Eurasia Journal of Science and Technology
ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3077

STREETSCAPE GREENNESS AND PARK SERVICE EVALUATION IN ZHENGZHOU, CHINA: A SPATIAL MULTI-ZONING PERSPECTIVE

Da Mao[1*], ZhiYu Yuan[1], MengLei Zhao[1], HuaYu Fu[2]
[1]*School of Horticulture and Landscape Architecture, Henan Institute of Science and Technology, Xinxiang 453003, Henan, China.*
[2]*Xinxiang Santian Landscape Engineering Co., Ltd., Xinxiang 453003, Henan, China.*
Corresponding Author: Da Mao, Email: maoda@foxmail.com

Abstract: This study investigates the spatial association between streetscape greenness (Green View Index, GVI) and park service evaluations in Zhengzhou, China, integrating multi-source geospatial data, including 131 park POIs and 23,866 street view images with a multi-zoning analytical framework (grid-based, radial-sector, and Voronoi zoning). Using spatial autocorrelation (Global/Local Moran's I) and bivariate LISA cluster analyses, key findings include: (1) Radial-sector zoning outperformed other methods in capturing spatial heterogeneity; (2) High GVI clusters concentrated in the urban core, while top-rated parks exhibited concentric patterns, with low-value zones coupled at the periphery; (3) Significant synergy emerged between peak park ratings and mean GVI (I = 0.135–0.196), revealing asymmetric interactions. A three-tiered planning strategy is proposed: radial-sector green space allocation, targeted upgrades in mismatch zones, and flagship park-driven green networks. This research advances methodological innovation in green infrastructure optimization for urbanizing cities.
Keywords: Streetscape; Green view index; Multi-zoning; Park service

1 INTRODUCTION

Urban green spaces, encompassing streetscapes and parks, serve as critical infrastructure for advancing ecological sustainability, promoting public health outcomes, and addressing urban social equity challenges. Despite their shared objectives in urban greening, parks and streetscapes exhibit distinct spatial service units that rarely overlap geographically. This spatial divergence has historically hindered comprehensive investigations into their service correlations, particularly under technological constraints of spatial multi-source data scarcity in earlier decades [1, 2]. The emergence of geospatial big data and computational advancements now enables precise quantification of public service facility distributions through innovative metrics such as street view image analytics and Point of Interest (POI) data mining, revolutionizing urban landscape assessments [3].

The proliferation of web-mapping services (e.g., Google Street View, Baidu Map, Amap, Tencent Map) has democratized access to streetscape imagery, facilitating large-scale urban analyses at unprecedented granularity [4]. Seminal work by Li et al. pioneered the use of Google Street View (GSV) imagery with fisheye projection algorithms to quantify pedestrian-scale green exposure [5]. This methodology laid the foundation for the Green View Index (GVI), a standardized metric quantifying visible vegetation proportions in streetscapes through semantic segmentation of street-level imagery [6-8]. Concurrently, POI data has emerged as a vital tool for urban analytics, enabling researchers to:Map facility distribution patterns, Assess urban functional vitality hotspots, and Evaluate service catchment areas of green spaces through spatial interaction modeling [9-12].

The methodological core of this study lies in addressing the spatial mismatch between streetscape greenness service radii and park accessibility through a multi-zoning analytical framework. We operationalize this approach by:

Calculating neighborhood-level GVI scores using street view imagery, Quantifying park service performance through POI-based visitation patterns and facility quality metrics, and applying spatial regression models to identify zone-specific associations between streetscape greenness and park service efficacy.This study employs a multi-zoning analytical framework to test diverse spatial unit delineation methods. The underlying scientific hypothesis posits that the Green View Index (GVI)—quantifying streetscape greenness—exhibits statistically significant correlations with public evaluations of park services, with such associations being spatially scale-dependent. Specifically, we postulate that the strength and direction of GVI-park service relationships vary across different hierarchical spatial units (e.g., 1000m grids, voronoi area, concentric zone area).

2 DATA AND METHODS

2.1 Study Area

This study focuses on Zhengzhou City, the provincial capital of Henan Province, strategically positioned as a key socioeconomic and transportation hub in Central China. As a rapidly urbanizing megacity, Zhengzhou has witnessed over 50% expansion in built-up areas during the past two decades, while persistent disparities in green space accessibility and quality remain unresolved. These dynamics position Zhengzhou as a critical case for examining the challenges of reconciling green infrastructure development with population growth (exceeding 10 million residents) and spatial intensification.

The study area encompasses the urban core within Zhengzhou's Third Ring Road (Figure 1), comprising four expressway segments: the North Third Ring Road (N3RR), East Third Ring Road (E3RR), South Third Ring Road (S3RR), and West Third Ring Road (W3RR). This enclosed 202 km² zone represents the city's primary urbanized territory, characterized by systematic street networks, multi-tiered park systems, and representative streetscape greenery configurations.

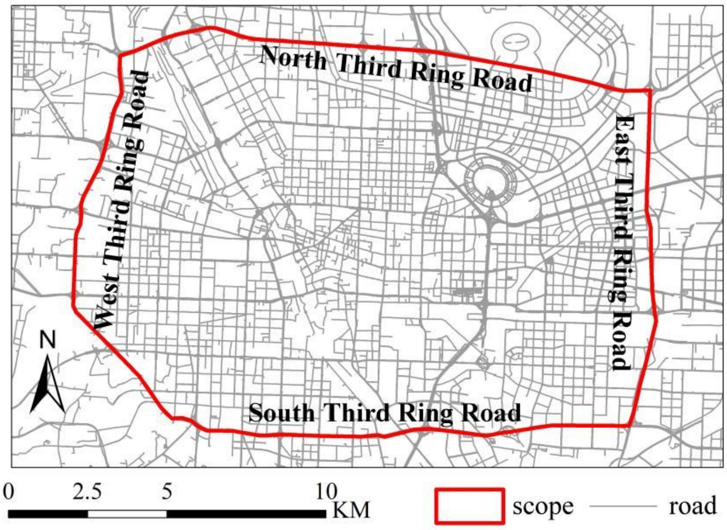

Figure 1 Scope Diagram of Study Area
Edited on this map source: https://www.openstreetmap.org/

2.2 Data

2.2.1 POI data and park rating score

The POI data in this study were sourced from AutoNavi Map (Amap), China's leading digital mapping platform, with all records timestamped for 2023 to ensure temporal consistency with concurrent streetscape imagery. Amap was prioritized over alternative providers due to its unique integration of crowdsourced facility ratings—a critical feature enabling quantitative assessment of public perception toward park services. Each park's composite rating, ranging from 0 (lowest) to 5 (highest), was calculated as the arithmetic mean of individual user evaluations, reflecting collective satisfaction levels.

Through protocol-driven web scraping techniques, we systematically collected georeferenced POI records for 131 municipal parks within Zhengzhou's Third Ring Road boundary. The automated harvesting pipeline included:

(1) Spatial filtering: Restricting queries to parks located within the 202 km² urban core.

(2) Data validation: Eliminating duplicate entries to ensure statistical reliability.

(3) Attribute extraction: Capturing essential metadata (park name, GPS coordinates, rating score).

2.2.2 Street view images and GVI

The streetscape imagery was sourced from Baidu Map, China's leading provider of panoramic street view services. It is critical to note that while data acquisition occurred between December 2022 and January 2023, the actual capture dates of Baidu Map images may span multiple years due to the platform's asynchronous update cycles. A systematic sampling protocol yielded 23,866 georeferenced street view points within the study area, spaced at 50-meter intervals along road networks. The technical process (Figure 2) is as follows:

Step 1: Programmatic Street View Data Harvesting

Georeferenced 360° panoramic images were systematically retrieved through Baidu Map's API (v4.0) using a spatially stratified sampling strategy. To comply with platform rate limits, we implemented token-bucket throttling algorithms (50 requests/second) while ensuring complete coverage across all road segments within Zhengzhou's Third Ring Road. Each panorama was acquired at 4,096×2,048 resolution (RGB, 8-bit depth).

Step 2: Cubemap Projection via PTGui Professional

The acquired 23,866 street view panoramas underwent systematic geometric processing following established protocols in urban visual perception studies [13-15]. Using PTGui Pro's batch processing module, each spherical panorama was decomposed into six perspective-corrected cube faces (front/back/left/right/top/bottom) through equiangular cubemap projection, which generated 143,196 directional images (23,866×6). Outputs were standardized as 960×960 JPG tiles per face (8-bit RGB).

Step 3: Human-Centric Visual Field Simulation

To ensure ecological validity in simulating pedestrian visual experiences, zenith and nadir projections (47,732 images) were excluded based on empirical evidence that vertical extremes contribute minimally to human horizontal field-of-view perception [16]. The final dataset comprised 95,464 street view images (23,866 × 4). For pedestrian visual emulation, the upper 2/3 portion (960×720 pixels) was extracted from front/back/left/right faces. This cropping strategy aligns with:
(1) Eye-level perspective: 1.2-1.8 m vertical focus matching human height percentiles.
(2) Urban context preservation: Maximizes street-level vegetation visibility.
Step 4: GVI Computation via Deep Learning Pipeline
A pretrained PSPNet-101 model (initialized with ADE20K weights) was fine-tuned on our UrbanGreen-15K dataset (containing 12 vegetation classes) using transfer learning. The processing pipeline included:
(1) Semantic segmentation: Pixel-wise classification at 512×512 resolution
(2) Vegetation masking: Thresholding greenness (HSV ranges: H = 80-160°, S > 20%, V > 15%)
(3) GVI calculation:

$$GVI = (\frac{Vegetation\ Pixels}{Total\ Valid\ Pixels}) \times 100\% \tag{1}$$

Ultimately, the GVI of each point is the average of the GVI of the four directions' images.

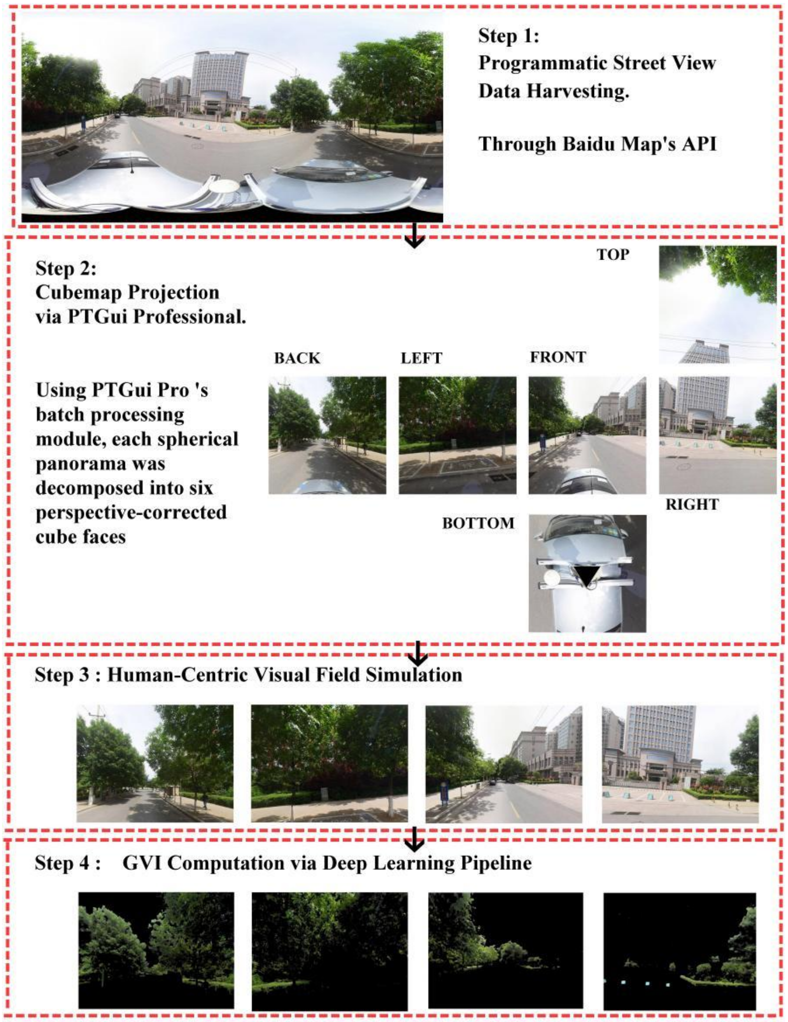

Figure 2 Technical Flow chart

2.3 Methods

2.3.1 Spatial multi-zoning

The multi-zoning framework constitutes the methodological nucleus of this investigation. We systematically implemented and compared three distinct spatial zoning paradigms (Figure 3) to address scale-dependent heterogeneity in green service associations:
(1) Grid-based Zoning
Adopting a regular square tessellation approach, the study area was partitioned into 1 km × 1 km grid cells (1 km² each), aligned with the Universal Transverse Mercator (UTM) Zone 50N coordinate system. This isotropic partitioning facilitates density-based spatial analysis while minimizing shape-induced biases, particularly suitable for examining city -wide greenness distribution patterns.

(2) Radial-sector Zoning
Centered on Zhengzhou's urban green heart (Zijinshan Park), we constructed concentric buffer rings at 1 km radial intervals extending outward. Each annular zone was further subdivided into eight cardinal and intercardinal sectors (N, NE, E, SE, S, SW, W, NW), creating combined radial-sector units. This dual-axis partitioning enables directional analysis of green space diffusion patterns and distance-decay modeling of park service effectiveness.
(3) Voronoi Zoning
The Voronoi diagram (also termed Thiessen polygons), named after mathematician Georgy Voronoi , was employed to delineate park service boundaries through spatial partitioning. Geometrically, Voronoi diagrams are constructed by generating perpendicular bisectors between adjacent control points, forming continuous polygonal cells where any location within a cell is closer to its generating point than to others [16]. Operationalizing this theoretical framework, we generated Voronoi polygons using 131 park POIs from Amap within Zhengzhou's Third Ring Road through ArcGIS' Voronoi tool . This approach defines the maximum theoretical service extent for each park, assuming users prioritize nearest-facility access.

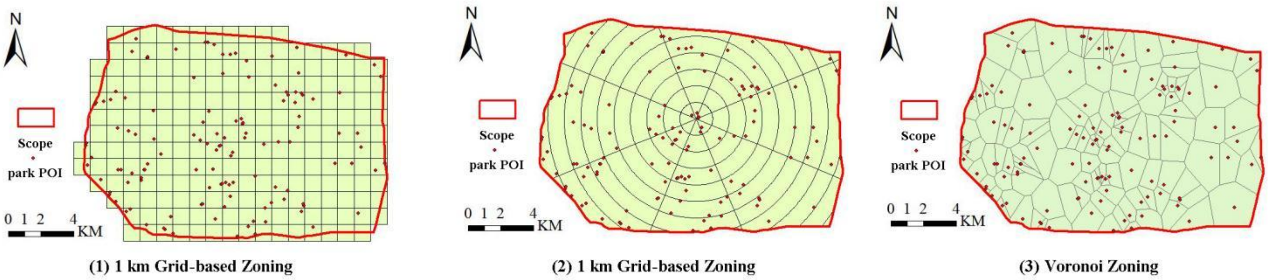

Figure 3 Three Distinct Spatial Zoning Paradigms

2.3.2 Spatial unit attribute assignment
This study incorporated two primary datasets for spatial unit characterization: park ratings derived from POI evaluations, and streetscape greenness measured through Green View Index (GVI).
(1) GVI Integration:
With dense sampling points (23,866 locations at 50m intervals), all spatial units contained sufficient GVI measurements. Using ArcGIS Pro's spatial join tool , three greenness metrics were computed for each unit:MeanGVI, MaxGVI and MinGVI.
(2) Park Rating Interpolation:
Given sparse POI distribution (131 parks), non-Voronoi zoning methods (grid/radial) contained null units. To address this spatial discontinuity, we implemented ordinary Kriging interpolation (spherical semivariogram model, 0.5 km search radius) to create continuous rating surfaces. The interpolated raster was subsequently integrated with spatial units via zonal statistics, yielding Unit Rating.
2.3.3 Spatial correlation methodology
The values of the above spatial units were analyzed by applying the method of spatial correlation. Exploratory Spatial Data Analysis (ESDA) provides a suite of statistical techniques to quantify and visualize spatial autocorrelation patterns. This study employs both global and local indicators to examine the spatial association between streetscape greenness and park service evaluations.
(1) Global Spatial Autocorrelation
The *Moran's I* statistic (Moran, 1950) measures overall spatial dependence across the study area:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \varpi_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \quad (2)$$

where:
n: Number of spatial units
ϖ_{ij} : Spatial weight matrix (queen contiguity)
S_0 : Sum of all spatial weights
x_i : Attribute value at location
$\bar{x}$: Mean attribute value
Interpretation:
I∈[−1,1]: Positive values indicate clustering (similar values aggregate), negative values dispersion, and 0 random distribution. Statistical significance tested via permutation tests (999 simulations, α=0.05).
(2)Local Indicators of Spatial Association (LISA)

Developed by Anselin (1995), LISA identifies localized clustering patterns and spatial outliers through:
Local Moran's I computation for each spatial unit:

$$I_i = \frac{\left(x_i - \bar{x}\right)}{s^2} \sum_{j=1}^{n} \varpi_{ij} \left(x_j - \bar{x}\right) \tag{3}$$

where S^2 is the variance of x.

3 RESULTS

3.1 Univariate Global Spatial Autocorrelation Analysis

The Global *Moran's I* statistic was computed using GeoDa 1.20 to quantify spatial clustering patterns of streetscape greenness (GVI) under three distinct zoning frameworks:

Table 1 The Univariate Global *Moran's I*

Zoning Method	MeanGVI	MaxGVI	MeanGVI	Mean Park rating score	Max Park rating score	Min Park rating score
Grid	0.407	0.469	0.214	0.351	0.698	-0.121
Radial-sector	0.405	0.362	0.047	0.401	0.314	0.534
Voronoi	0.346	0.399	0.162	0.286	0.716	0.400

As can be seen from the univariate global *Moran's I* table (Table 1) above, the performance of several variables differs across the three spatial zoning methods. Among them, Mean GVI, Max GVI, Mean Park Rating Score, and Max Park Rating Score exhibit significant positive spatial autocorrelation in all three zoning frameworks. However, Min GVI and Min Park Rating Score show insignificant spatial clustering. Numerically, the Radial-sector method demonstrates the best overall performance, indicating that Radial-sector is a highly suitable approach.

3.2 Bivariate Local *Moran's I*

Using GeoDa 1.20's bivariate Local *Moran's* I (LISA) module, we systematically analyzed spatial cross-correlations between paired variables (e.g., GVI vs. park ratings) . Representative cases are described below.
(1) 1 km Grid-based Zoning
Within the 1 km grid-based zoning spatial units, no significant bivariate spatial autocorrelation was observed between Mean Park Rating Score and Mean GVI. However, relatively significant spatial autocorrelation features were identified between:
Mean Park Rating Score and Max GVI (*Moran's I* = 0.153).
Max Park Rating Score and Mean GVI (*Moran's I* = 0.135).
In the LISA map(Figure 4) of Mean Park Rating Score vs. Max GVI, High-High (H-H) clusters exhibited distinct concentric patterns, while GVI itself demonstrated a spatial gradient characterized by higher values in the urban core and lower values in peripheral areas. Similarly, the LISA map(Figure 5) of Max Park Rating Score vs. Mean GVI revealed annular distributions of H-H and Low-High (L-H) units. These patterns indicate that while streetscape greenness (GVI) peaks in Zhengzhou's central urban area, park service ratings display annular differentiation features.

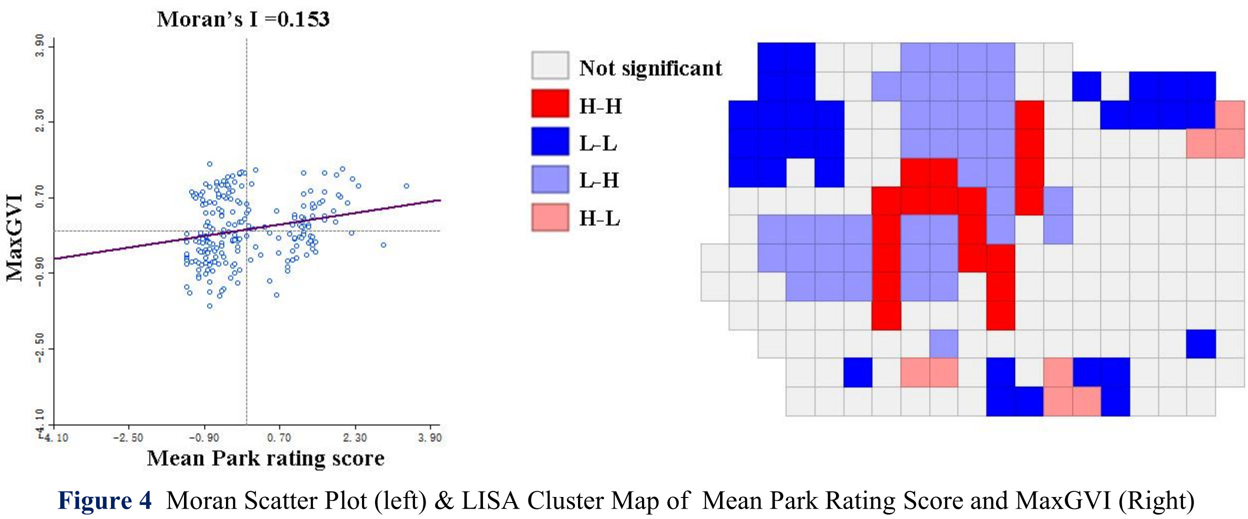

Figure 4 Moran Scatter Plot (left) & LISA Cluster Map of Mean Park Rating Score and MaxGVI (Right)

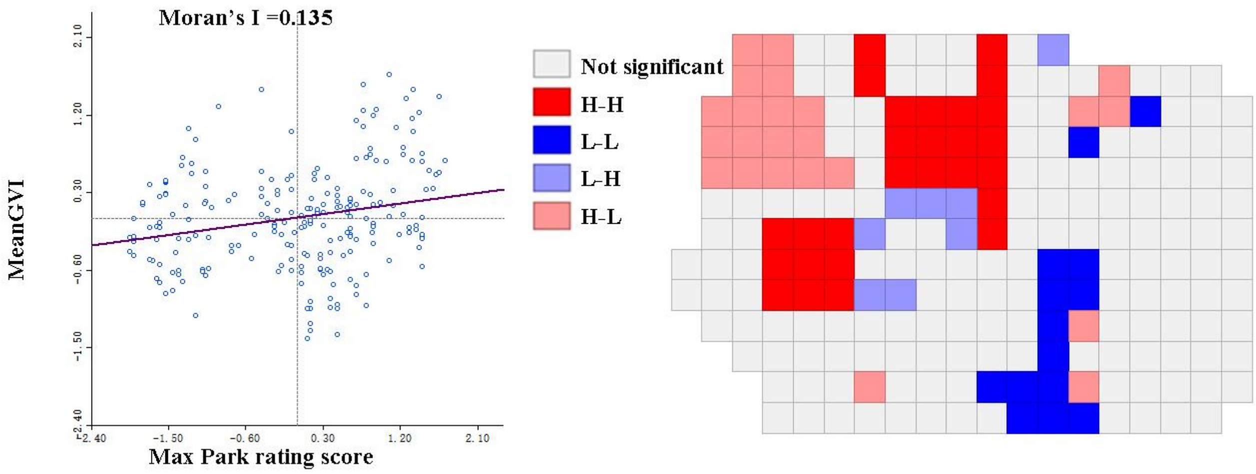

Figure 5 Moran Scatter Plot (left) & LISA Cluster Map of Max Park Rating Score and Mean GVI (Right)

(2) 1 km Radial-sector Zoning

Within the 1 km Radial-sector Zoning spatial units, relatively pronounced bivariate spatial autocorrelation was observed between Mean Park Rating Score and Mean GVI (*Moran's I* = 0.169). Similarly, Max Park Rating Score and Mean GVI also exhibited significant spatial autocorrelation (*Moran's I* = 0.216).

In the LISA map(Figure 6) of Mean Park Rating Score vs. Mean GVI, High-High (H-H) clusters were concentrated in the central radial sectors, while Low-Low (L-L) units predominantly aggregated in the east-central sectors. The distribution of H-H and L-L units in the LISA map(Figure 7) of Max Park Rating Score vs. Mean GVI mirrored this pattern. These findings demonstrate that the 1 km Radial-sector Zoning method effectively captures the concentric spatial stratification of urban units.

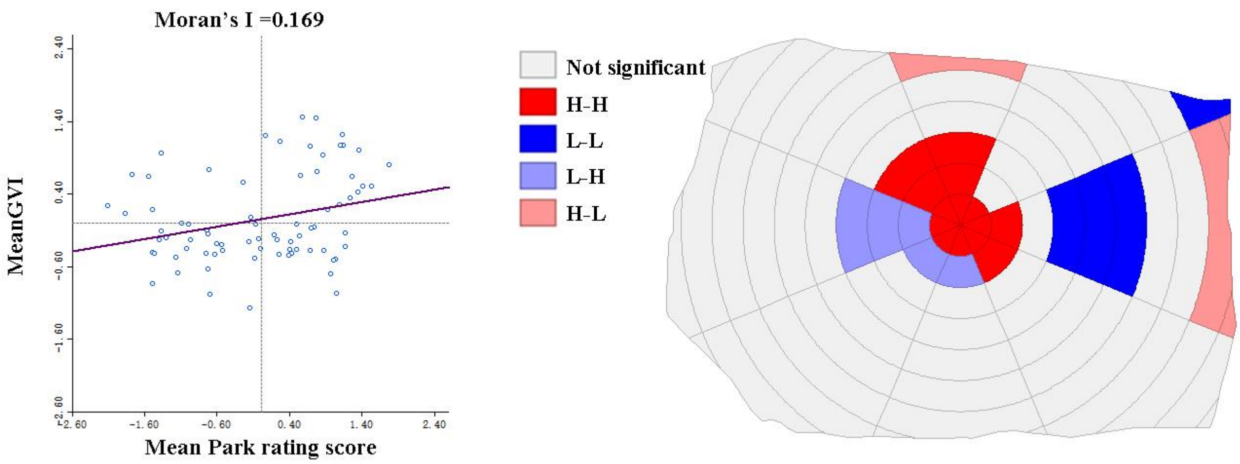

Figure 6 Moran Scatter Plot (left) & LISA Cluster Map of Mean Park Rating Score and Mean GVI (right)

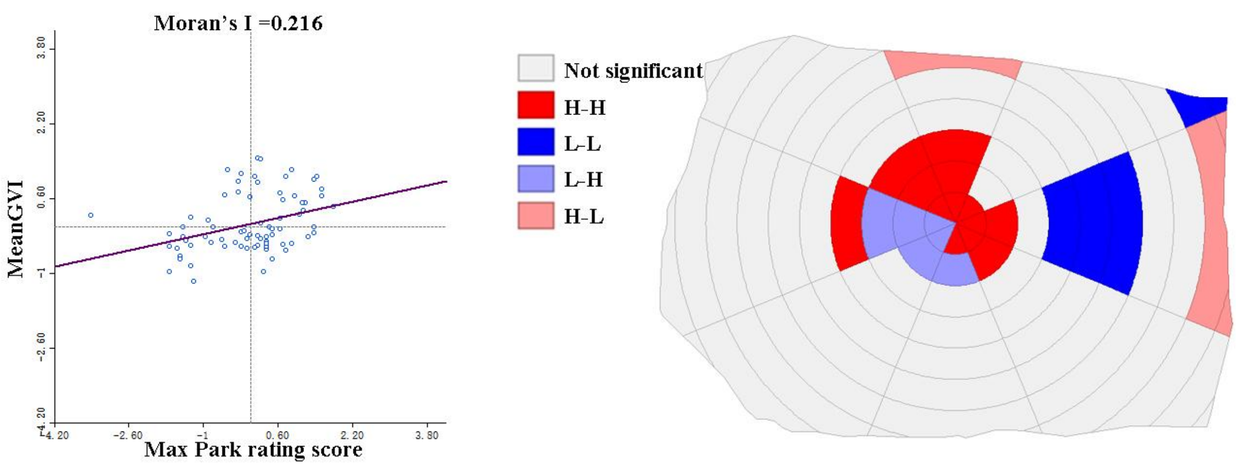

Figure 7 Moran Scatter Plot (left) & LISA cluster map of Max Park rating score and Mean GVI (right)

(3) Voronoi Zoning

Within the Voronoi Zoning spatial units, no significant bivariate spatial autocorrelation was detected between Mean Park Rating Score and Mean GVI (*Moran's I* = 0.033). However, Max Park Rating Score and Mean GVI exhibited relatively significant spatial autocorrelation (*Moran's I* = 0.196). Notably, the spatial morphology of units in Voronoi diagrams is challenging to characterize systematically(Figure 8). In the LISA map (Figure 9)of Mean Park Rating Score vs. Max GVI, High-High (H-H) and Low-High (L-H) clusters were concentrated in central areas, while Low-Low (L-L) and High-Low (H-L) units were scattered across the southwestern periphery. These results suggest that while Voronoi Zoning can analyze spatial correlations, its morphological interpretation is less intuitive compared to the previous two zoning methods.

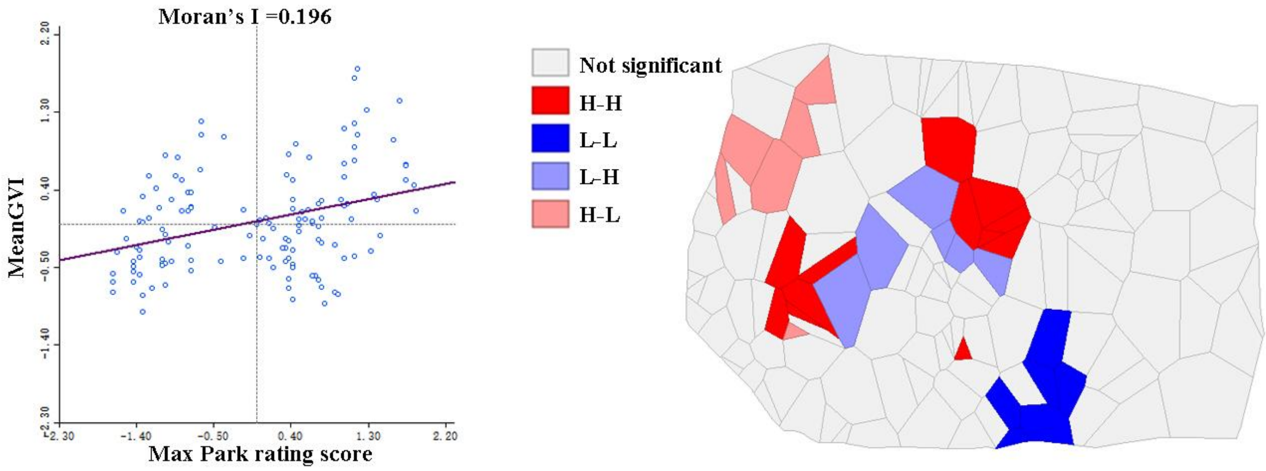

Figure 8 Moran Scatter Plot (left) & LISA Cluster Map of Max Park Rating Score and Mean GVI (Right)

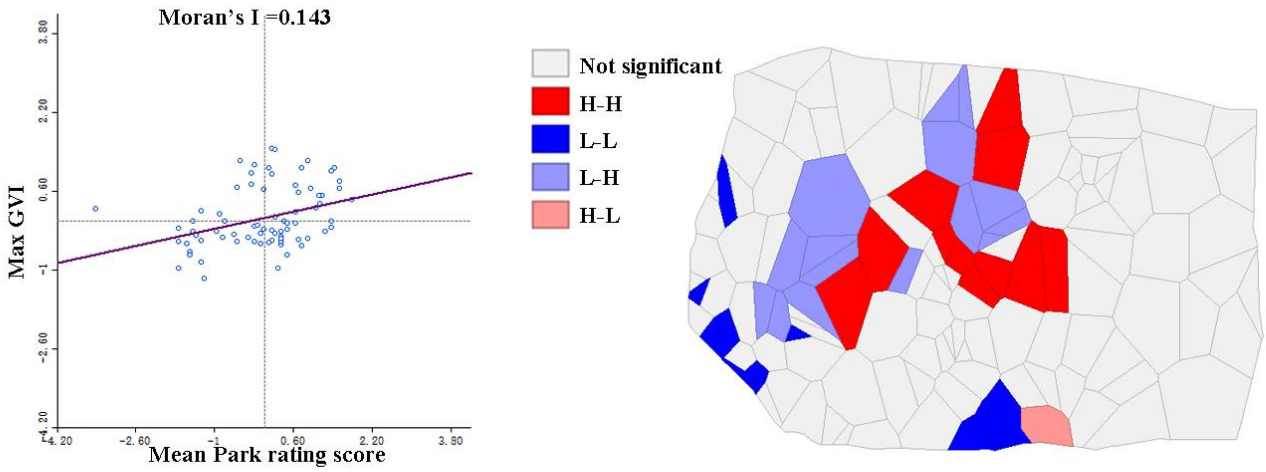

Figure 9 Moran Scatter Plot (left) & LISA Cluster Map of Mean Park Rating Score and Max GVI (Right)

4 CONCLUSIONS

The Zhengzhou case study yielded the following key findings:

(1) Spatial Association between Park Services and Streetscape Greenery

A significant correlation exists between park service evaluations and streetscape greenness. Crowdsourced park ratings (derived from POI data) and Green View Index (GVI) metrics (extracted from street view imagery) effectively captured this relationship, with *Moran' s I* values ranging from 0.135 to 0.216 ($p < 0.05$) under optimal zoning frameworks.

(2) Comparative Efficacy of Zoning Methods

All three spatial partitioning approaches—Grid-based, Radial-sector, and Voronoi Zoning—demonstrated utility in analyzing park-greenery associations. However, Radial-sector Zoning exhibited superior analytical capacity, achieving the highest *Moran' s I* values for both univariate and bivariate spatial autocorrelation analyses.

(3) Spatial Gradient Patterns

Streetscape Greenery: High-GVI clusters formed contiguous agglomerations in the urban core, reflecting centralized green infrastructure investments. Park Services: High-rating parks exhibited concentric distributions, aligning with

Zhengzhou ’ s radial-concentric development model. Low-Value Zones: Peripheral areas showed synchronized deficiencies in both GVI and park ratings, highlighting urban-rural green equity gaps.
(4) Asymmetric Interaction Mechanisms
While no significant correlation emerged between mean park ratings and mean GVI , robust associations were observed between Peak park ratings and mean GVI ,Mean park ratings and peak GVI .This asymmetry suggests that superior streetscape greenness serves as a foundational element for high park service ratings, while flagship parks can elevate neighborhood perceptions of green quality.

5 DISSCUSIONS

This study underscores the critical role of spatial zoning framework selection in urban green space analysis. While Voronoi partitioning demonstrated mathematical-theoretical rigor, it faced interpretive limitations in capturing gradient patterns. These findings advocate for context-sensitive zoning protocols, suggesting future exploration of hierarchical hexagonal spatial indexing and temporally weighted Voronoi models incorporating POI dynamics.
Practically, we propose a three-tiered spatial strategy for Zhengzhou:
(1) Strategic development of wedge-shaped green corridors aligned with anisotropic urban expansion along primary development axes to enhance sectoral spatial configurations, urban ventilation, and ecological connectivity.
(2) Precision interventions in peripheral mismatch zones—intensifying street greening in Low-High (L-H) clusters (GVI: 0.18–0.25, Park Ratings: 2.1–3.4) and modernizing recreational facilities in High-Low (H-L) areas.
(3) Strategic anchoring through flagship parks, establishing 500-meter radiating greenway networks with pedestrian/bicycle priority design standards, coupled with community co-management initiatives.
This integrated approach synthesizes analytical rigor with implementable planning solutions, addressing both scale-dependent spatial heterogeneity and green service equity through adaptive governance mechanisms and multi-stakeholder participatory frameworks.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

FUNDING

This research was funded by the following projects: Cultivation Plan of Young Backbone Teachers in Colleges and Universities of Henan Province, China (2021GGJS118), Key Science and Technology Research and Development Program of Henan Province, China (232102320180), Key Science and Technology Research and Development Program of Henan Province, China (222102320233).

REFERENCES

[1] Tang Z L, Gu S. An Evaluation of Social Performance in the Distribution of Urban Parks in the Central City of Shanghai: From Spatial to Social Equity. Urban Planning Forum, 2015(2): 48-56.
[2] Huang Z, Tang L, Qiao P, et al. Socioecological justice in urban street greenery based on green view index- A case study within the Fuzhou Third Ring Road. Urban Forestry & Urban Greening, 2024. DOI: 10.1016/j.ufug.2024.128313
[3] Wang H, Zhang W, Song H, et al. Spatial Evolution of Urban Population in Changsha and Its Simulation: Based on the Multi-source Data. Economic Geography, 2023, 43(8): 49-61.
[4] Cheng L, Chu S S, Zong W W, et al. Use of Tencent Street View Imagery for Visual Perception of Streets. International Journal of Geo-Information, 2017, 6(9): 265.
[5] Carrasco-Hernandez R, Smedley A R D, Webb A R. Using urban canyon geometries obtained from Google Street View for atmospheric studies: Potential applications in the calculation of street level total shortwave irradiances. Energy and Buildings, 2015, 86: 340-348.
[6] Dong R C, Zhang Y L, Zhao J Z. How Green Are the Streets Within the Sixth Ring Road of Beijing? An Analysis Based on Tencent Street View Pictures and the Green View Index. International Journal of Environmental Research And Public Health, 2018, 15(7): 1367.
[7] Fry D, Mooney S J, Rodriguez D A, et al. Assessing Google Street View Image Availability in Latin American Cities. Journal of Urban Health-Bulletin of the New York Academy of Medicine, 2020, 97(4): 552-560.
[8] Aikoh T, Homma R, Abe Y. Comparing Conventional Manual Measurement of the Green View Index with Modern Automatic Methods Using Google Street View and Semantic Segmentation. Urban Forestry & Urban Greening, 2023. DOI: 10.1016/j.ufug.2023.127845.
[9] Zhao H B, Yu D F, Miao C H, et al. The Location Distribution Characteristics and Influencing Factors of Cultural Facilities in Zhengzhou Based on POI Data. Scientia Geographica Sinica, 2018, 38(9): 1525-1534.
[10] Ta N, Zeng Y T, Zhu Q Y, et al. Relationship between built environment and urban vitality in Shanghai downtown area based on big data. Scientia Geographica Sinica, 2020, 40(1): 60-68.

[11] Mu H K, Gao Y, Wang Z Y, et al. Equity Evaluation of Park Green Space Service Level from the Perspective of Supply and Demand Balance: An Empirical Analysis based on big Data. Urban Development Studies, 2019, 26 (11): 10-15.
[12] Qi R H, Yang H, Wang S L, et al. Study on Evaluation and Planning of Urban Parks Based on Baidu POI Data. Chinese Landscape Architecture, 2018, 34(3): 32-37.
[13] Carrasco-Hernandez, R, Smedley A R D, Webb A R. Using urban canyon geometries obtained from Google Street View for atmospheric studies: Potential applications in the calculation of street level total shortwave irradiances. Energy And Buildings, 2015, 86: 340-348. DOI: 10.1016/j.enbuild.2014.10.001.
[14] Li X J, Ratti C. Mapping the spatial distribution of shade provision of street trees in Boston using Google Street View panoramas. Urban Forestry & Urban Greening, 2018, 31: 109-119. DOI: 10.1016/j.ufug.2018.02.013.
[15] Cinnamon J, Gaffney A. Do-It-Yourself Street Views and the Urban Imaginary of Google Street View. Journal of Urban Technology, 2022, 29(3): 95-116. DOI: 10.1080/10630732.2021.1910467.
[16] Wang X, Li Q, Guo Q, Wu H, et al. The generalization and construction of Voronoi diagram and its application on delimitating city' s affected coverage. Journal Of Central China Normal University(Nat .Sci .), 2002, 36(01): 107-111. DOI: 10.19603/j.cnki.1000-1190.2002.01.027.