climatic extremes.

Specifically, a two-step aggregation strategy was implemented to derive park-week-level extreme weather indicators for 2019. First, for each pixel s intersecting the boundary of a park neighborhood p, we computed the cumulative daily exceedance for each calendar week w, using the fixed historical threshold Thr_s for that pixel. Second, for each park, we averaged the weekly exceedance values across all pixels. This process yielded three weekly park-level indicators, CEHTI, CELTI, and CEPI, as defined in Eqs. (4)– (6):

$$\mathrm{CEHTI}_{p,w} = \frac{1}{|S_p|}\sum\nolimits_{s\in S_p}\left[\sum\nolimits_{d\in D_w}\left(T^{\max}_{d,w,s} - \mathrm{Thr}^{\max}_s\right)\cdot I_{\mathrm{Thr}^{\max}_s}\left(T^{\max}_{d,w,s}\right)\right] \tag{4}$$

$$\mathrm{CELTI}_{p,w} = \frac{1}{|S_p|}\sum\nolimits_{s\in S_p}\left[\sum\nolimits_{d\in D_w}\left(\mathrm{Thr}^{\min}_s - T^{\min}_{d,w,s}\right)\cdot I_{\mathrm{Thr}^{\min}_s}\left(T^{\min}_{d,w,s}\right)\right] \tag{5}$$

$$\mathrm{CEPI}_{p,w} = \frac{1}{|S_p|}\sum\nolimits_{s\in S_p}\left[\sum\nolimits_{d\in D_w}\left(P_{d,w,s} - \mathrm{Thr}^{P}_s\right)\cdot I_{\mathrm{Thr}^{P}_s}\left(P_{d,w,s}\right)\right] \tag{6}$$

where D_w denotes the set of days in week w, and $I_{Thr_s}(x)$ is an indicator function, as defined in Eq. (7):

$$I_{\mathrm{Thr}_s}(x) = \begin{cases} 1, & x > \mathrm{Thr}_s \\ 0, & x \leq \mathrm{Thr}_s \end{cases} \tag{7}$$

This formulation ensures that only values exceeding the defined thresholds contribute to cumulative exposure. By capturing both the frequency and magnitude of exceedance events, the CEHTI, CELTI, and

CEPI indices facilitate a more robust assessment of extreme weather stressors and their potential behavioral associations with park visitation.

3.3.4. Violent crime data

Violent crime data were sourced from the Police Incidents dataset published by Dallas Open Data (Dallas OpenData, 2025). This dataset provides detailed records of reported crimes in the city, including location, time of occurrence, National Incident-Based Reporting System (NIBRS) codes, and crime category classifications. We filtered the dataset for cases that occurred in 2019 and involved gun violence, as firearm-related crimes are known to generate greater public fear and exert a stronger deterrent effect on outdoor recreation (Han et al., 2018). The sample was further restricted to incidents with NIBRS codes corresponding to robbery, assault, and homicide offenses. After removing entries with missing or invalid geographic coordinates, 5090 unique firearm-related incidents remained for analysis. A spatial join and weekly temporal aggregation were then performed to associate each crime incident within the park neighborhood boundary with its corresponding calendar week.

To account for differences in park neighborhood population density, we converted weekly crime counts into population-normalized crime rates, following the approach of previous studies (Marquet et al., 2019). Using population estimates from the ParkServe® database, we calculated weekly crime rates as the number of crime incidents per 10,000 residents within each park neighborhood, as shown in Eq. (8):

$$CR_{p,w} = \left(\frac{CC_{p,w}}{POP_p}\right) \times 10,000 \quad (8)$$

where $CR_{p,w}$ is the weekly population-normalized violent crime rate for park neighborhood p; $CC_{p,w}$ is the number of crime incidents that occurred within that area during week w; and POP_p is the total population within the park neighborhood, based on ParkServe® estimates.

We then constructed a set of lagged crime features at multiple temporal scales, based on the assumption that the behavioral effects of violent incidents are not immediate (Marquet et al., 2019). Residents may adjust their park visitation habits with a delay, as perceptions of safety and personal risk evolve over time. To capture this potential delayed response, we created twelve lagged features for three crime types—robbery, assault offenses, and homicide offenses—including single-week lags (lag1, lag2, lag3) and a four-week cumulative lag (lag_sum_4w), defined as the rolling sum of incidents over the prior four weeks, shifted forward by one week to avoid overlap with the current week. Pearson correlation analysis was conducted to assess potential multicollinearity among these features. As shown in Fig. A2, only the variable *Assault offenses_lag3* was removed. To ensure complete lagged information and avoid missing values, we restricted the sample to park-week observations beginning from the fifth week of the study period for each park.

3.4. Analysis methods

Due to the skewed distribution of the dependent variable (Fig. 3c1–c3), we applied a natural logarithm transformation to improve its normality for the modeling process. To reduce multicollinearity and variable redundancy, we calculated the Pearson correlation coefficients among all candidate independent variables and excluded those with coefficients greater than 0.8. As a result, 35 independent variables were retained for subsequent modeling. Descriptive statistics of these variables are presented in Table 1.

3.4.1. Decoupling empirical model

Park visitation behavior is shaped by complex environmental and social factors. As predictors increase, models become susceptible to the curse of dimensionality, compromising accuracy and generalizability. To address this challenge, we employed LightGBM, an efficient gradient boosting framework, to model park visitation volume (Ke et al., 2017). LightGBM integrates multiple base learners to achieve superior accuracy and stability while being robust to noise and outliers, making it well-suited for complex, high-variability datasets (X. Liu et al., 2025). The dataset was chronologically split into training (80 %) and testing (20 %) sets based on calendar weeks to prevent data leakage from time-lagged crime variables. Model training used five-fold time-series cross-validation. We also compared its performance with several widely used machine learning models, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Gradient Boosted Decision Trees (GBDT), using the same standard hyperparameter settings. LightGBM demonstrated consistently superior baseline performance among all the park groups, notably with an R^2 of 0.84 in high-poverty-rate neighborhoods, surpassing XGBoost (0.81), RF (0.78), and GBDT (0.75) (Table A2). Therefore, LightGBM was selected for the subsequent advanced hyperparameter tuning phase using BO.

BO constructs a probabilistic surrogate model based on past evaluations and iteratively proposes configurations expected to improve performance (Qiao et al., 2025; Snoek et al., 2012). This enables efficient exploration of high-dimensional hyperparameter space under computational constraints. BO was implemented via Optuna over 50 trials, minimizing root mean squared error on out-of-fold predictions. The final model was retrained using optimal hyperparameters and average boosting rounds from cross-validation. The performance of the BO-LightGBM framework, as shown in Table A2, demonstrates that it achieved the highest predictive accuracy and lowest error rates across all groups (e.g., increasing R^2 to 0.87 in high-poverty-rate neighborhoods), confirming its superior capability to capture the complex, non-linear associations related to park visitation. However, it should be noted that although the model identifies statistical associations among variables, the relationships revealed do not imply causation.

3.4.2. Interpretation method of determinants

To reveal the association between determinants and park visitation captured by the BO-LightGBM model, we used SHAP, a unified interpretation framework based on cooperative game theory. SHAP quantifies the marginal contribution of each feature to individual predictions through Shapley values, enabling both local and global interpretability (Gong et al., 2025; Rui and Gong, 2026). In this study, SHAP dependence plots visualized how each predictor is associated with park visitation, with SHAP values representing its contribution to the model's predicted visitor volume.

For further interpretability, we applied Locally Weighted Scatterplot Smoothing (LOWESS) curves to the SHAP scatter plots, following previous studies (Liu and Hang, 2025; Qi et al., 2025). As a non-parametric regression technique, LOWESS fits smoothed curves to data, effectively revealing subtle or non-monotonic relationships. We quantified the uncertainty of these relationships by constructing 95 % confidence intervals (CIs) via bootstrap resampling (Bland and Altman, 2015), performing 500 resamples per feature and calculating empirical percentiles at each grid point. This combined SHAP–LOWESS–bootstrap approach offers a transparent and robust framework for identifying non-linear and threshold effects in the associations between park visitation and key factors.

4. Results

4.1. Spatiotemporal disparity analysis by park neighborhood poverty level

This section first provides a descriptive analysis of the spatiotemporal characteristics of park visitation across neighborhoods with varying poverty levels. Then we examine how patterns of extreme weather and violent crime vary across space and time within these communities. By comparing these contextual factors across high-, medium-, and low-poverty-rate park neighborhoods, we aim to highlight structural disparities in environmental and social conditions that may

Table 1
Descriptive statistics of variables.

Category		Variables	Description (Units)	Mean	S.D.	Min	Max
Dependent variables		Visitor volume	Weekly count of visitors to a park (number)	493.987	541.446	7.368	4789.650
Park-level factors		Park area	Area of a park (m^2)	189232.967	302707.797	2277.281	2251570.214
		LSI	Landscape Shape Index (LSI) of a park	2.874	2.605	1.125	14.893
		NDVI	The mean Normalized Difference Vegetation Index (NDVI) value of a park	0.417	0.103	0.111	0.663
		Water	If a park has water bodies	0.454	0.498	0.000	1.000
		Playground	Number of each park facility category in a park (number)	0.045	0.206	0.000	1.000
		Fountain		0.024	0.152	0.000	1.000
		Bench		0.578	2.539	0.000	21.000
Neighborhood-level factors	Spatial structure factors	Education	Number of each POI category within a park neighborhood (number)	0.414	0.829	0.000	4.000
		Retail		1.374	2.749	0.000	14.000
		Services		1.040	1.696	0.000	8.000
		Road density	Total road length per km^2 within a park neighborhood (km/km^2)	24.075	16.082	5.811	73.482
	Socioeconomic factors	Population	Total Population within a park neighborhood (number)	6895.661	5620.533	292.000	30508.000
		Child	The proportion of residents for each age group within a park neighborhood	0.253	0.092	0.054	0.398
		Senior		0.128	0.056	0.029	0.359
		Black	The proportion of residents for each ethnic group within a park neighborhood	0.227	0.199	0.012	0.753
		Asian		0.034	0.030	0.001	0.139
		Hispanic		0.372	0.247	0.070	0.925
		White		0.330	0.266	0.013	0.843
	Extreme weather factors	CEHTI	Weekly Cumulative Excess High Temperature Index (CEHTI) within a park neighborhood (℃)	1.048	2.845	0.000	14.238
		CELTI	Weekly Cumulative Excess Low Temperature Index (CELTI) within a park neighborhood (℃)	1.164	3.565	0.000	18.863
		CEPI	Weekly Cumulative Excess Precipitation Index (CEPI) within a park neighborhood (mm)	7.498	16.064	0.000	91.657
	Violent crime factors	Robbery	Weekly population-normalized crime rate for each category within a park neighborhood (incidents per 10,000 residents)	0.538	3.875	0.000	116.959
		Assault offenses		0.340	3.389	0.000	175.439
		Homicide offenses		0.009	0.156	0.000	7.207
		Robbery_lag1	One-week lag of weekly population-normalized crime rate for each category within a park neighborhood (incidents per 10,000 residents)	0.514	3.854	0.000	116.959
		Assault offenses_lag1		0.312	3.310	0.000	175.439
		Homicide offenses_lag1		0.009	0.158	0.000	7.207
		Robbery_lag2	Two-week lag of weekly population-normalized crime rate for each category within a park neighborhood (incidents per 10,000 residents)	0.503	3.743	0.000	116.959
		Assault offenses_lag2		0.304	3.275	0.000	175.439
		Homicide offenses_lag2		0.009	0.158	0.000	7.207
		Robbery_lag3	Three-week lag of weekly population-normalized crime rate for each category within a park neighborhood (incidents per 10,000 residents)	0.501	3.806	0.000	116.959
		Homicide offenses_lag3		0.009	0.158	0.000	7.207
		Robbery_lag_sum_4w	Cumulative population-normalized crime rate over the past four weeks for each category within a park neighborhood (incidents per 10,000 residents)	2.034	8.741	0.000	233.918
		Assault offenses_lag_sum_4w		1.204	6.574	0.000	175.439
		Homicide offenses_lag_sum_4w		0.036	0.315	0.000	7.207

contribute to differential park usage.

4.1.1. Park visitor volume

Park visitor volumes exhibit notable spatial and temporal disparities across neighborhoods with differing poverty levels in the City of Dallas (Fig. 3). Spatially, parks located in low-poverty-rate neighborhoods, concentrated primarily in the northern and central areas of the city, tend to have more consistent visitor activity, while those in high-poverty-rate areas, especially in the southern and peripheral regions, exhibit greater variability in visitation levels (Fig. 3a).

The violin plots of visitor volume indicate further contrasts across poverty groups (Fig. 3b1–b3). Parks in high-poverty-rate neighborhoods exhibit a broader distribution with a pronounced right tail, suggesting that while many parks experience low visitation, a subset attract exceptionally high volumes. Medium-poverty-rate parks fall in between, with moderately wide distributions. In contrast, parks in low-poverty-rate neighborhoods show a more compact distribution concentrated at lower visitation levels, with fewer outliers on the high end. These differences are statistically supported by kernel density estimates and KS tests (Fig. 3c1–c3). The KS statistics confirm significant disparities in distribution shapes across groups ($p < 0.001$), with the largest divergence observed between high- and low-poverty-rate areas (KS = 0.1369).

Temporally, weekly trends reveal persistent disparities in mean visitor volume across neighborhoods with different poverty levels (Fig. 3d). Although all groups exhibit notable seasonal fluctuations, parks in high-poverty-rate neighborhoods consistently maintain higher average visitation, generally fluctuating around 600 visitors per week, compared to those in low-poverty-rate neighborhoods, which typically range between 300 and 500 visitors. This gap is especially evident during peak periods in spring and early summer, when visitation tends to rise across all groups but remains consistently stratified by poverty level.

4.1.2. Extreme weather

Extreme weather patterns across the City of Dallas reveal clear temporal clustering, with spatial disparities most pronounced in extreme precipitation and heat across park neighborhoods of varying poverty levels (Fig. 4). Percentile thresholds calculated from the 30-year historical reference period (1989–2018) exhibit clear spatial gradients. The 90th percentile of daily Tmax (Fig. 4a) is highest in the western and southern regions, where thresholds exceed 36.1°C. The 10th percentile of daily Tmin (Fig. 4b) indicates that the northeastern areas experience the coolest extremes, with values dropping below 0.2°C. For extreme precipitation, the 95th percentile of daily PRCP (Fig. 4c) peaks in the southern region, surpassing 20.2 mm.

The weekly trends of extreme weather indices aggregated by neighborhood poverty level exhibit distinctive seasonal peaks (Fig. 4d). The CEHTI reveals a concentrated heatwave period between mid-July and August, during which high-poverty-rate park neighborhoods experienced relatively higher average CEHTI values. The CELTI peaks in early March, with weekly mean values surpassing 15°C, reflecting intensified cold extremes during late winter. The CEPI cluster primarily occurs between April and June, with a secondary peak occurring in November. During these periods, differences in CEPI across poverty groups become more pronounced, while the direction of disparity is not consistent.

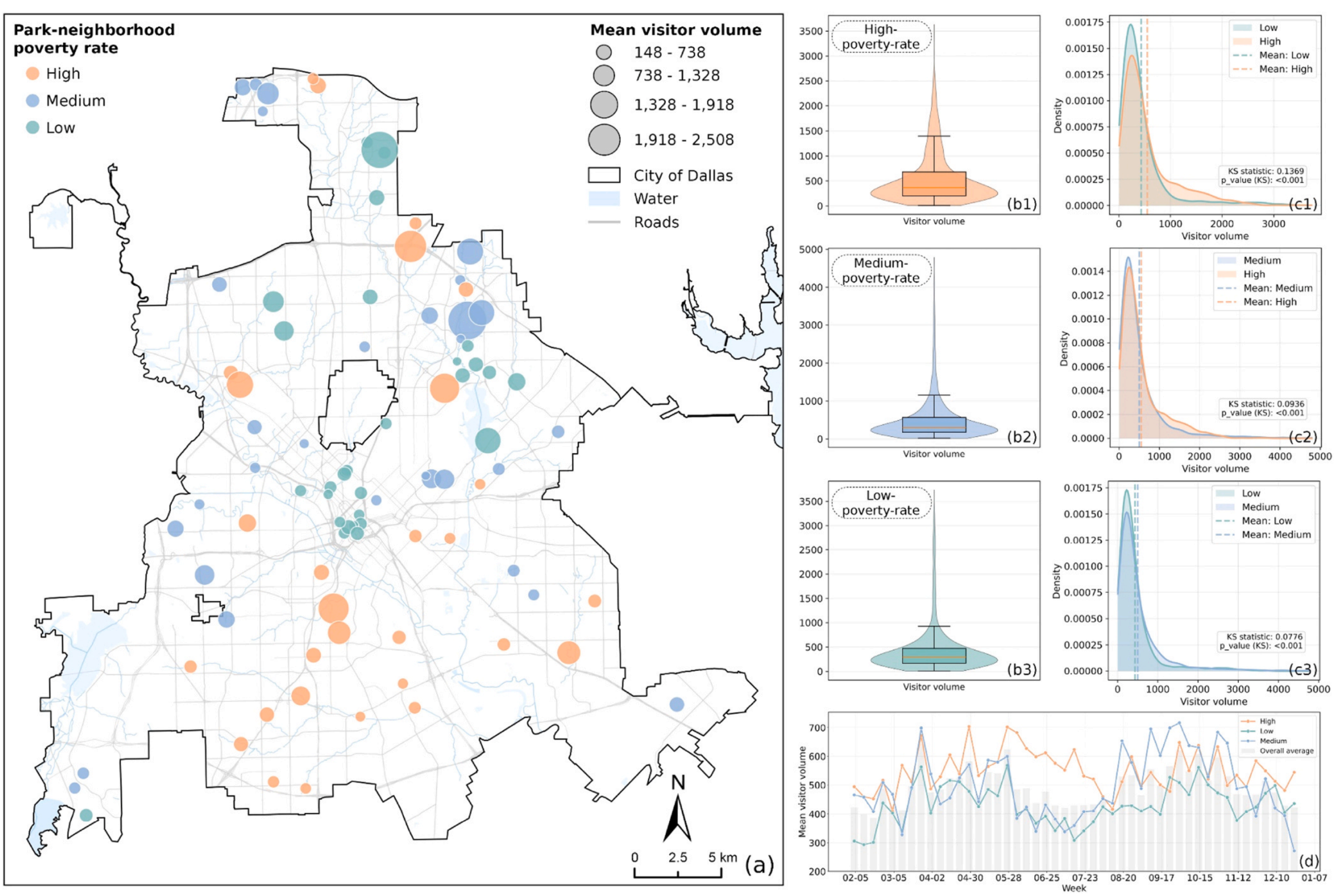

Fig. 3. Park visitation patterns in the City of Dallas by neighborhood poverty level. (a) Spatial distribution of mean visitor volume across parks; (b1–b3) Violin plots of visitor volume for parks in low-, medium-, and high-poverty-rate neighborhoods; (c1–c3) Kernel density plots with Kolmogorov–Smirnov statistics comparing distributions across poverty groups; (d) Temporal trends of weekly average visitor volume over the study period.

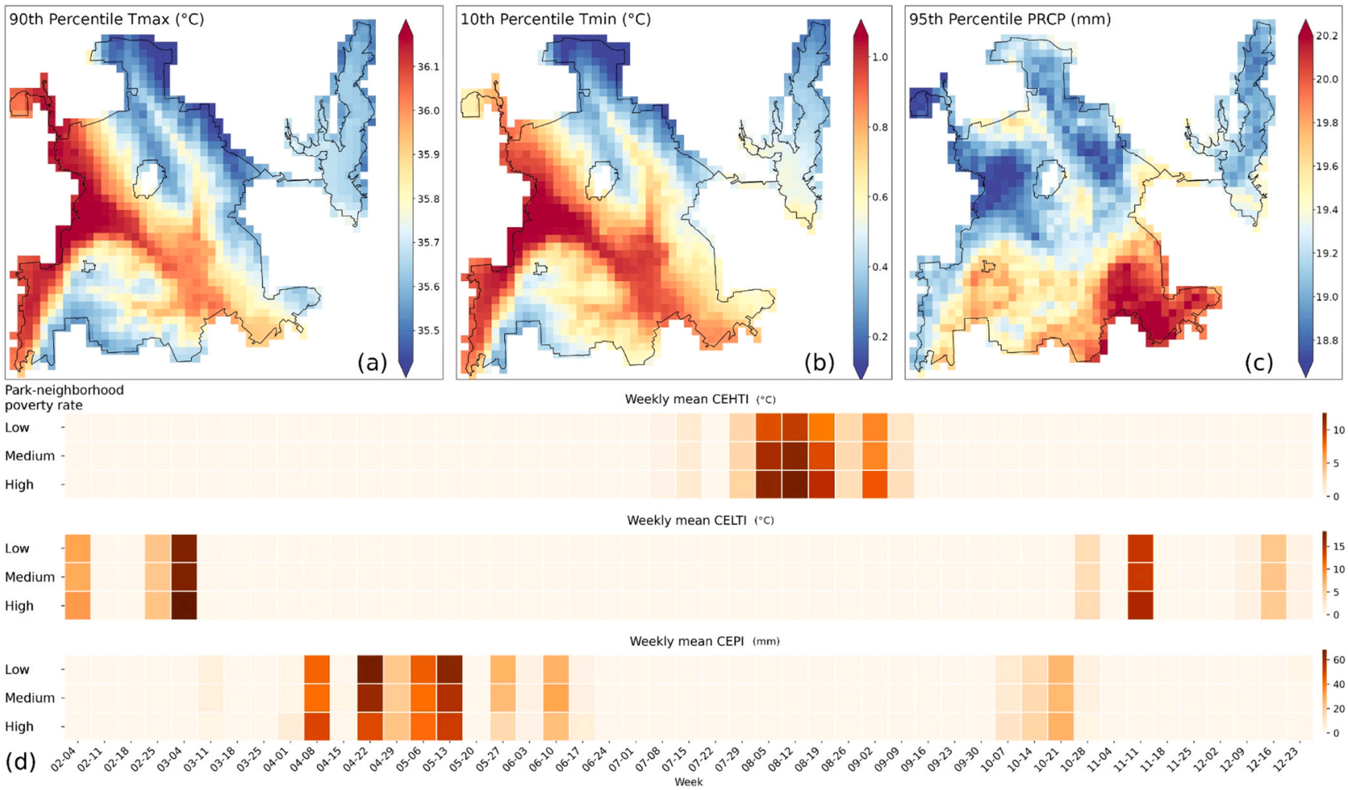

Fig. 4. Extreme weather patterns in the City of Dallas and park neighborhoods. (a)–(c) Gridded maps of the 90th-percentile daily maximum temperature, 10th-percentile daily minimum temperature, and 95th-percentile daily precipitation calculated from the 30-year historical reference period 1989–2018; (d) Heatmaps of weekly mean extreme weather indices (CEHTI, CELTI, CEPI) for different park neighborhood poverty levels.

4.1.3. Violent crime

Violent crime patterns in Dallas park neighborhoods exhibit marked spatial, temporal, and socioeconomic disparities (Fig. 5). Robbery, assault, and homicide incidents are widely distributed but cluster most

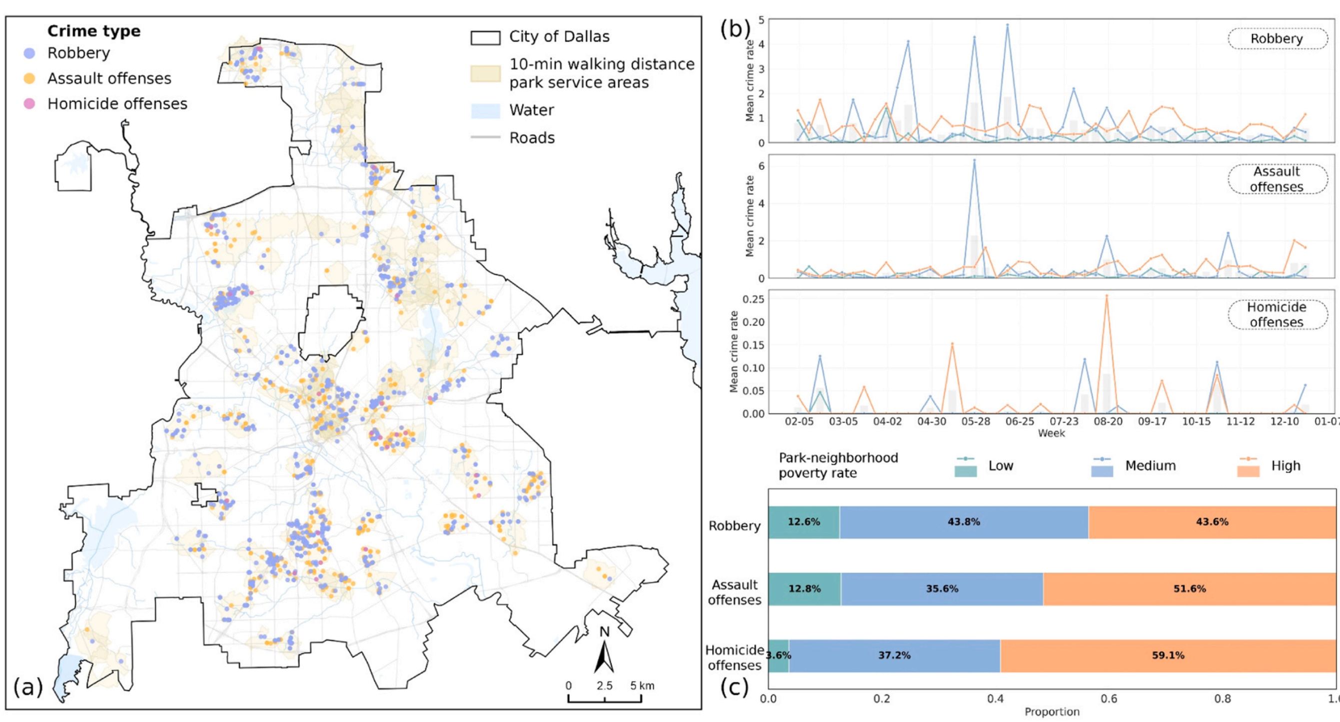

Fig. 5. Violent crime patterns in the City of Dallas park neighborhoods. (a) Spatial distribution of crime incidents recorded within park neighborhoods; (b) Weekly mean crime rate (per 10,000 residents) for each crime type, stratified by neighborhood poverty level; (c) Proportional distribution of mean crime rates across park neighborhood poverty levels.

densely in the central and southern regions of the city (Fig. 5a). Weekly mean crime rates (per 10,000 residents) for robbery, assault, and homicide show substantial fluctuations, with pronounced spikes, particularly for robbery and assault, occurring from late spring through summer (Fig. 5b). Homicide offenses are less frequent but manifest as sharp, episodic peaks. Across nearly all crime types and time periods, medium- and high-poverty-rate neighborhoods consistently record higher crime rates, whereas low-poverty-rate neighborhoods exhibit persistently lower rates and minimal seasonal variation. These disparities are further reflected in the proportional distribution of mean crime rates (Fig. 5c): high-poverty-rate neighborhoods account for 43.6 % of robberies, 51.6 % of assaults, and 59.1 % of homicides recorded in park neighborhoods, while low-poverty-rate areas account for just 12–13 % of robberies and assaults and 3.6 % of homicides.

4.2. Global effects of determinants on park visitor volume

Across Dallas park neighborhoods with varying poverty levels, the top 20 factors associated with park visitor volume reveal both shared and context-specific patterns (Fig. 6). Socioeconomic and park-level features consistently account for the largest shares of model importance across all three groups, but their relative importance varies along the urban poverty gradient. In high-poverty-rate neighborhoods, socioeconomic composition is most prominent, with a notable contribution from violent crime and extreme weather indicators. For medium-poverty-rate neighborhoods, park-level attributes and spatial structure features rise in relative importance, while the associations of violent crime with park visitation are weaker. In low-poverty-rate neighborhoods, the dominance of socioeconomic factors becomes more pronounced, and both extreme weather and crime play relatively minor roles.

In high-poverty-rate park neighborhoods (Fig. 6a), socioeconomic

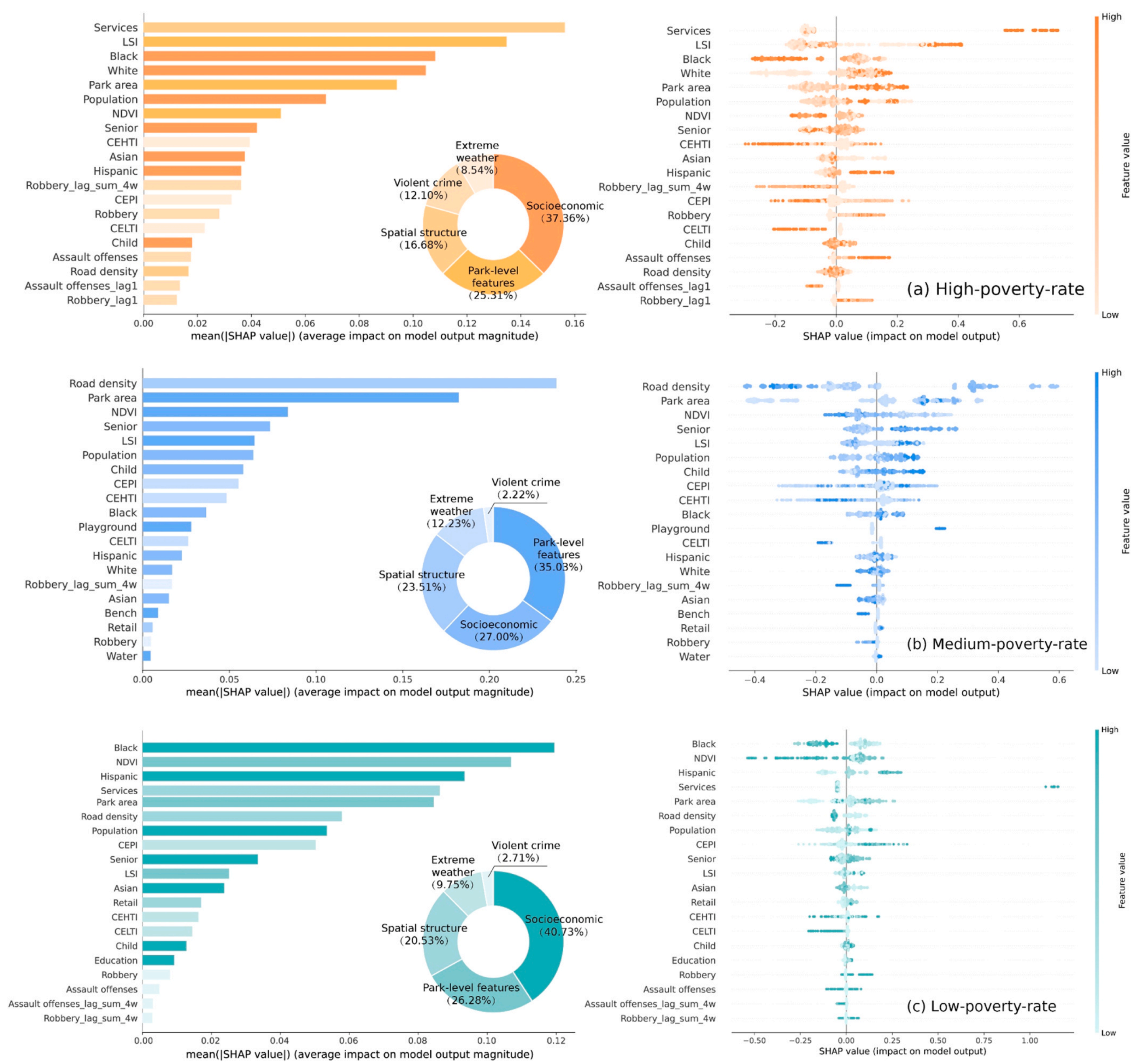

Fig. 6. Relative importance and SHAP summary plot of the top 20 factors influencing park visitor volume across neighborhoods with different poverty levels.

factors account for the greatest proportion of variation in park visitor volume (37.36 %), closely followed by park-level features (25.31 %). Violent crime and extreme weather together contribute over 20 % of model importance, underscoring the complex interplay between social vulnerability, environmental risks, and recreational behavior in disadvantaged areas. Within the top features, the number of service POIs, LSI, the proportions of Black and White residents, and park area stand out as the strongest predictors. The SHAP summary plot indicates that higher service counts, a greater proportion of White residents, and larger park areas are the strongest positive predictors of park visitation. Among the extreme weather indices, CEHTI and CEPI show less clear associations with park visitation, displaying both positive and negative patterns across their value ranges, whereas CELTI exhibits a consistent negative relationship, with higher extreme low temperature exposure linked to reduced visitor volumes. Notably, the association of violent crime with park visitation is substantial and nuanced. The cumulative robbery over the previous four weeks (Robbery_lag_sum_4w) shows the strongest negative association with visitor volume, indicating that sustained increases in robberies are linked to pronounced declines in park use. Similarly, Assault offenses_lag1 also show a negative association. In contrast, the current week's values of robbery, assault offenses, and robbery rate in the previous week show positive associations.

In medium-poverty-rate park neighborhoods (Fig. 6b), the relative importance of park-level (35.03 %) and spatial structure (23.51 %) variables is enhanced, together accounting for nearly 60 % of model contribution, while socioeconomic factors and extreme weather remain important. Road density, park area, NDVI, LSI, and the proportions of senior residents emerge as leading predictors. Among these, the park area and the senior population proportion show primarily positive relationships with visitation. Road density, NDVI, and LSI show mixed relationships with park visitation, displaying both positive and negative patterns that may vary under specific contextual conditions or threshold effects. Extreme weather indicators show an increased overall importance in medium-poverty-rate neighborhoods (12.23 %). Similar to the patterns observed in high-poverty-rate park neighborhoods, CEHTI and CEPI show mixed patterns, whereas CELTI consistently shows a negative relationship with park visitation. The associations of violent crime are noticeably weaker in this group, accounting for only 2.2 % of total feature importance. Nonetheless, both Robbery_lag_sum_4w and Robbery are among the top 20 predictors and show detrimental associations with park visitor volume, as indicated by their negative SHAP values.

For low-poverty-rate park neighborhoods (Fig. 6c), socioeconomic

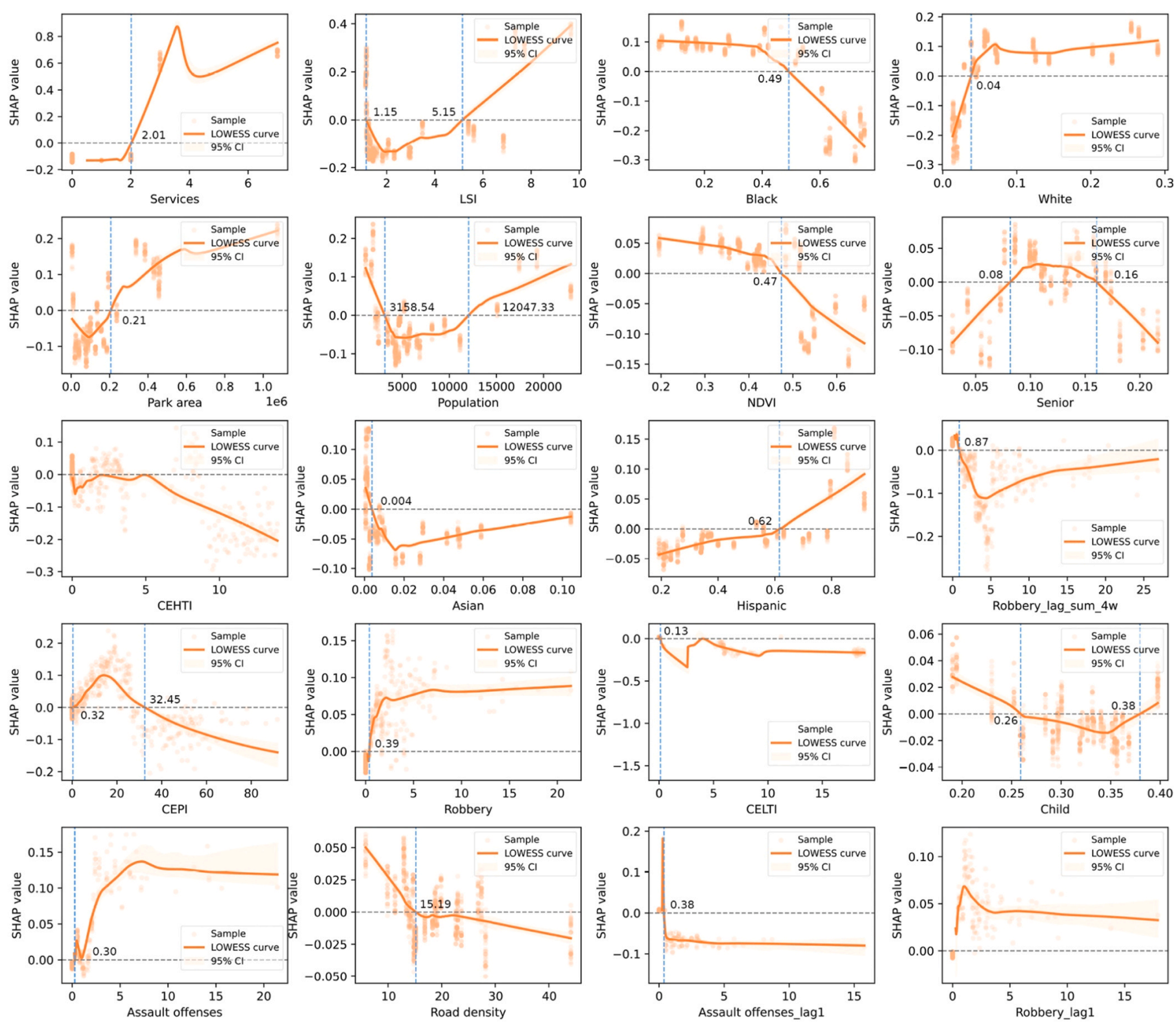

Fig. 7. SHAP dependence plots of key factors influencing park visitor volume in high-poverty-rate neighborhoods.

variables are the most important factors, accounting for over 40 % of model importance, while park-level features (26.28 %) and the spatial structure (20.53 %) also play meaningful roles. The top features include the proportions of Black and Hispanic residents, NDVI, park area, and the number of service POIs. The SHAP summary plots show that a higher proportion of Black residents is primarily associated with decreased park visitation, whereas a higher proportion of Hispanic residents is positively associated with visitor volume. The relationships of NDVI, park area, and service provision are less consistent. Notably, the associations of both extreme weather and violent crime are minimal in these settings, contributing only 9.75 % and 2.71 % to model importance, respectively. Among the extreme weather indices, CEPI is mainly positively associated with park visitation, while CEHTI shows mixed relationships, and CELTI is predominantly negative. For violent crime variables, both Robbery and Robbery_lag_sum_4w are positively related to visitor volume, whereas Assault offenses and Assault offenses_lag1 display negative associations.

4.3. Nonlinear effects of determinants on park visitor volume

4.3.1. High-poverty-rate park neighborhoods

Fig. 7 shows that key variables associated with park visitor volume in high-poverty-rate neighborhoods exhibit clear non-linear and threshold patterns. For park-level features, the LSI yields negative SHAP values when it falls between 1.15 and 5.15, and the park area begins to show a positive association only after surpassing 210,000 m^2. NDVI also displays a critical threshold at 0.47, beyond which its association with visitation becomes negative.

At the neighborhood level, the number of service POIs reveals a marked threshold: once more than two, the SHAP value shifts to positive, indicating increased visitation, whereas road density turns negative after exceeding a value of 15.19 km/km^2. Socioeconomic neighborhood variables display similarly nuanced relationships. Total population demonstrates a distinct U-shaped relationship, with negative SHAP values within the 3159–12,047 range, but positive associations at both lower and higher population sizes. The proportion of Black residents is associated with negative SHAP values once it exceeds 0.49, while the Asian resident share also becomes negative beyond 0.004. In contrast, a positive association with park visitation is observed for Hispanic

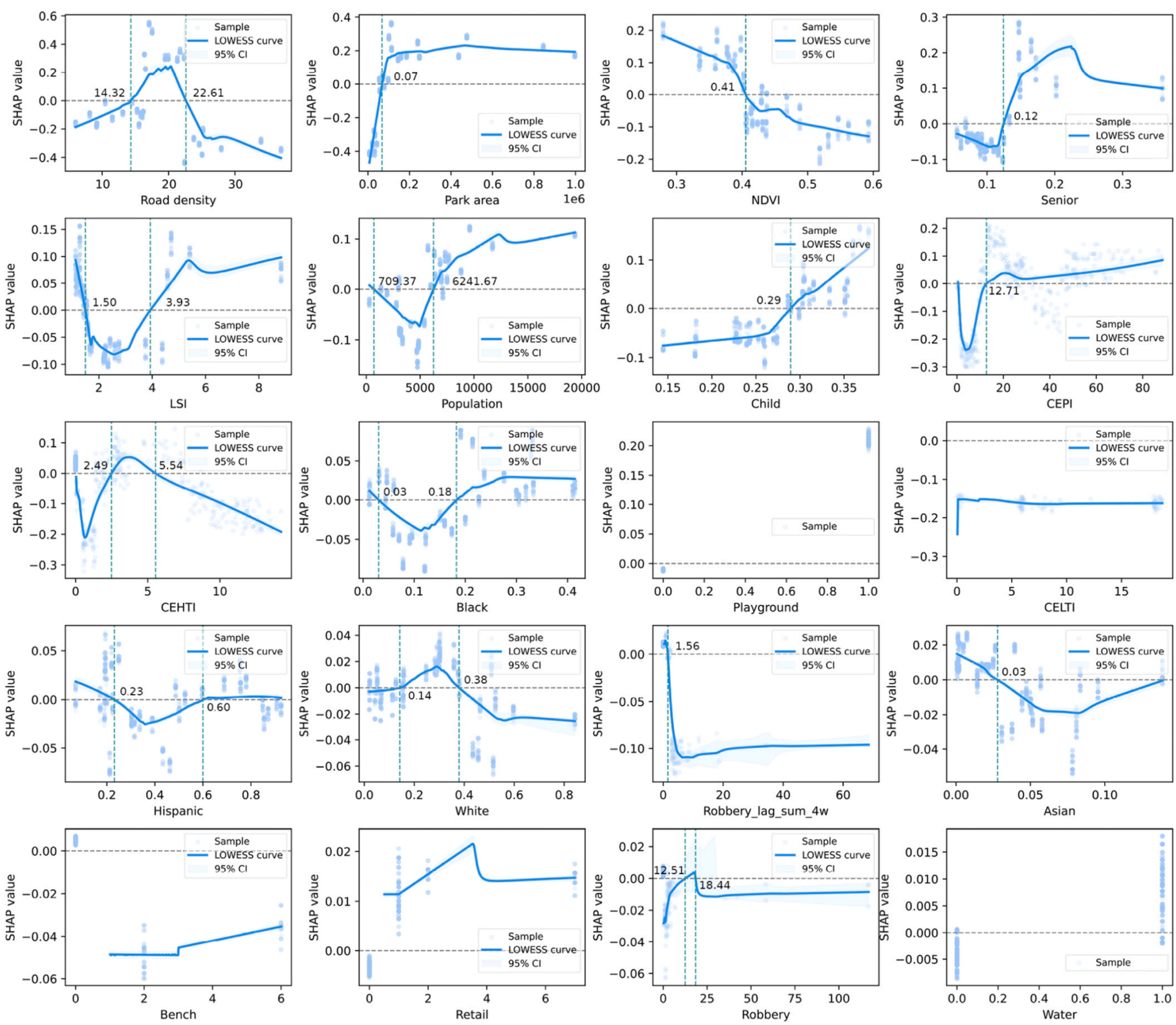

Fig. 8. SHAP dependence plots of key factors influencing park visitor volume in medium-poverty-rate neighborhoods.

residents when their proportion surpasses 0.62, and for White residents above 0.04. Age structure also matters: the proportion of seniors shows an inverted-U relationship, producing negative SHAP values below 0.08 and above 0.16. By comparison, the relationship of children is opposite, as SHAP values become positive when the proportion is below 0.26 or above 0.38.

Among extreme weather variables, no obvious threshold is detected for CEHTI; instead, it consistently exerts a negative association on park visitor volume. However, CELTI shows a clear threshold at 0.13°C, beyond which its association turns negative. CEPI follows an inverted-U pattern, with negative SHAP values below 0.32 mm and above 32.45 mm. For violent crime variables, the cumulative robbery rate over the previous four weeks becomes detrimental to visitation when it exceeds 0.87 incidents per 10,000 residents. The lagged assault offense rate from the previous week becomes negative once it exceeds 0.38 incidents per 10,000 residents, highlighting a delayed but significant negative relationship with park visitation. Notably, positive SHAP values emerge when current-week robbery and assault rates are higher than 0.39 and 0.30 incidents per 10,000 residents, suggesting that these incidents may coincide with busier periods.

4.3.2. Medium-poverty-rate park neighborhoods

Fig. 8 demonstrates nonlinearities and threshold patterns among key variables associated with park visitor volume in medium-poverty-rate neighborhoods. For park-level variables, park area exhibits a critical threshold at approximately 70,000 m^2, above which its SHAP value becomes positive. NDVI shows a negative association beyond a threshold of 0.41, while LSI displays a U-shaped association—positive SHAP values are observed when LSI is below 1.50 or above 3.93.

Among neighborhood-level spatial structure features, road density reveals a clear inverted-U pattern, with positive associations between 14.32 and 22.61 km/km^2. Socioeconomic variables at the neighborhood level also exhibit distinct threshold effects: the proportion of seniors demonstrates an S-shaped relationship, with SHAP values turning positive above 0.12, and the relationship for children becomes positive when their proportion exceeds 0.29. The total population within park neighborhoods is associated with negative SHAP values when ranging between 709 and 6242. For racial and ethnic composition, the proportion of Black residents is negatively associated with visitation over the range 0.03–0.18, while the proportion of Hispanic residents shows a similar negative association over the range 0.23–0.60. In contrast, the share of White residents exerts a positive association within the

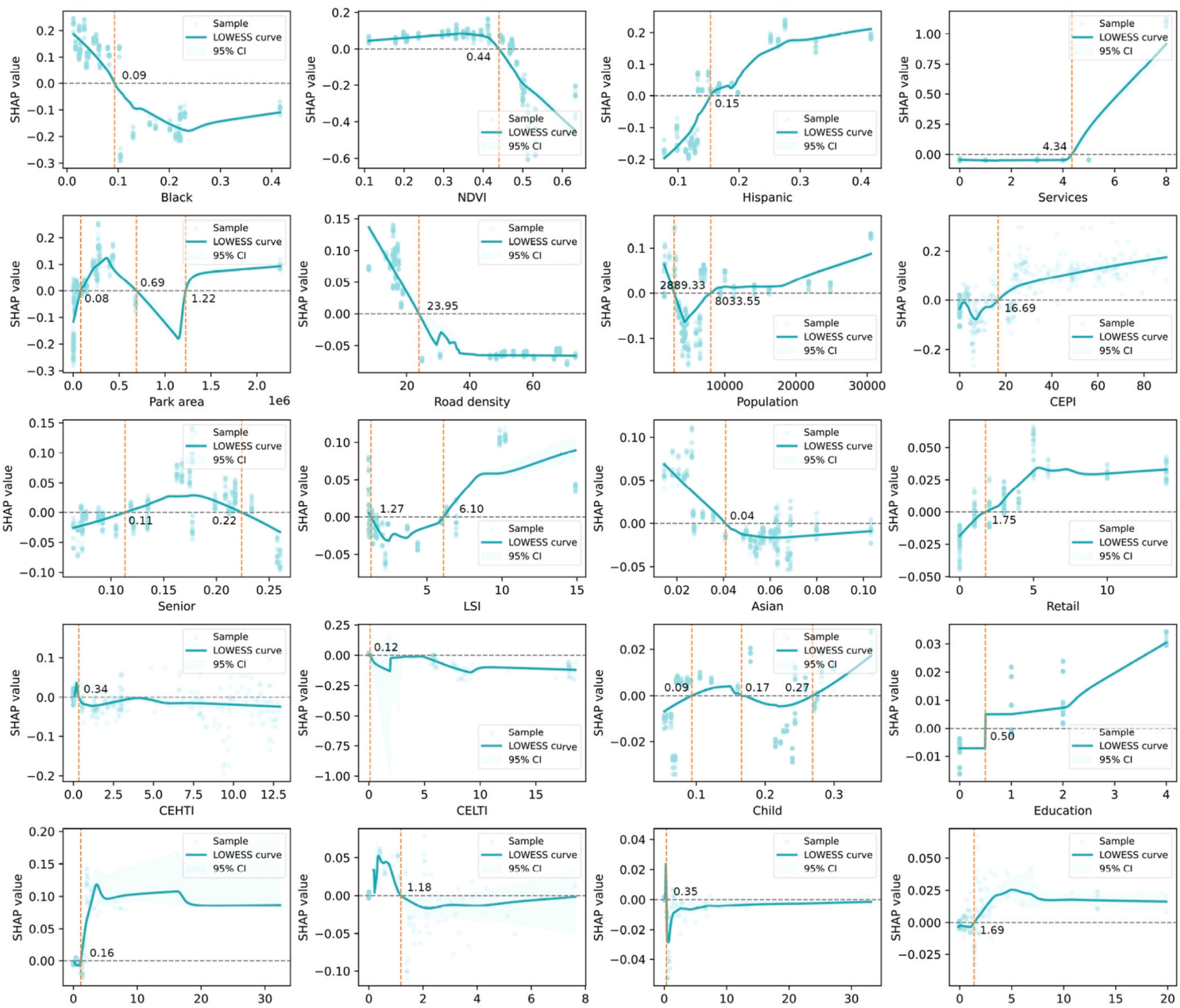

Fig. 9. SHAP dependence plots of key factors influencing park visitor volume in low-poverty-rate neighborhoods.

0.14–0.38 range, and Asian residents show a negative association when their proportion exceeds 0.03.

Extreme weather variables further contribute to threshold-dependent patterns. CEPI displays a critical threshold at 12.71 mm, beyond which its SHAP value turns positive. CEHTI is negatively associated with park use both below 2.49°C and above 5.54°C. CELTI does not present a clear threshold and consistently shows a negative association across its range. Regarding violent crime, the cumulative robbery rate over the previous four weeks demonstrates a threshold at 1.56 incidents per 10,000 residents, with SHAP values turning negative above this point. For current-week robbery, both rates above 18.44 and below 12.51 incidents per 10,000 residents are associated with negative SHAP values. These results indicate that persistent high robbery rates, as well as weekly rates that fall outside a moderate range, are linked to reduced park visitation.

4.3.3. Low-poverty-rate park neighborhoods

Fig. 9 reveals nonlinear and threshold effects among the key determinants shaping park visitation in low-poverty-rate neighborhoods. For park-level features, NDVI shows a negative association with visitation once it exceeds 0.44. Park area demonstrates positive SHAP values between 80,000 and 690,000 m^2, and again above 1220,000 m^2, while LSI shows a positive association at values below 1.27 or above 6.10.

In terms of neighborhood-level spatial structure, the number of service POIs above four, retail POIs above two, and education POIs above one all correspond to positive SHAP values. Road density exhibits a threshold at 23.95 km/km^2, beyond which its association becomes negative. Socioeconomic factors at the neighborhood level also display clear threshold effects. The proportion of Black residents above 0.09 and Asian residents above 0.04 is associated with negative SHAP values, while a Hispanic population share greater than 0.15 is linked to a positive relationship. The total population within the park neighborhood yields negative SHAP values when ranging between 2889 and 8034. Age structure displays an inverted-U pattern for the proportion of seniors, with negative associations below 0.11 and above 0.22. The child population proportion shows an S-shaped association, being positively related to visitation between 0.09 and 0.17, as well as above 0.27.

For extreme weather variables, CEPI exhibits a critical threshold at 16.69 mm, above which SHAP values turn positive. Both CEHTI and CELTI are negatively associated with park visitation once they exceed 0.34°C and 0.12°C, respectively. For violent crime variables, both a current-week robbery rate above 0.16 incidents per 10,000 residents and a cumulative robbery rate over the previous four weeks exceeding 1.69 incidents per 10,000 residents are associated with increased park visitation. In contrast, a current-week assault rate above 1.18 incidents per 10,000 residents and a four-week lagged assault rate above 0.35 incidents per 10,000 residents are linked to reduced visitation, highlighting the divergent relationships of different crime types and timeframes on park use.

5. Discussion

5.1. Inequalities and differential associations in urban park visitation

Integrating large-scale mobile device data with multi-source urban data, this study reveals differential park visitation patterns across Dallas neighborhoods of varying economic levels. The results show that although parks in high-poverty-rate neighborhoods face more severe risks from violent crime and extreme weather, their average weekly visitor volume is the highest among all groups. In contrast to previous environmental justice research that has focused on resource scarcity and lower quality of parks in disadvantaged communities (Rigolon et al., 2018), this study, from the perspective of objective park visitation, adds a complementary dimension: parks in these neighborhoods may function as essential infrastructure. For residents of these communities, who may lack access to private yards or air-conditioned spaces, parks become indispensable hubs for social interaction, recreation, and crucially, as refuges from heat. Therefore, the high visitation volumes observed in this study are likely a manifestation of adaptive behaviors by residents in disadvantaged environments with limited choices. This finding, supported by large-scale objective mobility data, corroborates the "space poverty-high park dependence" hypothesis proposed by Lo et al. (2022), based on a small-sample survey. It also resonates with the findings of Cohen et al. (2012), whose observations and interviews revealed that parks in high-poverty-rate neighborhoods experience more intensive and frequent use.

Further interpretation using SHAP analysis reveals a poverty gradient in the mechanisms associated with park use. Parks in high-poverty-rate neighborhoods demonstrate a heightened sensitivity in their visitation behavior to the dual risks of safety and climate, with these two domains totally accounting for over 20 % of the model's feature importance. This suggests that visiting parks in high-poverty-rate neighborhoods involves a greater consideration of personal safety threats and physiological discomfort from extreme climate, particularly the safety dimension (12.10 % contribution). Nevertheless, socioeconomic attributes remain the most important predictors for this group, especially racial factors; for instance, a proportion of Black residents exceeding 0.49 has a negative association with visitation. This finding is similar to the lower park usage among minorities observed in Michigan (Reed et al., 2012), yet our study, through a data-driven approach, reveals that this relationship is not linear but exhibits a clear threshold effect. In comparison, the associations of environmental threats are greatly diminished in medium- and low-poverty-rate communities. In medium-poverty-rate neighborhoods, intrinsic park features and accessibility become the most critical factors. This suggests that the attractiveness of parks in these communities is related to quality-of-experience factors such as design, greenness, and accessibility. In low-poverty-rate neighborhoods, the most important attribute group is socioeconomic (over 40 % contribution), while the associations of environmental risks are minimal. This pattern reflects the higher resilience to environmental risks in affluent areas, where park use is shaped more by the internal demographic composition and social dynamics of the community.

5.2. Nonlinear effects of extreme weather and violent crime

Utilizing high-resolution extreme climate data, this study reveals the differentiated response patterns of park visitation to three types of extreme weather indices (CEHTI, CELTI, CEPI) across communities of varying poverty levels. The relationships of extreme heat and precipitation with park visitation exhibit complex, highly context-dependent nonlinearities, whereas extreme cold demonstrates a relatively uniform negative association with park visitation. In high-poverty-rate neighborhoods, CEHTI consistently shows a negative association without a clear threshold, reflecting the low resilience of these communities to extreme heat risk. In contrast, in medium-poverty-rate neighborhoods, the relationships of CEHTI with visitation are negative when the index falls below 2.49°C or rises above 5.54°C, suggesting the existence of a suitable range of high temperatures and the potential for residents to mitigate extreme heat through resources like indoor facilities or private transport. This finding resonates with previous research by Song et al. (2024), which also identified threshold effects of temperature on park visitation, but our study provides a more granular differentiation of these relationships across socioeconomic contexts.

CEPI exhibits the most consistent threshold patterns, though the tipping points differ across communities, likely reflecting varying sensitivities to post-precipitation environmental improvements. Moderate extreme precipitation may improve air quality and lower temperatures, thereby promoting outdoor activity after rainfall (Yang and Shao, 2021). This is further supported by a study of a major urban park in Singapore, which found that rainfall can significantly reduce post-precipitation air temperatures and enhance thermal comfort, with parks often remaining noticeably cooler for extended periods following rain events (Acero et al., 2024). This mechanism is more pronounced in medium- and low-poverty-rate communities, possibly because their parks have better maintenance and drainage systems that allow for a quicker return to suitable conditions. CELTI is the only factor to show a consistent negative association across all poverty levels, reflecting that fundamental physiological limits imposed by cold are difficult to buffer through social or spatial means. This finding is consistent with research by Sun et al. (2024), which noted that winter weather hinders park access.

The association of violent crime with park visitation is marked by heterogeneity across crime type, temporal scale, and community poverty context. In high-poverty-rate neighborhoods, for instance, short-term crime events (e.g., current-week robbery and assault) are associated with higher park visitor volume, whereas cumulative risk (e.g., previous four-week robbery totals) has a strong negative association. This suggests that the public may tolerate isolated, acute incidents—or that periods of high visitation themselves attract criminal activity—but that a perceptible and stable unsafe environment accumulating over time is linked to avoidance behavior. This result supports the "time-lag" pattern identified by Marquet et al. (2019) and further specifies that this dynamic of risk perception is particularly pronounced within economically vulnerable contexts, providing an empirical basis for targeted community safety strategies. In low-poverty-rate neighborhoods, robbery, whether current-week or cumulative, is positively associated with visitor volume, whereas assault, both current-week and cumulative, shows a negative association after reaching a low threshold. This may reflect the fact that robberies in these safer neighborhoods often coincide with periods of high park traffic (Cohen and Felson, 1979) or do not serve as an effective deterrent; in contrast, assaults are more likely to trigger both short- and long-term avoidance, underscoring public sensitivity to different types of criminal risk. Homicide had low importance in all models, likely because it is a low-frequency event that does not form a stable community risk perception, thus having less predictive power for routine, high-frequency behaviors like park visitation.

Finally, this study's BO-LightGBM-SHAP framework demonstrates an exceptional capacity for revealing these non-linear and threshold effects. In contrast to previous research that often assumes a uniform relationship between predictor variables and park visitation, our study uncovers the complexity and variability of these relationships across different socioeconomic contexts. This nuanced understanding challenges the "one-size-fits-all" conclusions common in the literature and provides a more powerful tool for capturing the relationships underlying urban park visitation. Consequently, our research not only extends the theoretical frameworks of behavioral geography and environmental justice by emphasizing the importance of intra-urban variations but also offers practical guidance for more targeted and effective urban planning and the enhancement of urban resilience.

5.3. Policy implications

The findings of this study provide valuable insights that can inform more equitable and resilient urban park planning and management. First, our results suggest that parks in disadvantaged communities should be recognized not merely as recreational amenities but as critical components of community well-being and resilience. Because parks in high-poverty-rate neighborhoods face compounded climate and safety risks, planners may consider integrated approaches that jointly address climate adaptation and public safety objectives. In practice, this may involve aligning park greening, lighting, and maintenance strategies with neighborhood safety assessments to foster both thermal comfort and community trust in public spaces. Given the observed association of cumulative robbery risk on park visitation, urban safety departments could explore the development of high-resolution, short-term risk monitoring systems to guide proactive interventions, such as targeted patrols or community events, when risk indicators rise.

In medium-poverty communities, the higher sensitivity to park environmental quality highlights the importance of nuanced spatial design and management. Road density, for instance, exhibited a nonlinear association with park visitation—beneficial up to a point but detrimental when excessive. Planners may thus explore "traffic buffer zones" or traffic calming measures, including vegetative buffers and pedestrian-prioritized streets, to balance accessibility and environmental quality (Chng et al., 2022; Gonzalo-Orden et al., 2018). Similarly, greenery and landscape complexity thresholds identified in the analysis could help prioritize areas with the greatest marginal benefits from greening and connectivity improvements. The adaptive responses to heat observed in these communities also indicate opportunities for flexible park design to maintain comfort under varying climatic conditions. In low-poverty-rate neighborhoods, environmental factors had a relatively minor association with visitation, yet social and cultural characteristics remained influential. Hence, planning interventions may move beyond physical improvements to address perceptual and cultural inclusion.

Finally, the data-driven and machine learning-based methodological framework presented in this study offers a new technical pathway for urban management and policy formulation. We recommend the establishment of an integrated park usage monitoring system based on multi-source big data, using machine learning algorithms to identify key influencing factors and threshold effects, thereby providing a robust evidence base for planning decisions. Park governance should develop comprehensive policies that integrate land use, transportation, public safety, and climate adaptation, while also instituting social impact assessments and continuous improvement mechanisms to ensure both equity and adaptability. Through differentiated and targeted interventions, cities can more effectively address the specific needs of diverse communities, promote fair allocation of park resources, and foster more inclusive and resilient urban development.

5.4. Limitations and future research

This study has several limitations. First, at the data level, the Advan Research dataset used in this research has uneven coverage across different population groups. In particular, it may underrepresent young children and elderly individuals who are less likely to use smartphones (Li et al., 2024), potentially leading to an underestimation of how environmental risks affect park use among physiologically or socially vulnerable groups. Additionally, by retaining only parks with visit data available for over 80 % of the study period, the analysis may introduce potential selection bias toward more frequently visited or centrally located parks, possibly overlooking usage dynamics in less active or peripheral sites. Future studies could combine mobility big data with small-scale, targeted surveys or interviews to more comprehensively capture the behavioral patterns and subjective experiences of these populations (Larson et al., 2021). Second, due to data availability constraints, the analysis period is relatively short, limiting the ability to assess the cumulative patterns associated with long-term weather trends or changes in public safety governance. Future research should expand the data collection period to examine whether the identified thresholds shift over time. In terms of geographic scope, this study focuses solely on the case of Dallas, so the generalizability of its findings remains to be tested. Future research should apply this analytical framework to cities with different urban forms, climatic conditions, and sociocultural contexts to conduct cross-regional comparisons and identify both universal patterns and local variations.

6. Conclusions

In an era of intensifying climate change and increasingly complex urban safety risks, understanding and addressing the dual environmental risks, ranging from the physical to the social, facing public spaces is crucial for promoting urban resilience and environmental justice. This study integrates large-scale smartphone mobility data with multi-source urban data and employs an explainable machine-learning framework to analyze park visitation patterns and their heterogeneous associations across communities of varying socioeconomic levels in Dallas, USA. The results indicate that: (1) parks in high-poverty-rate neighborhoods, despite enduring the most severe dual risks of climate and safety, function as essential infrastructure and exhibit the highest average weekly usage; (2) the patterns of association vary along the poverty gradient: high-poverty-rate communities show heightened sensitivity to safety–climate risks; medium-poverty-rate communities show stronger associations with park landscape and accessibility thresholds; whereas in low-poverty-rate communities, visitation is more strongly associated with internal socioeconomic composition; (3) extreme heat and precipitation show context-dependent, non-linear effect with visitor volume, whereas extreme cold shows a generally negative association across all communities; and (4) the association between violent crime and park use exhibits a threefold heterogeneity across crime type, time lag, and poverty context. This research not only extends the theoretical frameworks of behavioral geography and environmental justice but also provides empirical insights for building more equitable, resilient, and sustainable urban park systems. Future urban planning could place greater emphasis on the spatiotemporal heterogeneity and social differentiation of environmental risks, employing data-driven methods and precise policy interventions to promote the effective utilization of urban park resources.

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CRediT authorship contribution statement

Wenjing Gong: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Ling Wu:** Writing – review & editing, Methodology, Conceptualization. **Chunwu Zhu:** Writing – review & editing, Methodology. **Yang Song:** Writing – review & editing, Methodology. **Xinyue Ye:** Writing – review & editing, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors employed the OpenAI GPT-5 model as a language-editing aid to enhance readability, grammar, and stylistic clarity. GPT-5 was not used to create, expand, or alter the scientific ideas, data analyses, or conclusions presented herein, and no AI-generated text has been included verbatim in the article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

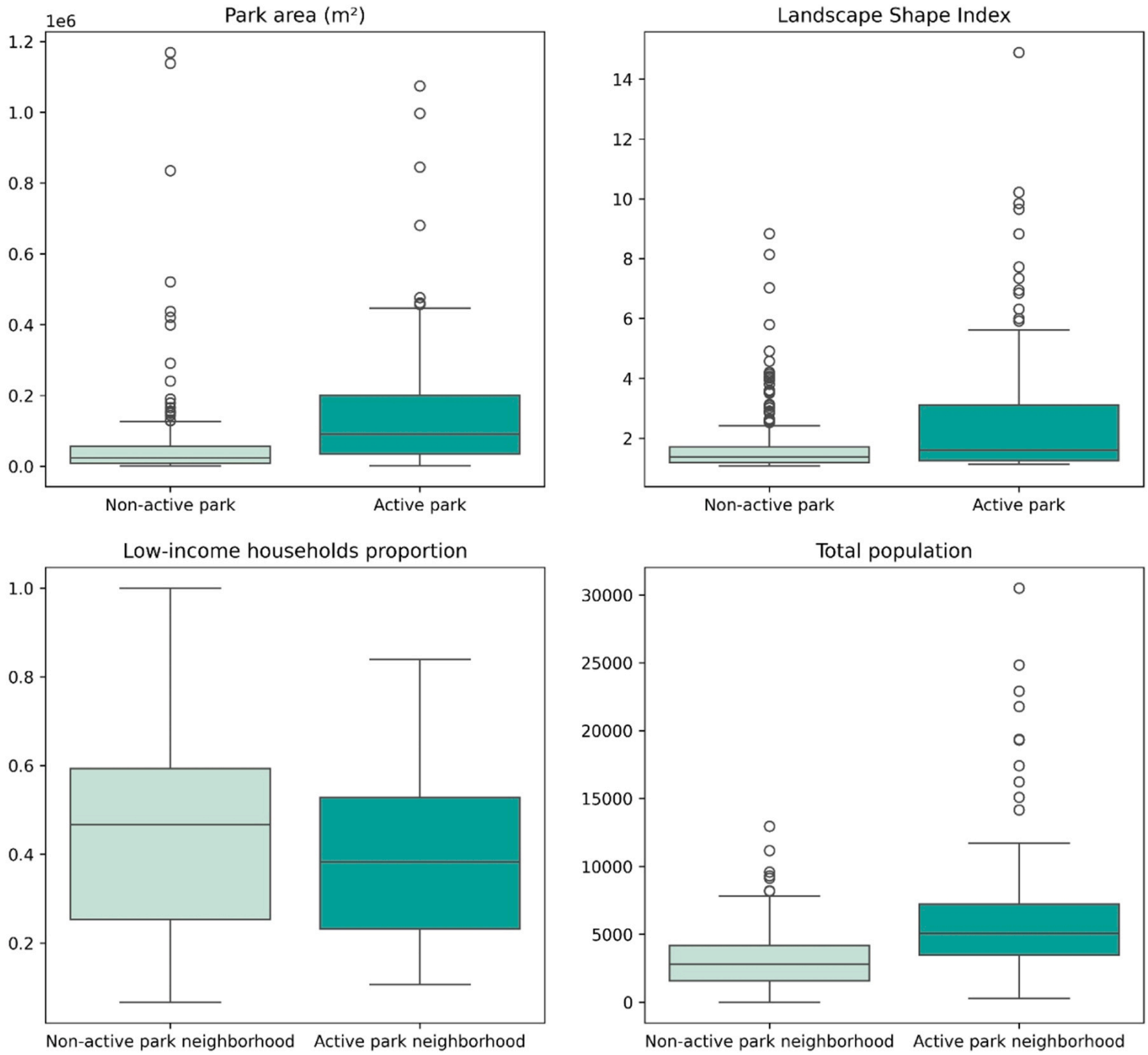

Fig. A1. Descriptive distributions of characteristics for active and non-active parks

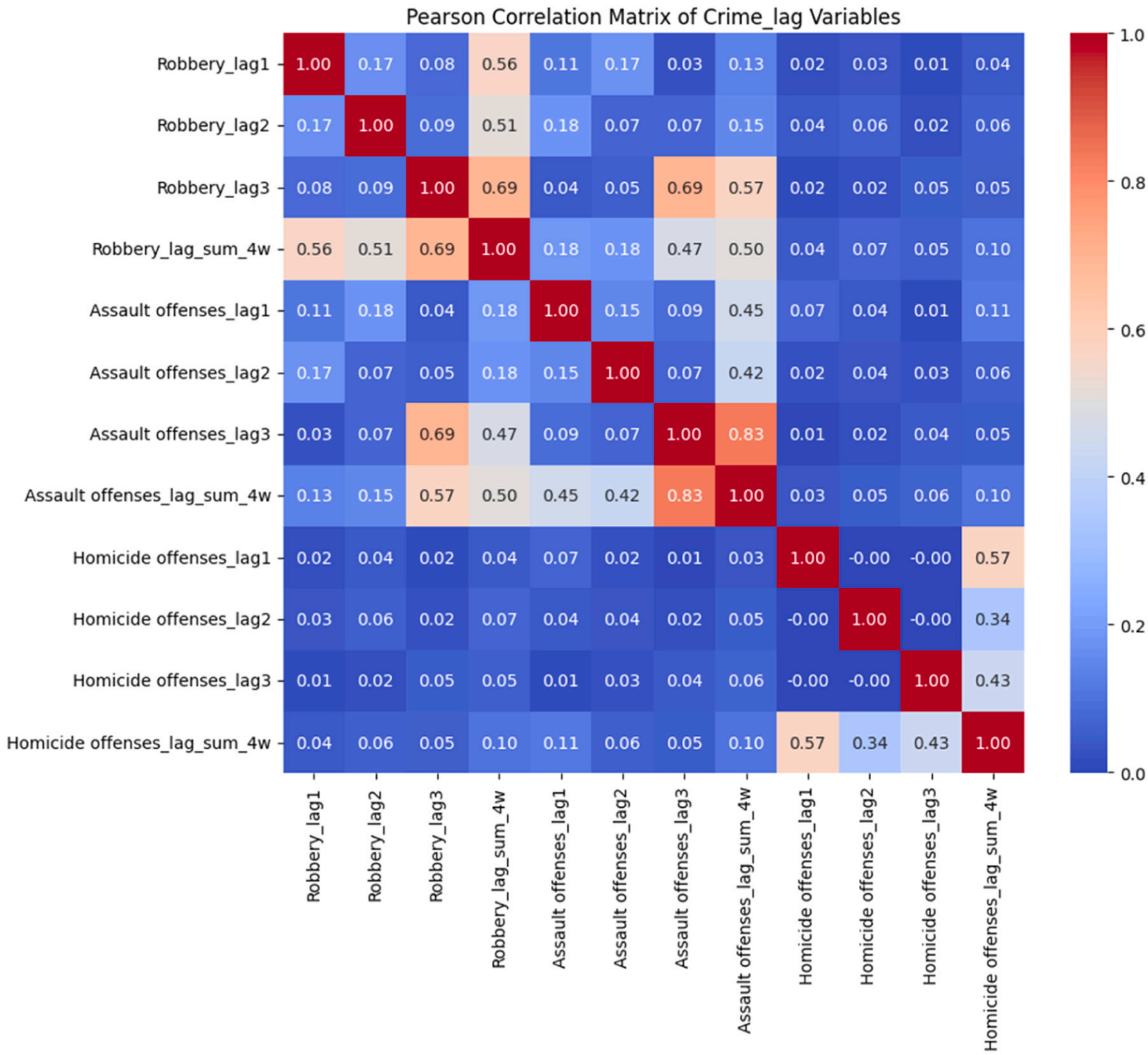

Fig. A2. Pearson correlation matrix of crime_lag variables

Table A1
POI classification

POI category	Fclass
Food	restaurant, fast food, cafe, bar, pub
Education	school, college, kindergarten, museum, theatre, library, arts_centre
Retail	clothes, convenience, supermarket, mobile_phone_shop, department_store, bakery, jeweller, shoe_shop, beverages, bookshop, sports_shop, car_dealership, furniture_shop, stationery, florist, optician, toy_shop, mall, gift_shop, garden_centre
Services	post_box, bank, pharmacy, beauty_shop, dentist, hairdresser, post_office, doctors, laundry, hospital, chemist, veterinary

Table A2
Model performance comparison

Model	Park-neighborhood poverty rate	R^2	RMSE	MAE
RF	High	0.78	0.40	0.22
	Medium	0.66	0.47	0.28
	Low	0.75	0.38	0.23
XGBoost	High	0.81	0.37	0.20
	Medium	0.69	0.45	0.26
	Low	0.78	0.35	0.21

(*continued on next page*)

Table A2 (*continued*)

Model	Park-neighborhood poverty rate	R^2	RMSE	MAE
GBDT	High	0.75	0.43	0.25
	Medium	0.63	0.50	0.30
	Low	0.72	0.41	0.26
LightGBM	High	0.84	0.34	0.18
	Medium	0.71	0.42	0.25
	Low	0.81	0.32	0.19
BO-LightGBM	High	0.87	0.32	0.17
	Medium	0.74	0.40	0.24
	Low	0.84	0.30	0.18

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