J. Resour. Ecol. 2025 16(2): 1-12
DOI: 10.5814/j.issn.1674-764x.2025.02.000
www.jorae.cn

Integrating Accessibility and Green View Index for Human-scale Street Greening Initiatives: A Case Study of Chengdu's Third Ring Road

HUANG Zhongshan[1], LUO Shixian[2,*], CAI Yiqing[3], LU Zhengyan[3]

1. Graduate School of Techno Design (TED), Kookmin University, Seoul 02707, Korea;
2. School of Architecture, Southwest Jiaotong University, Chengdu 611756, China;
3. College of Architecture and Art, Hefei University of Technology, Hefei 230009, China

Abstract: Street greening is a popular topic in urban design research. Traditionally, assessments for urban greening levels using Normalised Difference Vegetation Index (NDVI) from satellite remote sensing images, often overlooking street greening from a human-scale perspective. This study combined spatial syntax, machine learning techniques, streetscape images, and remote sensing data to comprehensively assess thoroughly analyse street greening levels in Chengdu's Third Ring Road. Additionally, by integrating accessibility analysis with GVI, this study identified areas that should be prioritised for street greening interventions. The results indicate that: (i) Streets in the western and southern regions of Chengdu City's Third Ring Road possessed higher GVI. (ii) There is a significant difference in the overall distributions of GVI and NDVI, particularly in the central and eastern regions. (iii) Streets with "high commuting and walking accessibility (low GVI) overlapped in the area east of Shuncheng Avenue. The methodology presented in this study can serve as a reference for human-scale street greening in Chengdu and other cities.

Key words: accessibility; deep learning; Green vision rate (GVI); Normalised differential Vegetation Index (NDVI); SPACE Syntax

1 Introduction

The level of street greening is a key indicator of urban environmental quality (Yue et al., 2023). Research has demonstrated a close link between street greening and people's physical and mental health. which is demonstrated by the fact that street greening with High visibility street greening not only enhances residents' walking experience of but also but also alleviates psychological stress, promotes outdoor activities, and purifying urban air (Zhang et al., 2024). To provide residents with high-quality street space, the Chinese government, launched the Green Travelling Action Plan in 2019, aiming to create green, continuous, and comfortable street environments, achieving positive results (Sun et al., 2021). However, owing to financial constraints, in the process of street greening construction, particularly small- and medium-sized city governments struggle to implement high-quality greening of city streets on a large scale and efficiently (Daixin and Mingyang, 2023). Consequently, identifying priority streets in for greening is a significant challenge for city managers. Numerous studies have examined street greenery. Initially, most research assessed city greening levels by determining the Normalised Difference

Received: 2024-04-28 **Accepted:** 2024-08-10
Foundation: The Sichuan Province Philosophy and Social Science Foundation Project (SCJJ23ND494); The Fundamental Research Funds for the Central Universities-Scientific Innovation Project (XJ2023009801).
First author: HUANG Zhongshan, E-mail: hzs342601@gmail.com
***Corresponding author:** LUO Shixian, E-mail: shixianluo@swjtu.edu.

Citation: HUANG Zhongshan, LUO Shixian, CAI Yiqing, et al. 2025. Integrating Accessibility and Green View Index for Human-scale Street Greening Initiatives: A Case Study of Chengdu's Third Ring Road. *Journal of Resources and Ecology*, 16(2): 1–12.

Vegetation Index (NDVI) using satellite remote sensing images. For example, Wang et al. (2005) calculated NDVI by manually extracting vegetation areas from satellite images (Wang et al., 2005). MacFaden et al. (2012) combined satellite remote sensing images and with high-resolution Light Detection and Ranging (LIDAR) data to create a canopy map that proved to be suitable for assessing urban greening environments (MacFaden et al., 2012). Building on this, Beyer et al. (2014) used NDVI to show that green space and canopy cover can improve mental health (Beyer et al., 2014). However, while satellite remote sensing can accurately quantify large-scale urban greening, they are not suitable for quantifying small-scale street-level greening because of the difficulty in detecting ground-level details, such as the contours and features of ground-level plants, and in modelling residents' actual perceptions of street-level greening (Ye et al., 2019).

In recent years, advancements in street view image data and computer vision techniques, such as deep learning and image semantic segmentation, have enabled of street greenness visualisation (GVI) from a human-scale perspective. Scholars been applied GVI to access street greening quality (Ye et al., 2019), greening and safety (Theodorou et al., 2021), and greening and mental health (Soga et al., 2021). The GVI is the proportion of green plants in objects seen by people's eyes. Compared with the NDVI, the GVI better reflects the residents' perceptions of greening by emphasizing street greening quality from a human-scale perspective (Xiao et al., 2021). "Human-scale" street greening refers to the fine scale characterised by the human body and its surroundings, i.e. the scale that is directly visible, and accessible in people's daily lives (Ye et al., 2019). While deep learning and image semantic segmentation can effectively assess street greening from a human scale perspective, there is still insufficient attention to quantitatively measure street greening that is accessible and visible to the residents in their daily lives. This often leads to neglecting the potential foot traffic of the streets in the street greening process, resulting in the focus of street greening that may not align with daily visits. Therefore, it is necessary to add an accessibility indicator to the quantification of human-scale street greening.

Accessibility refers to "the opportunity for a person or a specific type of person to participate in a particular activity or set of activities at a given location" (Rollero and De Piccoli, 2010). In other words, accessibility represent the pedestrian potential of a street, indicating the easy or difficulty for an individual to reach it. Streets with higher accessibility are more likely to be used by residents and to have human activities and social interactions occurring within them (Yin, 2017). Spatial syntax has long been widely used in studies exploring accessibility, including analysing the relationship between street accessibility and urban public service facilities (Gonzalez et al., 2020), evaluating the accessibility of urban parks (Tannous et al., 2021), and quantifying point-of-interest (POI) accessibility (Liu et al., 2020). However, few studies have linked accessibility to green visibility in street greening research; therefore, more empirical evidence is required.

In this context, studies that combine deep learning and spatial syntax to quantify street greening are valuable. The green visual index (GVI) in street view images, obtained through deep learning and semantic segmentation techniques, accurately reflect the resident's actual feelings of street greening. However, it can guide relevant personnel in the process of street greening construction, focusing on greening construction on streets with high accessibility. This approach promotes a reasonable allocation of urban construction funds and improves the efficiency of urban planning.

Therefore, this study first extracts the percentage of green vegetation pixels in Baidu Street View Images (BSVI) using the semantic segmentation model SegNet. The distribution of the Green View Index (GVI) in the study area was then determined by dividing the number of vegetation pixels by the total number of pixels in the street view images followed by multidimensional analyses of the GVI distribution. Comparative analyses between GVI and NDVI were subsequently to explore differences in assessing urban greenery quality these indicators. Finally, spatial syntax was employed to quantify the accessibility of the street network in the study area. This accessibility was integrated with GVI to identify streets prioritised for greening construction and improvement.

2 Materials and methods

2.1 Research framework

The research framework comprised three main components: data collection and processing, analysis methods and processes, and analysis results and recommendations (Fig. 1). This framework is delineated into five steps: 1) utilise OpenStreetMap (OSM) to gather street network data for the study area, followed by merging, simplifying, and topologically processing the road network. Street-level sampling points were generated along roads, and Baidu Street View Images (BSVIs) were collected via the Baidu Street View application programming interface (API) using Python scripts. 2) Employing stitching algorithms in OpenCV to create panoramic images and using a deep learning model (SegNet) for the semantic segmentation of BSVI data to estimate vegetation coverage and compute the Green View Index (GVI). 3) Quantification of vehicular and pedestrian accessibility within the study area using spatial syntax analysis. 4) Conducting comparative analysis between GVI and NDVI. 5) Integrating the analysis of street accessibility with GVI to identify streets in a city that should focus on greening.

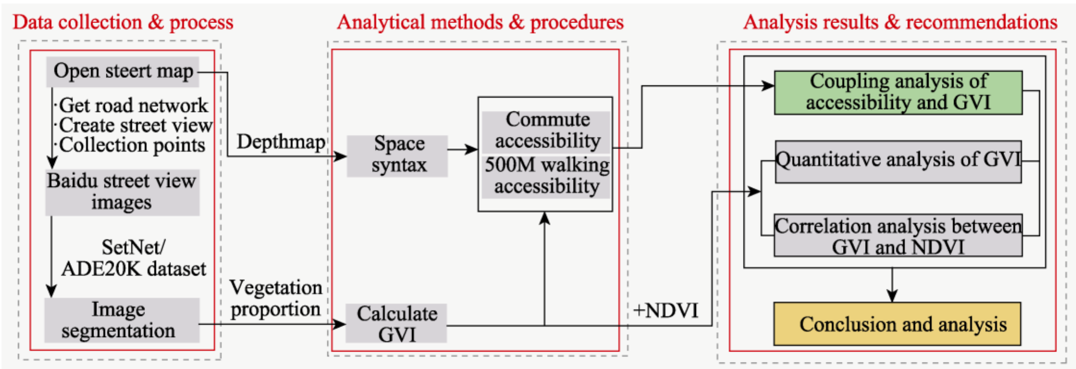

Fig. 1 Research framework

2.2 GVI Measurement using SegNet Semantic Segmentation

To obtain the percentage of vegetation elements in the street view image and calculate the GVI, we used the deep- learning SegNet model for semantic segmentation. SegNet is an open-source image segmentation project developed by the University of Cambridge, which can accurately segment object regions in an image, such as vegetation, roads, cars, and pedestrians, at the pixel level (Kolhar and Jagtap, 2021). The model comprises a convolutional neural network including two parts: an encoder and a decoder. encoder is based on the VGG16 network model and is responsible for parsing the object information; decoder converts the parsed information into the final image form, where each pixel is represented by the corresponding object information colour (or label) (Badrinarayanan et al. 2017). In short, the encoder analyses the low-level pixel values of the image to obtain high-level semantic information (e.g., “car、vegetation、pedestrian”), while the decoder maps these semantic information to the corresponding pixel points to represent each object with different colours (Lu, 2018).

The ADE20K dataset was used as the training dataset (https://github.com/CSAILVision/semantic-segmentation-pytorch). ADE20K is an open-source semantic segmentation dataset released by the CSAILVision team at MIT that contains 150 types of daily life objects, such as plants, roads, sky, terrain, and traffic signals. The segmentation results provided a reliable basis for the calculation of street GVI (Fig. 2). The GVI was calculated using the following formula:

$$Green\ view\ index = \frac{\sum_{i=1}^{4} Green\_i}{\sum_{i=1}^{4} Total\_i} \tag{1}$$

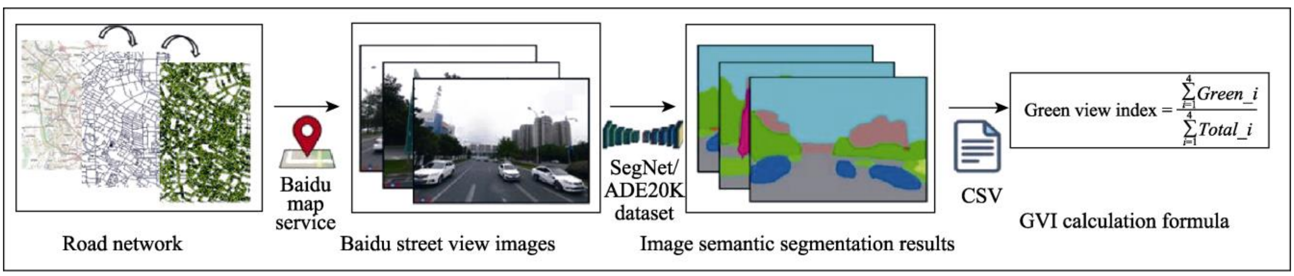

Fig. 2 GVI calculation process using SegNet semantic segmentation

In the formula, *Green_i* represents the number of green pixels in each of the four directions (front, back, left, right) from the four images, while *Total_i* represents the total number of pixels in the four images combined. In addition, based on a previous study (Jiang et al., 2023), this study divides GVI into five classes: L1 (0–0.05), L2 (0.05–0.15), L3 (0.15–0.25), L4 (0.25–0.35) and L5 (0.35–1). In general, a green visibility higher than 0.25 can bring residents a better green feeling (Xiao et al., 2021).

2.3 Measuring street accessibility using spatial syntax

The topological characteristics and spatial distribution of urban streets determine pedestrian potential and accessibility. Spatial Syntax, developed by University College London in the early 1980s, analyses the relationship between spatial networks and social activities (Derya Arslan and Ergener, 2023). Its strength lies in its ability to quantify the accessibility of urban spaces, particularly streets, by establishing topological relationships between points and lines. Streets with high accessibility are more likely to be frequented by residents, contributing to higher foot traffic, urban vitality, and social engagement (Karimi, 2023). Therefore, quantifying street accessibility using Spatial Syntax and assessing green visibility on highly accessible streets can help evaluate the quality of street greenery when pedestrian activities are frequent.

Integration, a common measure of street accessibility in Spatial Syntax, refers to the normalisation of the reciprocal of the total depth from one axis to all others, describing the distance from one street segment to others, and thus measuring its spatial potential. The higher the degree of integration, the greater the spatial accessibility. Depending on the calculation radius, the integration degrees are categorised into global and local integrations. Global integration measures how easily one can reach other spatial elements from any location within a study area, whereas local integration assesses access to specific elements within a defined range (Yunitsyna and Shtepani, 2023).

In this study, a line-segment model was employed to measure urban street accessibility. Considering that the average daily walking distance of urban residents in China is approximately 500 m (Lyu and Forsyth, 2021), a 500-meter radius is chosen for local (walking) accessibility, while global accessibility pertains to vehicular (commuting) access. The methodology involved merging, simplifying, and topologically processing the road network in a GIS. Subsequently, the processed network is imported into the Spatial Syntax software "Depthmap" to compute global and local integration degrees (accessibility). Finally, in the GIS, the top 20% of streets in Chengdu with high accessibility were juxtaposed with the bottom 20% of streets with a low Green Visibility Index (GVI) to identify streets that are highly accessible yet exhibit low greening potential.

2.4 Hotspot analysis and correlation analysis

Hotspot analysis is based on the Getis-Ord *Gi* statistic, which identifies statistically significant hotspots and cold spots, that is, spatial clusters of high or low values. The statistic returns *Z*-scores and *P*-values for the input features. A high *Z*-score and a low *P*-value indicate a hotspot, whereas a low or negative *Z*-score with a low *P*-value indicates a cold spot. Additionally, Spearman correlation analysis was performed to compare NDVI with GVI. The Spearman correlation coefficient (r) evaluates the strength of the linear relationship between two variables, ranging from –1 to +1. A positive value indicates a positive correlation, whereas a negative value indicates a negative correlation. Values closer to +1 or –1 indicate a stronger correlation.

3 Study area and data

3.1 Study area

Chengdu is situated in the central part of Sichuan Province and the western region of the Sichuan Basin (102°54′E-104°53′E, 30°05′N-31°26′N), serving as the hub of Southwest China and emerging as one of China's most popular "tourist cities" (Dong et al., 2023). This study focused on neighbourhoods within Chengdu's Third Ring Road (Fig. 3), encompassing approximately 193.325 km^2. These neighbourhoods include Chenghua District (approximately 60.898 km^2), Jinniu District (approximately 34.017 km^2), Jinjiang District (approximately 27.365 km^2), Longquanyi District (approximately 1.193 km^2), Qingyang District (approximately 24.001 km^2), and Wuhou District (approximately 45.849 km^2). These areas are pivotal for Chengdu's population centres (the main city area) and host their political, economic, cultural, and educational resources (Gong et al., 2023).

In recent years, the Chengdu Municipal Government has emphasised the development of greener and healthier urban street spaces, encouraging outdoor recreation among residents. This initiative is reflected in urban planning documents, such as the Guidelines for the Construction of Greening

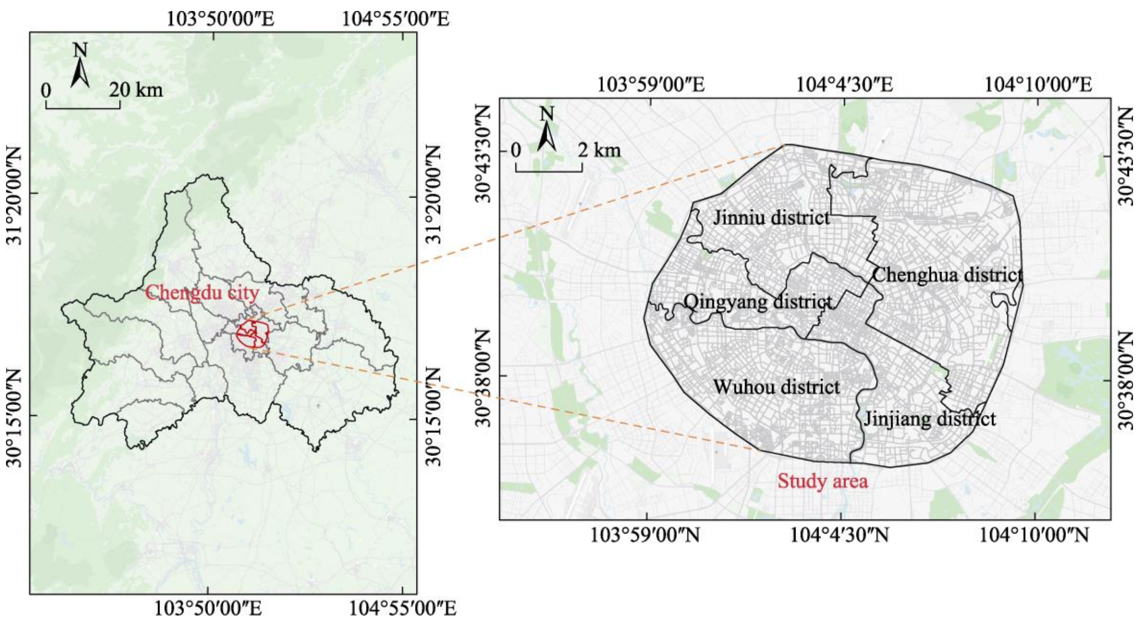

Fig. 3 Study area

on Chengdu's Urban Roads and the Chengdu Territorial Spatial Master Plan (2020–2035), aimed at enhancing the city's liveability and creating pleasant neighbourhood environments (https://mpnr.chengdu.gov.cn). Enhancing street environments through greenery has become a key aspect of Chengdu's future urban development strategies.

Therefore, this study focuses on the Third Ring Road of Chengdu City as a research area, integrating street accessibility and green visibility considerations. The goal is to propose an effective methodology for identifying streets in need of greening, providing practical insights for urban street greening practices.

3.2 Road network data and Baidu Street View Images (BSVIs) data

The road network data for this study were sourced from OpenStreetMap (http://www.openstreetmap.org). Streetview image data were obtained from Baidu Maps, one of China's largest online map service providers, offering an API interface for accessing streetview image data. The specific data acquisition process is as follows.

(1) Obtaining and processing road network data

•Obtain the road network data within the study area from OpenStreetMap (OSM).

• Simplify, merge, extract road centrelines, and perform topological processing on the OSM road network data.

After processing, 17988 road segments were identified.

(2) Converting coordinates and setting sampling points

• Use ArcGIS to convert the latitude and longitude coordinates of OSM road network data to BD09 coordinates (used by Baidu Maps).

• Set collection points along the road network at 50meter intervals, resulting in 85299 street view sampling points.

(3) Collection of Baidu Streetview images

Utilise Python scripts and Baidu Street View Map API to download street-view images.

• Images were captured at four angles (0°, 90°, 180°, and 270°) at each sampling point, for a total 360° panoramic views.

• Set the vertical angle to 22.5° and the field of view to 90°, providing a pedestrianlevel viewing experience (Kang et al., 2023; Rui, 2023; Zhou et al., 2024).

Stitch the images from four angles into 360° panoramic views with a maximum resolution of 1024×512 pixels.

• Filter out invalid street view images with inaccessible permissions.

• Collect a total of 77485 Baidu Street View images within the study area (Fig. 4) for subsequent image semantic segmentation and GVI calculation.

This comprehensive approach enabled the utilisation of accurate road network data and highquality streetview images from Baidu Maps for semantic image analysis and urban greening assessment.

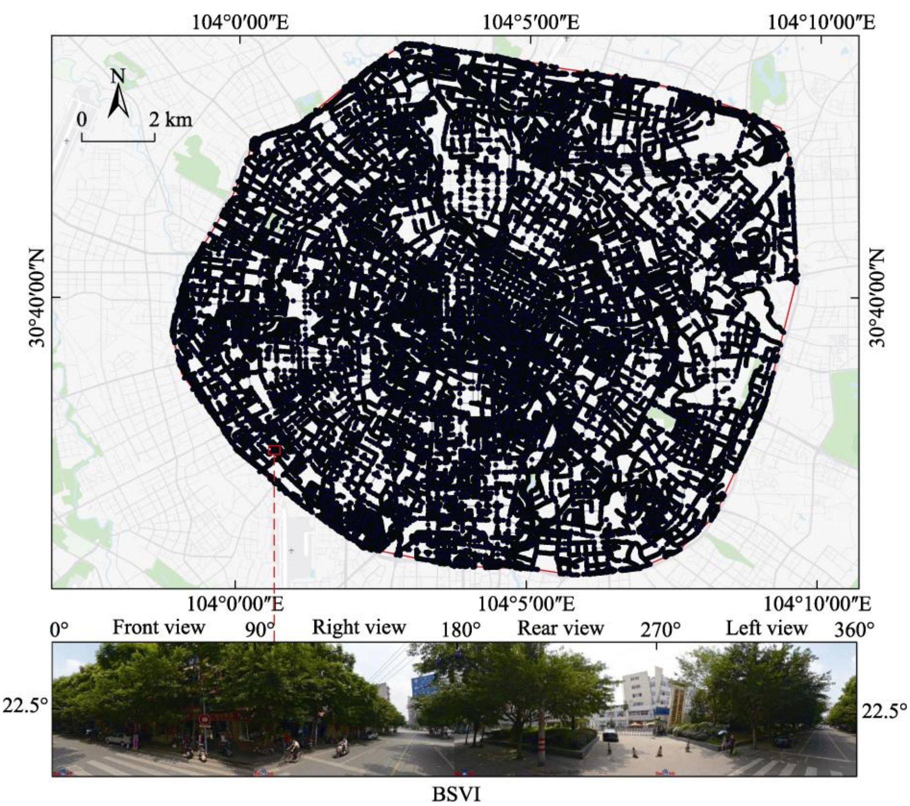

Fig. 4 Results of Baidu Street View image collection; the downside figure is an example of a street view map

3.3 Urban land use types and NDVI data

This study utilises 2018 urban construction land data for Chengdu City from Tsinghua University's EULUCChina dataset (http://data.ess.tsinghua.edu.cn). According to the Urban Land Use Classification and Planning and Construction Land Use Standards (GB50137-2011), the construction land in the study area is categorized into five major categories: residential land (Class R), commercial and service facilities land (Class B), roads and transport facilities land (Class S), industrial land (Class M), and land for public administration and public services (Class A).

The NDVI data were obtained from a Landsat series of satellite remote sensing images from July 2023 (https://earthexplorer.usgs.gov/). These image data were processed using radiometric calibration, atmospheric correction, cropping, and NDVI calculations in Envi software. NDVI was calculated using the following formula:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

where *NDVI* represents a metric used to measure urban greening based on the differential absorption of light wavelengths by vegetation canopies from a highaltitude perspective. *R* represents the red band and *NIR* represents the near-infrared band.

4 Results

4.1 Distribution of GVI within the study area

As shown in Fig.5, the distribution of the GVI in the study area exhibits clear spatial clustering characteristics. Areas with higher GVI were mainly concentrated in the west and south, whereas areas with lower GVI were mostly located in the centre and northeast. Additionally, the GVI of community-level streets were generally higher than that of motorways and urban arterial roads. Streets close to rivers, such as the Sha, Fu, and Nan Rivers, also show higher GVI. Finally, streets near parks and green spaces, such as Living Water Park, Chenghua Park, and Culture Park, also had a higher GVI.

To explore the differences in the GVI distribution among the five districts within the study area, we calculated the mean GVI and standard deviation for each district. Wuhou District had the highest mean GVI, whereas Qingyang District had the highest standard deviation. Chenghua District had the lowest mean GVI and Jinjiang District had the lowest standard deviation. The GVI ranked from high to low as follows: Wuhou District > Qingyang District > Jinniu District > Jinjiang District > Chenghua District. Unfortunately, none of the districts had a mean GVI value over 0.25 (Fig. 6a).

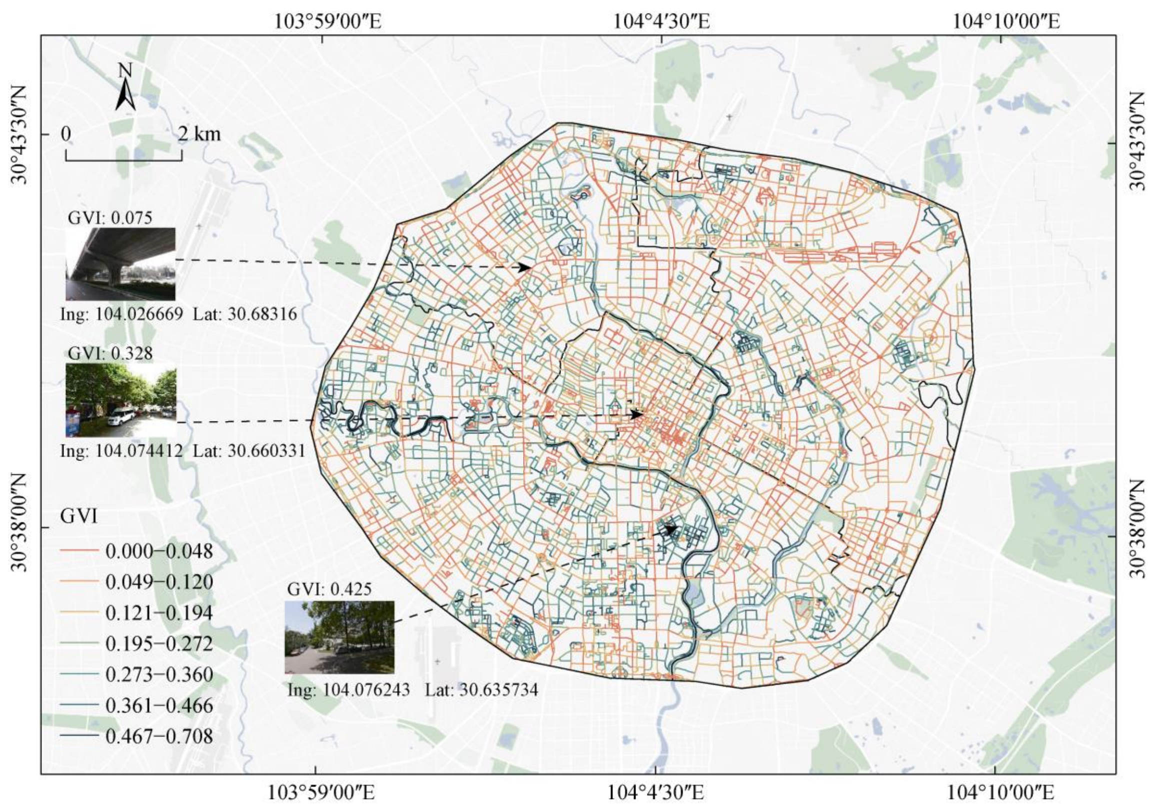

Fig. 5 Street level distribution of GVI in the study area

In the stacked map showing the GVI rank of each region, streets with a GVI rank of L3 or higher constituted more than half of the total number of streets in all five regions. In the Wuhou District, streets L5 and L4 accounted for the highest percentage. The highest percentage of L3 streets was found in the Jinjiang District, whereas the Chenghua District had the highest percentage of L2 streets (Fig. 6b).

Table 1 summarizes the GVI statistics for different site types. The maximum and minimum values demonstrate the extremes of GVI within the study area, in the greening reflecting areas with the best street greening, whereas minimum values indicate areas with the poorest greening (Zhang et al., 2023). Mean and standard deviation values reveal the overall level and variability of GVI. Higher mean values indicate better average greening levels, whereas larger standard deviations suggest greater variability in greening levels within a region (Wu et al., 2005).

The results indicate that public administration and public service land (A) had the highest mean GVI (0.201), signifying the highest overall greening level, as well as the largest standard deviation (0.158), indicating uneven distribution of GVI in this land type. Industrial land (M) had the lowest mean GVI (0.082), representing the poorest overall greening level. Roads and transport facilities (S) had the smallest standard deviation (0.061), suggesting a more uniform GVI distribution.

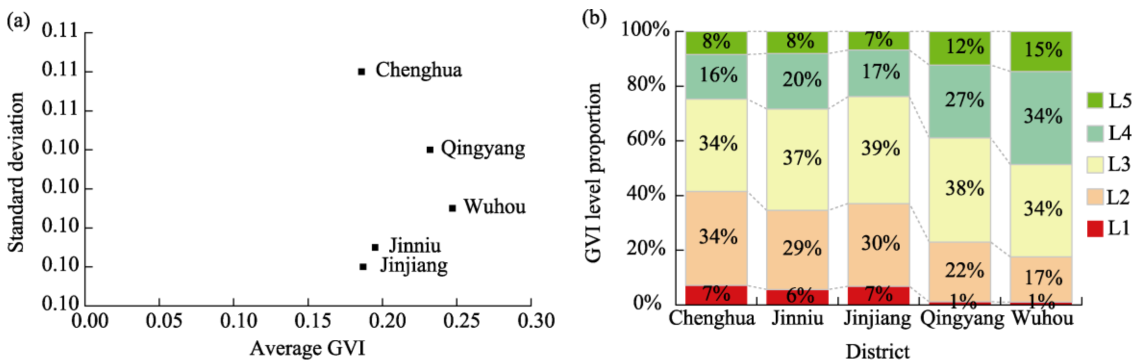

Fig. 6 Distribution of GVI in different zones (a) Mean and standard deviation of GVI in each zone; (b) Proportion of five GVI levels in five zones, with levels including L1 (0-0.05), L2 (0.05-0.15), L3 (0.15-0.25), L4 (0.25-0.35) and L5 (0.35-1)

Table 1 Summary statistics of green visual index (GVI) for different land use types

Land use function	Average value	Standard deviation	Minimum value	Maximum value
Residential land (R)	0.182	0.139	0.000	0.539
Land for commercial service facilities (B)	0.118	0.125	0.000	0.607
Industrial land (M)	0.082	0.108	0.000	0.401
Land for roads and transportation facilities (S)	0.127	0.081	0.000	0.245
Public management and public service land (A)	0.201	0.158	0.000	0.615

In conclusion, regarding land use types, the GVI levels in the study area were ranked as follows: public administration and public service land (A) > residential land (R) > commercial service facility land (B) > roads and transport facility land (S) > industrial land (M).

Additionally, to analyse the distribution of GVI hotspots and cold spots within urban construction land types, hotspot analysis (Getis-Ord Gi) was used to identify clustering areas of high and low GVI values (Fig. 7). The resukts show that the hotspots are predominantly found on residential land (R), public administration, and public service land (A), whereas the cold spots are primarily located on commercial service facility land (B) and industrial land (M). This result is consistent with those presented in Table 1.

4.2 Comparative analysis of GVI and NDVI

To explore the differences between the humanscale (bottom-up) Green Visual Index (GVI) and the (top-down) vegetation cover (NDVI) derived from satellite imagery, we utilized a 50m×50m grid "fishing net" tool in GIS to compare the distribution of GVI and NDVI within the third ring road of Chengdu (Fig. 8). The results indicated overall similarity between GVI and NDVI distribution; yet notable differences were observed in specific areas.

For instance, in areas labelled A, B, and C in Fig. 8, GVI and NDVI were closely aligned in area A, GVI surpassed NDVI in area B, and GVI lagged behind NDVI in area C. These discrepancies highlight that, while the overall GVI and NDVI generally show similar patterns, certain locations exhibit significant variations between the two indices.

4.3 Coupled analysis of accessibility and GVI

Figure 9 depicts the street accessibility for commuting and walking within Chengdu's Third Ring Road. Streets with high commuting accessibility are highlighted in red, whereas those with high walking accessibility are shaded in blue-green. The streets with high commuting accessibility exhibit a radial distribution, decreasing from the centre to the periphery. Streets with high walking accessibility are primarily situated east of the central area of the Third Ring Road, with lower accessibility noted in the northeast and southeast regions of the city.

To further integrate street accessibility with the GVI, we categorised the top 20% of streets with the highest commuting and walking accessibility as highaccessibility streets and the top 20% of streets with the lowest GVI as lowGVI

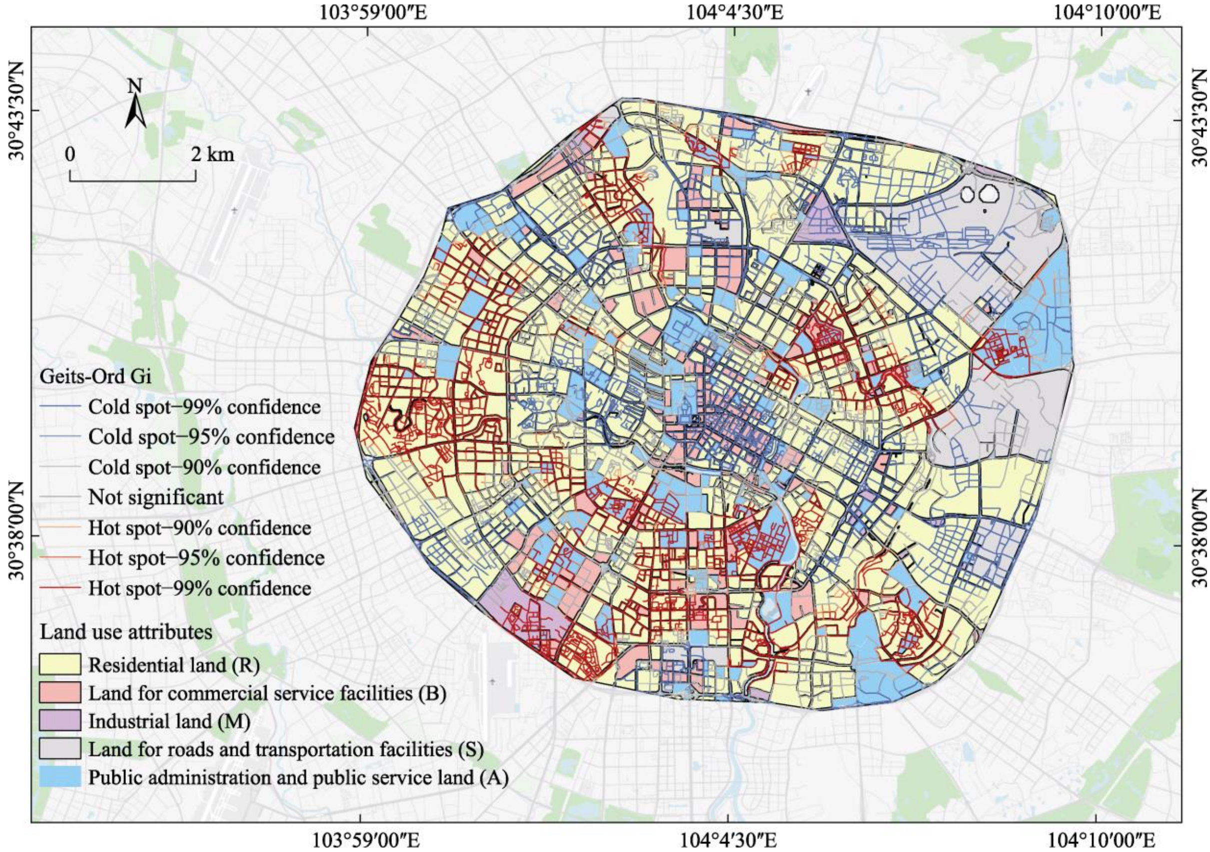

Fig. 7 Overlay map of hotspot analysis and urban construction land types

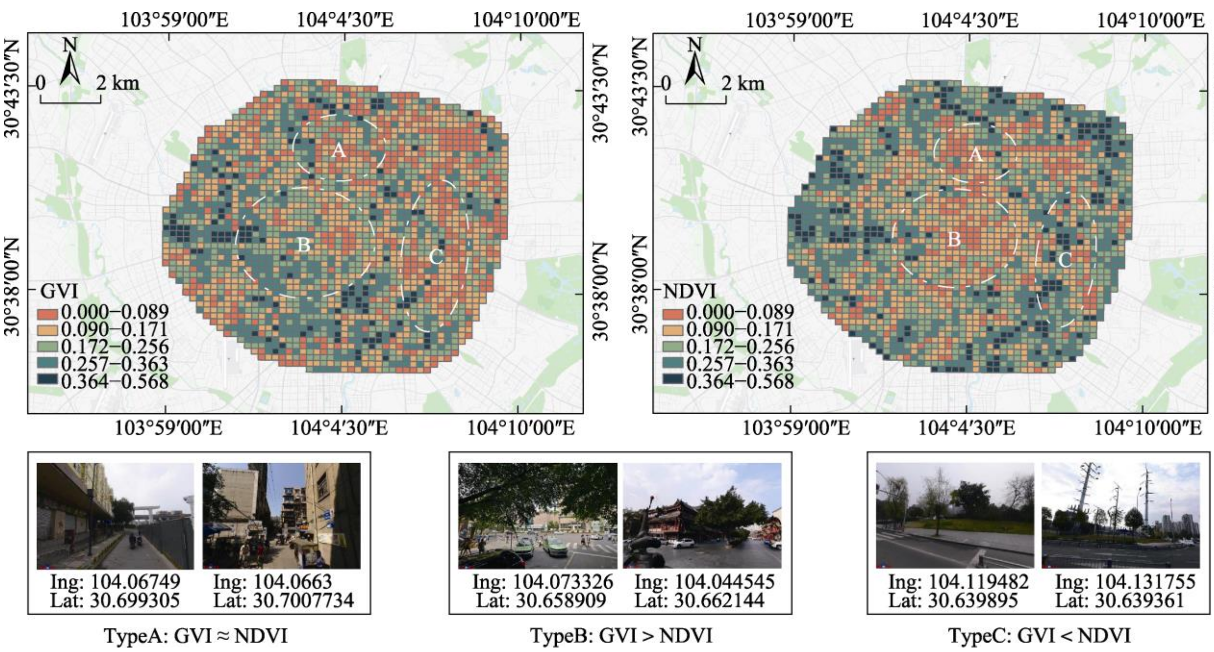

Fig. 8 Distribution differences between the GVI and NDVI

streets. Figure 10 illustrates the coupling analysis of these categories, showing that streets with "high vehicular accessibility (low GVI) are primarily major urban thoroughfares, such as the First Ring Road and the northern section of the West Second Ring Road. IN contrast, streets with " high pedestrian accessibility (low GVI) were more dispersed across various road levels. Notably, significant overlap of "high commuting and walking accessibility-low GVI" streets

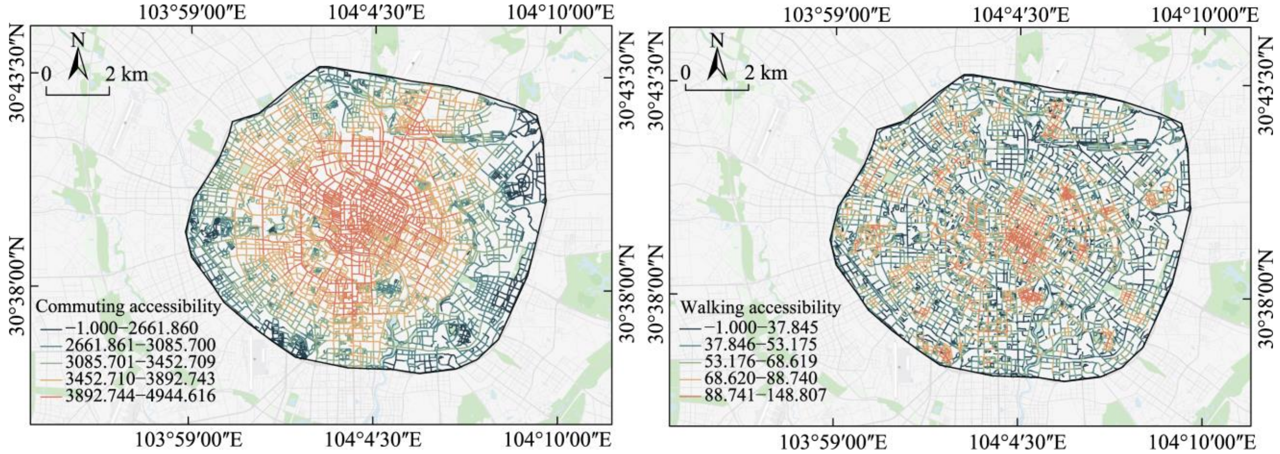

Fig. 9 Commuting and walking accessibility at the street level in the study area

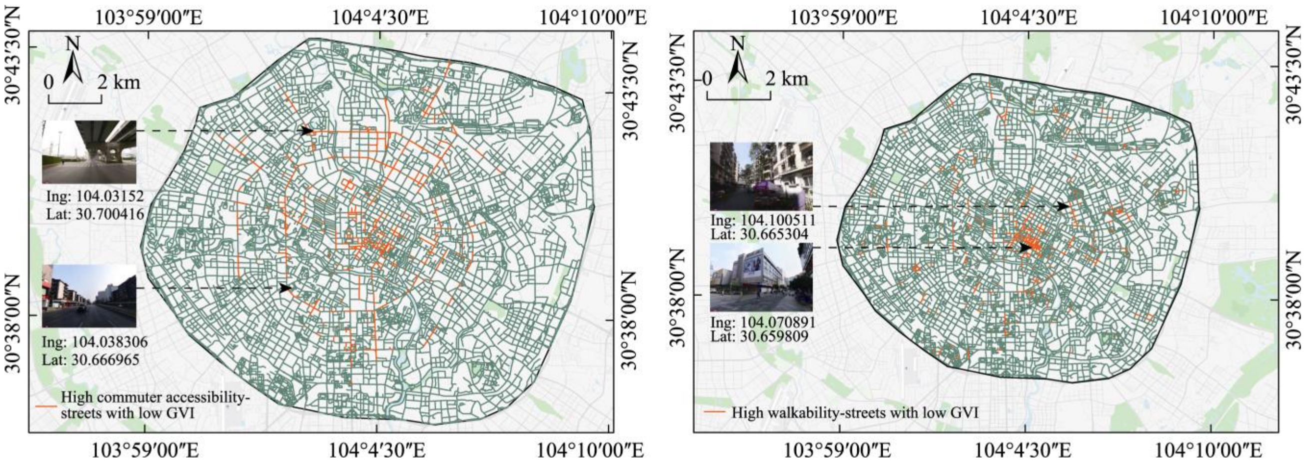

Fig. 10 Streets with high accessibility and low GVI

is observed east of the city centre.

5 Discussion

The level of street greening in the study area was assessed using three indicators: GIV, NDVI, and street accessibility. Compared to studies using a single assessment indicator, this study provides a more comprehensive and objective evaluation of street greening, particularly through the coupled analysis of street accessibility and GVI, which identifies key areas for potential street greening initiatives.

5.1 Analysis of research results

(1) Streets in the western and southern parts of the Third Ring Road in Chengdu exhibit higher GVI levels, possibly due to greater urban blue-green infrastructure in this area (Hou et al., 2023). Additionally, community-level streets overall showed higher GVI, consistent with findings from Long et al. in their study on street greening in Chengdu (Long and Zhou, 2016).

(2) The hot spots of GVI were primarily distributed in residential land (R), and public administration, and service lands (A), whereas the cold spots were predominantly distributed in commercial service facility land (B) and industrial land (M). This distribution aligns with expectations as residential land (R), public administration, and public service land (A), as the main activity spaces for residents' daily lives, usually receive more attention in greening construction, while the relatively low GVI of commercial service facility land (B) and industrial land (M) within Chengdu's Third Ring Road may stem from high building density and scarcity of land resources.

(3) Although the overall distributions of GVI and NDVI were generally similar, noticeable differences exist, particularly in the central and eastern regions. As illustrated in Fig. 8, the GVI and NDVI results are comparable in Area A. This similarity may stem from the presence of numerous construction sites and old communities in Area A, resulting in poor greening observed from both the GVI and NDVI perspectives. in contrast, GVI > NDVI in Area B likely relates to its designation as a high-density commercial zone with limited surface greenery, posing challenges for greening assessments using satellite remote sensing imagery. remote sensing imagery for greening assessment In the NDVI map, the central areas exhibits lower greening measurements than perceived from a human perspective, indicating

that some ground-level details are overlooked when using NDVI for urban greening assessment (Huang et al., 2024). The phenomenon of GVI<NDVI in region C may be attributed to the abundance of green spaces, parks, and other faceted green spaces near the street infrastructure in the vicinity within Area Consequently, the greenness index in this area appears higher in the NDVI map.

(4) The streets with "high commuting accessibility and low GVI" are primarily located on the main roads of the First Ring Road and the Northern section of the West Second Ring Road. This phenomenon may be attributed to less green semantic segmentation of streetscape images due to the wide roads and heavy traffic flow on these main thoroughfares, indicating that urban main roads prioritize traffic functions as the first orientation (Hao et al., 2016). In contrast, streets with "high walkability and low GVI" are generally more dispersed, with larger clusters observed in the eastern area of Shuncheng Street. This distribution may be influenced by the city's multi-centres layout favouring high walkability areas. Additionally, the presence of dense commercial complexes with high density and expensive land rent commercial buildings in the eastern area of Shuncheng Street. However, this may be related to the fact that the area east of Shuncheng Street is characterised by commercial complexes with high density and expensive land rents, which leave less space for greening.

5.2 Insights and recommendations

To further enhance street greening in the study area, this study proposes optimisation strategies from the following two aspects:

Firstly, it advocates for the comprehensive use of various methods and indicators in assessing street greening. This includes leveraging, street-view image data and machine learning technology for rapid measurement of street greening levels. Additionally, integrating both the GVI and NDVI indicators should be introduced to complement each other, providing a more comprehensive understanding of the street greening status in the study area. Furthermore, the key indicator of accessibility will prioritize the construction of streets by "high accessibility and low GVI".

However, the allocation of urban blue-green infrastructure (parks, green spaces, rivers, etc.) should also be rationalised. We observed that streets near urban blue-green infrastructure exhibit better greenery. Therefore, in the future, it will be possible to build pocket parks and green spaces in areas with overall greening, following a "plugging in greenery wherever possible". Additionally, in commercial districts and older neighbourhoods, characterised by dense urban buildings and limited street space, street greening can be enhanced through vertical greening initiatives.

6 Conclusions

In this study, we initially quantified and analysed the GVI of streets within Chengdu's, Third Ring Road by extracting the percentage of green plant pixels in streetscape images through deep learning. Secondly, by comparing and analysing GVI and NDVI at the street level, we identified spatial distribution differences. Finally, by highlighting disparities between accessibility and low green visibility (GVI), this study pinpointed key areas for urban street greening. Its primary contribution lies in integrating accessibility indicators with a comprehensive measurement of street GVI from a humanistic perspective, thereby methodological supporting for identification of areas in need of enhanced greening efforts in the city. In addition, this study conducted a comparative analysis of GVI and NDVI, highlighting the differences in urban greening assessment. This comparison enriches information for future greening projects. In conclusion, this study presented an effective combination of machine learning and spatial syntax offering rapid and effective evaluation methods for street greening assessment and construction.

Unlike previous studies (Hao et al., 2016; Huang et al., 2024), this new method considers the likelihood of a street being utilized, aligning more closely with residents' daily use of street space. Additionally, the study's methodology leverages AI technology and the accessibility of streetscape data, reducing time and cost in the acquisition of street GVI data. This framework can thus be expanded to assess street greening quality in diverse urban contexts.

Synthesis

study acknowledges some challenges, including technical limitations affecting streetview image data stability, which can vary with seasonal changes impacting model accuracy. Fortunately, advancements like Google Maps and Baidu Maps have recently introduced a new feature called "Time Machine", which offer opportunity to researchers to track the street GVI over time enhancing understanding of street greenery cycles. Additionally, while this study evaluates streets with high potential accessibility using spatial syntax method and advocates focusing on greening streets with high accessibility and low GVI, it is important to consider real-life factors such as number of Points of Interest (POIs) related to activities, social interactions, and weather conditions. Therefore, integrating realtime population data, such as mobile phone signal and heat maps, in future studies can provide a more objective assessment of street accessibility, more objectively.

Acknowledgement:

We are grateful to the editors and anonymous reviewers for their constructive comments.

References

Badrinarayanan V, Kendall A, Cipolla R. 2017. SegNet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(12), 2481–2495.

Beyer, K. M., Kaltenbach, A., Szabo, A., et al. 2014. Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. *International Journal Of Environmental Research And Public Health*, 11(3): 3453–3472.

Daixin D, Mingyang B. 2023. A resilience enhancement approach to the sponge city based on ecosystem-based disaster risk reduction—Taking the urban design of Jiangchuanlu Street in Shanghai, China as an example. *Journal of Resources and Ecology*, 14(6): 1113–1126. (in Chinese)

Derya A H, Ergener H. 2023. Comparative analysis of shopping malls with different plans by using space syntax method. *Ain Shams Engineering Journal*, 14(9): 102063. DOI: 10.1016/j.asej.2022.102063

Dong Q, Lu H, Luo X, et al. 2023. Evaluation and optimization of green space fairness in urban built-up areas based on an improved supply and demand model: A Case Study of Chengdu, China. *Sustainability*, 15: 15014. DOI: 10.3390/su152015014.

Gong Y, Ji X, Zhang Y, et al. 2023. Spatial Vitality Evaluation and Coupling Regulation Mechanism of a Complex Ecosystem in Lixiahe Plain Based on Multi-Source Data. *Sustainability*, 15(3): 2141. DOI: 10.3390/su15032141.

Gonzalez D, Rueda-Plata D, Acevedo A B, et al. 2020. Automatic detection of building typology using deep learning methods on street level images. *Building and Environment*, 177: 106805. DOI: 10.1016/ j.buildenv. 2020.106805.

Hao X H, Long Y, Shi M, Wang P. 2016. Street vibrancy of Beijing: Measurement, impact factors and design implications. *New Architecture*, (1): 52-57. (in Chinese)

Hou L G, Liu T, He X Q. 2023. The evolution of land spatial pattern in Chengdu during the period of rapid urbanization from the perspective of land function. *Journal of Resources and Ecology*, 14(2): 410‒422.

Huang Z, Tang L, Qiao P, et al. 2024. Socioecological justice in urban street greenery based on green view index—A case study within the Fuzhou Third Ring Road. *Urban Forestry & Urban Greening*, 95: 128313. DOI: 10.1016/j.ufug.2024.128313.

Jiang N, Li X, Peng Z, et al. 2023. Assessing Distributional and Perceived Equity of Urban Green Spaces in Qingdao’s Historic Urban Area. *Buildings*, 13(11): 2822. DOI: 10.3390/buildings13112822.

Kang Y, Kim J, Park J, et al. 2023. Assessment of perceived and physical walkability using street view images and deep learning technology. *ISPRS International Journal of Geo-Information*, 12(5): 186. DOI: 10. 3390/ijgi12050186.

Karimi K. 2023. The configurational structures of social spaces: Space Syntax and urban morphology in the context of analytical, evidence-based design. *Land*, 12(11): 2084. DOI: 10.3390/land12112084.

Kolhar S, Jagtap J. 2021. Convolutional neural network based encoder-decoder architectures for semantic segmentation of plants. *Ecological Informatics*, 64: 101373. DOI: 10.1016/j.ecoinf.2021.101373.

Long Y, Zhou Y. 2016, Quantitative evaluation on street vibrancy and its impact factors: A case study of Chengdu. *New Architecture*, (1): 52–57. (in Chinese)

Liu K, Yin L, Lu F, et al. 2020. Visualizing and exploring POI configurations of urban regions on POI-type semantic space. *Cities*, 99: 102610. DOI: 10.1016/j.cities.2020.102610.

Lu Y. 2018. The association of urban greenness and walking behavior: Using google street view and deep learning techniques to estimate residents’ exposure to urban greenness. *International Journal of Environmental Research and Public Health*, 15(8): 1576. DOI: 10.3390/ ijerph 15081576.

Lyu Y, Forsyth A. 2021. Attitudes, perceptions, and walking behavior in a Chinese city. *Journal of Transport & Health*, 21: 101047. DOI: 10. 1016/j.jth.2021.101047.

MacFaden S W, O’Neil-Dunne J P M, Royar A R, et al. 2012. High-resolution tree canopy mapping for New York City using LIDAR and object-based image analysis. *Journal of Applied Remote Sensing*, 6(1): 063567. DOI: 10.1117/1.Jrs.6.063567.

Rollero C, De Piccoli N. 2010. Place attachment, identification and environment perception: An empirical study. *Journal of Environmental Psychology*, 30(2): 198–205.

Rui J. 2023. Measuring streetscape perceptions from driveways and sidewalks to inform pedestrian-oriented street renewal in Düsseldorf. *Cities*, 141: 104472. DOI: 10.1016/j.cities.2023.104472.

Soga M, Evans M J, Tsuchiya K, et al. 2021. A room with a green view: The importance of nearby nature for mental health during the COVID-19 pandemic. *Ecological Applications*, 31(2): e2248. DOI: 10.1002/ eap. 2248.

Sun Y, Lu W, Sun P. 2021. Optimization of walk score based on street greening—A case study of Zhongshan Road in Qingdao. *International Journal of Environmental Research and Public Health*, 18(3): 1277. DOI: 10.3390/ijerph18031277.

Tannous H O, Major M D, Furlan R. 2021. Accessibility of green spaces in a metropolitan network using space syntax to objectively evaluate the spatial locations of parks and promenades in Doha, State of Qatar. *Urban Forestry & Urban Greening*, 58: 126892. DOI: 10.1016/j. ufug. 2020.126892.

Theodorou A, Panno A, Carrus G, et al. 2021. Stay home, stay safe, stay green: The role of gardening activities on mental health during the Covid-19 home confinement. *Urban For Urban Green*, 61: 127091. DOI: 10.1016/j.ufug.2021.127091.

Wang Q, Adiku S, Tenhunen J, et al. 2005. On the relationship of NDVI with leaf area index in a deciduous forest site. *Remote Sensing of Environment*, 94(2): 244–255.

Wu X, Jackson D J, Chen H C. 2005. A fast fractal image encoding method based on intelligent search of standard deviation. *Computers & Electrical Engineering*, 31(6): 402–421.

Xiao C, Shi Q, Gu C J. 2021. Assessing the spatial distribution pattern of street greenery and its relationship with socioeconomic status and the built environment in Shanghai, China. *Land*, 10(8): 871. DOI: 10. 3390/land10080871.

Xiao L, Wang W, Ren Z, et al. 2021. Two-city street-view greenery variations and association with forest attributes and landscape metrics in NE China. *Landscape Ecology*, 36(4), 1261–1280.

Yafei Y, Dongfeng Y, Dan X. 2023. The associations of green spaces with older adults’ mental health in perspective of spatiality, sociality and historicality. *Journal of Resources and Ecology*, 14(2): 299‒308.

Ye Y, Richards D, Lu Y, et al. 2019. Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices. *Landscape and Urban Planning*, 191: 103434. DOI: 10. 1016/j. landurbplan.2018.08.028.

Yin L. 2017. Street level urban design qualities for walkability: Combining 2D and 3D GIS measures. *Computers, Environment and Urban Systems*, 64: 288‒296.

Yunitsyna A, Shtepani E. 2023. Investigating the socio-spatial relations of the built environment using the Space Syntax analysis—A case study of Tirana City. *Cities*, 133: 104147. DOI: 10.1016/j.cities.2022.104147.

Zhang D, Guo H, Wu Y, et al. 2023. All-factor average method of reserve parameters with crude oil volume and mass constraints. *Processes*, 11(9): 2558. DOI: 10.3390/pr11092558.

Zhang Y Y, Xu H. 2024. The rationality of the spatial layout of Beijing Sports Parks and the evaluation of tourism experience quality. *Journal of Resources and Ecology*, 15(2): 496–509.

Zhou H, Wang J, Widener M, et al. 2024. Examining the relationship between active transport and exposure to streetscape diversity during travel: A study using GPS data and street view imagery. *Computers, Environment and Urban Systems*, 110: 102105. DOI: 10.1016/j.compenvurbsys.2024.102105.

结合可达性与绿视率为人本尺度的街道绿化建设提供有价值的信息——以成都市三环内区域为例

黄中山[1]，罗施贤[2*]，蔡亦青[3]，陆峥妍[3]

1. 韩国国民大学技术设计研究生院，首尔 02707，韩国；
2. 西南交通大学建筑学院，成都 611756；
3. 合肥工业大学建筑与艺术学院，合肥 230009；

摘 要：街道绿化一直是城市设计相关领域讨论的热点话题。在过去，大多数研究主要是通过卫星遥感影像计算归一化差异植被指数（NDVI）的方式来评估城市绿化水平，对人本尺度视角的街道绿化关注不足。因此，为了能够更全面地测量街道的绿化水平，支撑步行友好的街道绿化建设，本研究结合了空间句法、机器学习技术、街景图像及遥感影像数据等，综合分析了 GVI、NDVI 两个指标，对两者的差异性进行了探讨。此外，通过将可达性与 GVI 进行耦合分析，揭示了在街道绿化建设中应该优先干预的区域。结果表明：（1）成都市三环内西部与南部区域的街道拥有更高的 GVI。(2)GVI 与 NDVI 总体分布存在着明显的差异，特别是在中心及东部区域。（3）“通勤与步行可达性高—GVI 低”的街道在顺城大街以东的区域相重合。最后，本研究提供的方法能够为成都和其他城市人本尺度的街道绿化建设提供参考。

关键词：深度学习；空间句法；可达性；绿视率（GVI）；归一化差异植被指数（NDVI）