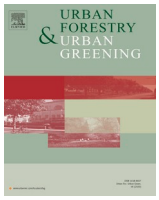
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Measuring pedestrian-level street greenery visibility through space syntax and crowdsourced imagery: A case study in London, UK

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ABSTRACT

Linear green spaces, composed of street trees, shrubs, and grass, provide diverse opportunities for human-nature interaction. However, current research tends to visualize street greenery from a single perspective, such as images or planar analysis and neglects pedestrian-scale street tree visual analytics. Space syntax relies on precise urban context data input, and street view image analysis does not cover sidewalk greenery visibility. This study integrates green visibility analysis based on space syntax's Visibility Graph Analysis (VGA) with the Pedestrian Green View Index (PGVI) calculated from street imagery to propose a comprehensive evaluation model for pedestrian-scale green visibility. To validate the accuracy of the methods, we established a participation scoring system involving 183 volunteers to collect their green perceptions of nine types of streets in the City of London, UK. The study reveals a complex relationship between VGA and PGVI, with VGA providing a robust, geometric-based visibility measure and PGVI offering a qualitative, human-centric perspective on urban greenery. Our findings indicate a significant correlation between PGVI and human evaluations, affirming PGVI's potential to reflect pedestrian experiences, while highlighting the limitations of VGA in capturing the nuanced, multi-dimensional aspects of human perception. This underscores the necessity of integrating human feedback in urban planning tools to ensure a comprehensive understanding of green spaces. Future research should enhance methodological rigor by incorporating temporal and seasonal dynamics, expanding datasets, and exploring the interplay between green visibility and other environmental factors.

1. Introduction

Urban green infrastructure, such as parks, street trees, greenways, forests, and private gardens (Ramyar et al., 2020), promotes environmental equity (Heckert & Rosan, 2016), human health and wellbeing (Navarrete-Hernandez & Laffan, 2019; Yu et al., 2024), and environmental quality and climate resilience (Gaffin et al., 2012). Green infrastructure systems can also help mitigate heat islands, create wind alleys, and promote sustainable urbanism (Chen et al., 2022; Farrell et al., 2022; Zhou et al., 2025). Street trees, shrubs, and plants, in particular, play an essential role in increasing the human-scale street greenery (Tang et al., 2020), creating multi-functional spaces for human-nature interaction like walking and sitting in the shade, aerobic jogging, and outdoor playing. The level of street greenery visibility and visual perception significantly influence how people behave, appreciate, and experience the environment (Mahmoud & Omar, 2015).

Various visibility methods, including agent-based visibility simulation in space syntax (Penn & Turner, 2003), spatial design network analysis (sDNA) (Ye et al., 2019), green view index (GVI) (Li et al., 2015a), virtual reality (VR) (Luo et al., 2022) were used in landscape and urban visual analytics. Space syntax is a method used to study the relationship between human societies and space by regarding the urban area (buildings, landscapes, and the built environment) as a matrix of connected spaces (Hillier, 1996). Space syntax can be used to calculate several positions' visibility, known as Visibility Graph Analysis (VGA) (Benedikt, 1979). VGA, as a space syntax method, can analyze the structural visibility of street networks from a top-down perspective. By integrating VGA with the pedestrian-scale greenery visibility measured by PGVI, our comprehensive model captures both the spatial configuration and the human-scale experience of street greenery. This

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dual-perspective approach addresses the limitations of relying solely on either space syntax or SVI methods. Street View Imagery (SVI) has been applied in diverse landscape and urban analytics, including greenery, walkability, and mobility (Biljecki & Ito, 2021). Yang et al. (2009)'s study first developed the green view index by evaluating the visibility of pedestrians' trees in color pictures. Afterward, the Google Street View images were widely used to calculate the green visibility index in the 'Treepedia' project by MIT (Li et al., 2015a; Li & Ratti, 2018; Seiferling et al., 2017). The image segmentation method is adopted to analyze the view imageries and calculate the color percentage of the street greenery, which can be applied to most streets that have view imageries. Various studies have used SVI to calculate the GVI and analyze the view imageries by applying the image segmentation method to most streets that have view imageries. However, most SVI is taken by cars, so the imagery is quite different from what pedestrians see and experience, especially in wide roads or those with on-street parking or street furniture that influences pedestrian view. In addition, the result can be affected by season, weather, and camera performance. Advancements in crowd-sourced services offering pedestrians' view images have improved the accuracy of SVI by providing imagery from pavements, cycle tracks, and walkways imagery.

Existing studies have increasingly recognized the value of in-person field observations as a ground-truthing mechanism for validating computational green visibility metrics. While remote sensing and image-based methods offer scalability, field assessments provide granular insights into pedestrians' real-time visual experiences, including obstructions, seasonal foliage changes, and human-nature interactions that static imagery may overlook (Biljecki & Ito, 2021; Da et al., 2024). For instance, Long and Ye (2019) employed observational audits to correlate greenery visibility with pedestrian dwelling activities in dense urban areas, revealing discrepancies between satellite-derived green indices and human perceptual outcomes. Similarly, Yang et al. (2019) combined street-level surveys with GPS tracking to demonstrate that human-scale greenery perception directly influences walkability preferences. However, field-based studies remain limited due to their labor-intensive nature, spatial coverage constraints, and subjective variability among assessors (Wang et al., 2022b). This underscores the need for hybrid methodologies that triangulate computational models (e.g., VGA, GVI) with systematic field observations to enhance methodological rigor and ecological validity.

Despite advancements in green visibility quantification, existing methods exhibit critical limitations that constrain their holistic application in urban greenery assessment. Space syntax-derived Visibility Graph Analysis (VGA), while effective in analyzing top-down spatial configurations (Benedikt, 1979; Hillier, 1996), often overlooks the granularity of human-scale visual experiences, particularly the dynamic interactions between pedestrians and street-level greenery (Wang et al., 2022a). Conversely, Street View Imagery (SVI)-based metrics like the Green View Index (GVI) capture pedestrian perspectives but face inherent biases due to vehicular imagery collection, seasonal variability, and inconsistent image resolution (Biljecki & Ito, 2021; Li et al., 2015a). These limitations are exacerbated in heterogeneous urban environments where obstructions (e.g., street furniture, parking) and roadway geometries distort pedestrian visibility (Gaw et al., 2022).

Furthermore, the lack of rigorous validation between computational models (e.g., VGA's structural visibility parameters) and ground-truth human perceptions raises concerns about methodological reliability (Luo et al., 2022; Ye et al., 2019). A dual-perspective framework integrating VGA's spatial-configurational analysis with Pedestrian Green Visibility Index (PGVI) metrics addresses these gaps by reconciling macro-scale urban structural patterns with micro-scale human sensory engagement. This synthesis not only mitigates the oversimplification of single-method approaches but also enhances precision in evaluating how greenery visibility influences behavioral responses and environmental equity—a critical step toward designing inclusive, human-centric urban green infrastructure (Heckert & Rosan, 2016; Yu et al., 2024). The current research method provides one perspective (human scale or top view) scale for visibility research. Limited research focuses on green visibility from a pedestrian perspective. Visual analysis is a comprehensive process to investigate the human-environment interaction, which needs more promised and accurate solutions. In addition, although both of the methods are proven to measure the green visibility, the accuracy of them have not yet been rigorously tested. It is unclear what parameters in space syntax (such as modeling methods and data input) and SVI characteristics (such as the image locations, quality, and quantity) can affect the level of accuracy. Therefore, this study validates their accuracy using in-person observations by multiple assessors.

This study introduces a novel integration of Pedestrian Green View Index (PGVI) with VGA to create a comprehensive model for evaluating green visibility from the pedestrian perspective, addressing the gaps in previous methodologies. This innovative approach provides a dual-perspective analysis, combining VGA's structural insights with PGVI's pedestrian-scale greenery measurements. Therefore, this study employs in-person assessments to validate the accuracy of each approach. The three objectives of this paper are:

1) How can space syntax and SVI methods measure the visibility of linear green infrastructure in urban areas according to the different street greenery types?
2) Between space syntax and SVI measurements, which one is closer to perceived pedestrian perception?
3) What parameters should be used in a comprehensive model of pedestrian greenery visibility?

2. Methodology

2.1. Study area

Our research was conducted in the city of London, UK. The City of London, a borough with a rich history, stands as not only the nucleus of global finance and commerce (Clark & WoÄjcik, 2001) but also a bastion of the United Kingdom's profound cultural heritage and diverse social fabric (Bagnall et al., 2018). Renowned worldwide for its modern skyline and commercial vibrancy, this area confronts unique challenges in environmental sustainability and urban greenery (Kolokotroni et al., 2012).

2.2. Research framework

Fig. 1 shows the working flow of this paper. Firstly, we applied the Google Street View technologies to select the initial street green visibility index measurement and define 9 street types. Secondly, we collect the pedestrian view imageries from Mapillary and manual acquisition and then apply the image segmentation model to calculate the Pedestrian Green View Index (PGVI). Thirdly we establish the street trees and 3D models according to the height, spread, and DBH attribute using the rhino-grasshopper platform. And then we conduct the visibility graph analysis from space syntax to calculate the VGA result. Fourthly, we created a comprehensive questionnaire and invited 183 volunteers to collect their qualitative ideas on the seven streetscape indicators for the 9 different types of roads and pedestrian perspective green visibility. Last, we use the correlation analysis and machine learning model to explore the reliability of the street view and space syntax compared with the questionnaire's result and explain what factors can better explain the pedestrian view green visibility.

2.3. Quantify the street greenery and definition of the pedestrian greenness types

2.3.1. SVI for quantifying the street green visibility

In the first phase of data acquisition, a systematic street view imagery

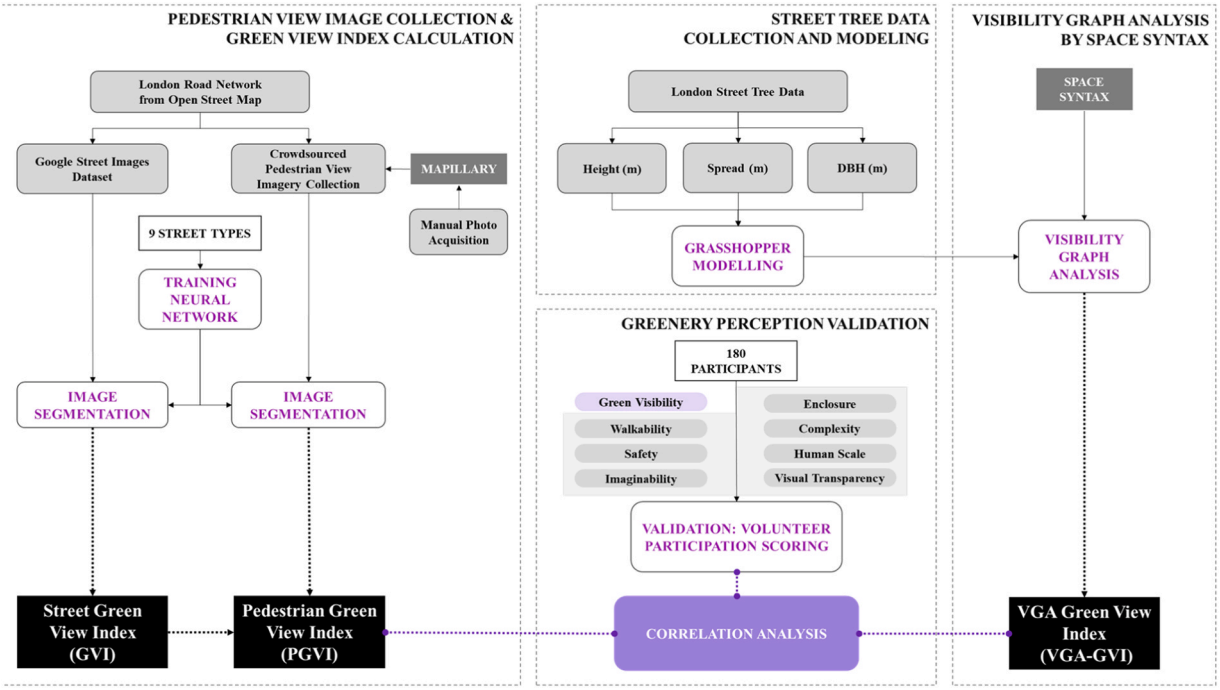


Fig. 1. Research Framework.

sampling framework was implemented across the City of London. Road network vectors were extracted from OpenStreetMap (OSM), an open-source geospatial database renowned for its global coverage and community-verified accuracy. To ensure spatially representative coverage, we strategically placed 2758 sample points at 50-meter intervals along all accessible road segments, generating a uniformly distributed grid of observation nodes. At each sampling location, 360° panoramic coverage was achieved by acquiring four directional views (front, back, left, right), yielding 11,032 high-resolution images in total. Google Street View images were subsequently extracted at each point using ArcGIS Pro 3.2 to generate a consistent dataset of urban scenes. Each available GSV can be requested and downloaded using GSV Image API (Li et al., 2015b). By setting up the angle parameters, only the imageries along the streets will be collected. In the second stage (Fig. 2), the model was trained on a publicly available dataset ADE20K that includes annotated classes for vegetation such as trees, shrubs, and grass (Zhou et al., 2019). All the model training process was employed in Python 3.8 for data cleaning and image segmentation. This model was specifically designed to extract greenery features from the street view data, achieving pixel accuracy exceeding 93.4 % for semantic segmentation of urban object classes, as demonstrated in prior studies (Zhou et al., 2019; Gaw et al., 2022). Finally, a supplementary code was implemented to extract green color features, enabling an automated calculation of green visibility for each sampled road segment.

$$GVI_i = \frac{1}{n}\sum_{n=1}^{n} Tree_n + \frac{1}{n}\sum_{k=1}^{n} Grass_n\{i \in (1, 2, \cdots, n\}$$

2.3.2. *Definition of the nine types of linear street greenery*

Table 1 illustrates the comparison of GVI and the current greenery situation for 9 example streets. The nine types of street greenery were selected to represent the main forms of greenery found along the streets in central London. This classification system was developed based on several considerations. First, the nine types aim to encompass the primary forms of street greenery observed in London's urban context, providing a comprehensive framework for analysis. Second, the classification takes into account various dimensions of greenery, such as scale, morphology, and vegetation type, enabling a systematic comparison of the characteristics of different greenery types (Rupprecht & Byrne, 2014). Finally, the selection of these types was informed by common street greenery classification methods used in previous studies (Lu et al., 2023). These methods were then optimized and adapted to better suit the specific context of London, ensuring the relevance and applicability of the classification system to the research object. By addressing these

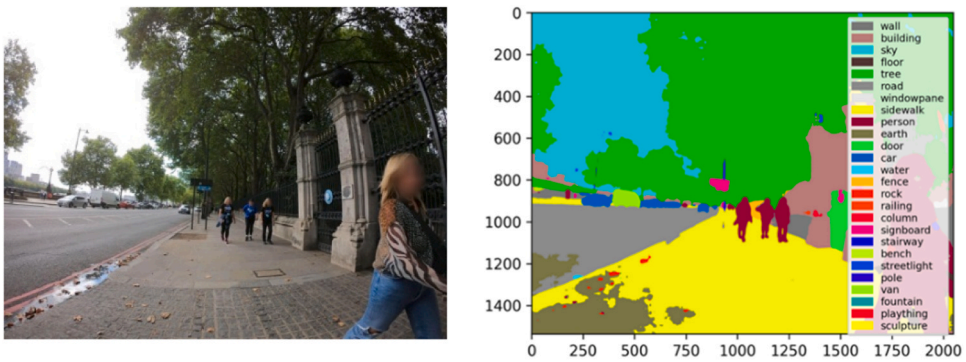
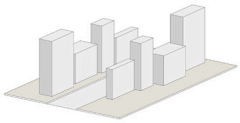
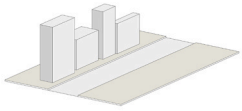
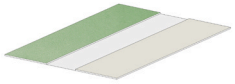
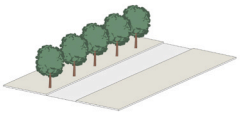
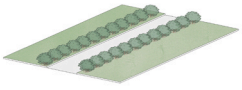
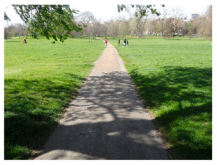
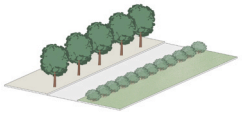
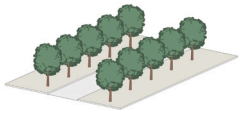


Fig. 2. The examples to show the result of image segmentation using ADE20K model.

Table 1
Classification of the nine pedestrian view green visibility types.

Type	Illustration	Description	Pedestrian-perspective streets
T1		No greenery, Both sides with building	
T2		No greenery, One side road, One side building	
T3		One line grass / shrub	
T4		One line tree	
T5		Two-line grass / shrub	
T6		One line grass / shrub + One-line tree	
T7		Two-line tree	
T8		One line grass / shrub and tree + One-line tree	
T9		Two-line grass/shrub + Tree	

key aspects, the nine types of street greenery provide a robust and tailored framework for evaluating the green infrastructure within London's urban streetscapes. These types provide a structured way to evaluate the greenery levels present in different street environments.

2.3.3. Manual photo collection for PGVI

However, GSV can only reflect the vehicle view rather than the pedestrian view. Moving to the PGVI analytics, we employed Mapillary, a platform that aggregates crowd-sourced, pedestrian-level street imagery, to gather images of the selected roads. These images were then compared to on-site photographs of nine streets. The images, as listed in Table 1, were utilized to measure the PGVI. For this measurement, we utilized the same dataset and deep learning model previously described in section 2.2.1 for calculating the GVI.

2.4. Space syntax visibility measurement

To achieve the research objective of examining the influence of sidewalk trees on visibility, we adopted a three-step methodology through 3D modeling and space syntax.

2.4.1. Step 1: Modelling of trees

To accurately model the trees on the sidewalks, we utilized the Rhino 7.0-Grasshopper platform, a flexible design tool that enabled us to generate detailed three-dimensional models of the trees. During the modeling process, we employed actual tree data downloaded from the London government data website, including Diameter at Breast Height (DBH), canopy width, trunk diameter, crown spread, and height. The tree data was sourced from the London Data Store, with detailed datasets prepared by the GLA Environment Team, and the data was collected in July 2021. This approach allowed us not only to reproduce the precise dimensions of each tree but also to pinpoint their exact locations on the sidewalks (Fig. 4).

2.4.2. Step 2: Selection and extraction of the cross-section

We strategically selected a representative street in the city center for an in-depth visibility test analysis. In this analysis, we specifically extracted a cross-section at a height of 1.51 m from the ground, a measurement that corresponds to the average eye height of typical participants (Ghasemi et al., 2023). This method not only embodies a true-to-life representation of street visibility from a human perspective but also ensures that the analysis results accurately reflect the actual visual experience of pedestrians on the street.

2.4.3. Step 3: Visibility Graph Analysis (VGA)

To conduct a thorough analysis of the cross-sections, we employed DepthmapX software, a tool based on space syntax theory designed specifically for analyzing visual and spatial networks (Gil et al., 2015). We utilized the Visibility Graph Analysis feature, which allowed us to calculate and comprehend how street trees and buildings influence the visual field available to individuals at a specific cross-section. The Visibility Graph Analysis reveals the precise visual impediments caused by street trees on the cross-section, offering a quantified metric of visibility. With these data, we can accurately assess the real impact of street trees on the visual accessibility of the selected street (Fig. 5).

Indeed, while the correlation between VGA and the perceived extent

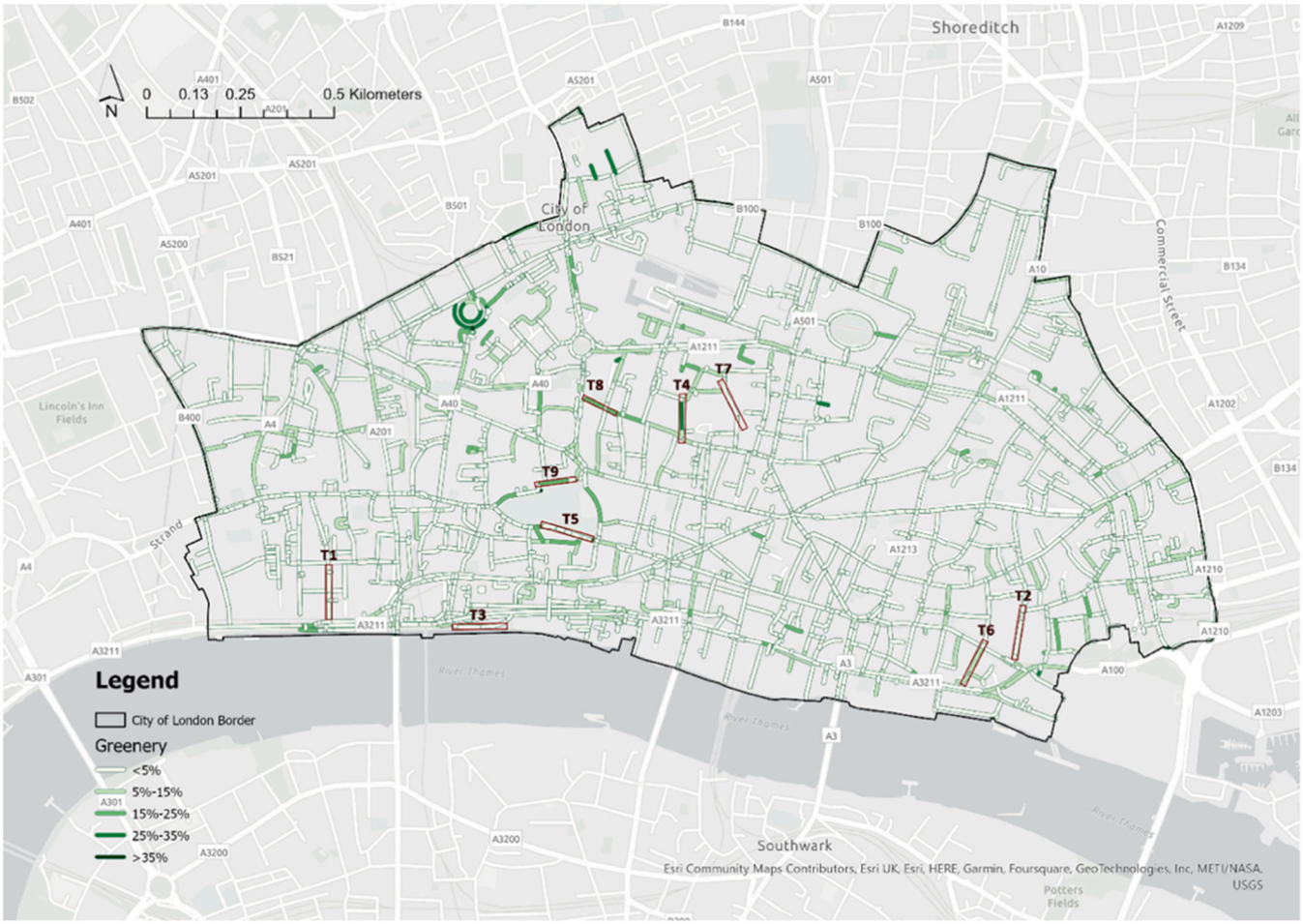


Fig. 3. Locations of nine road segments by street greenery types.

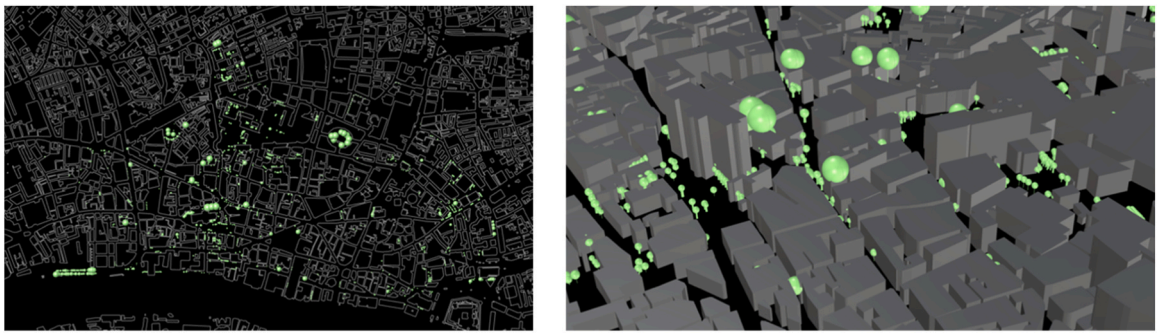


Fig. 4. Tree Modelling.

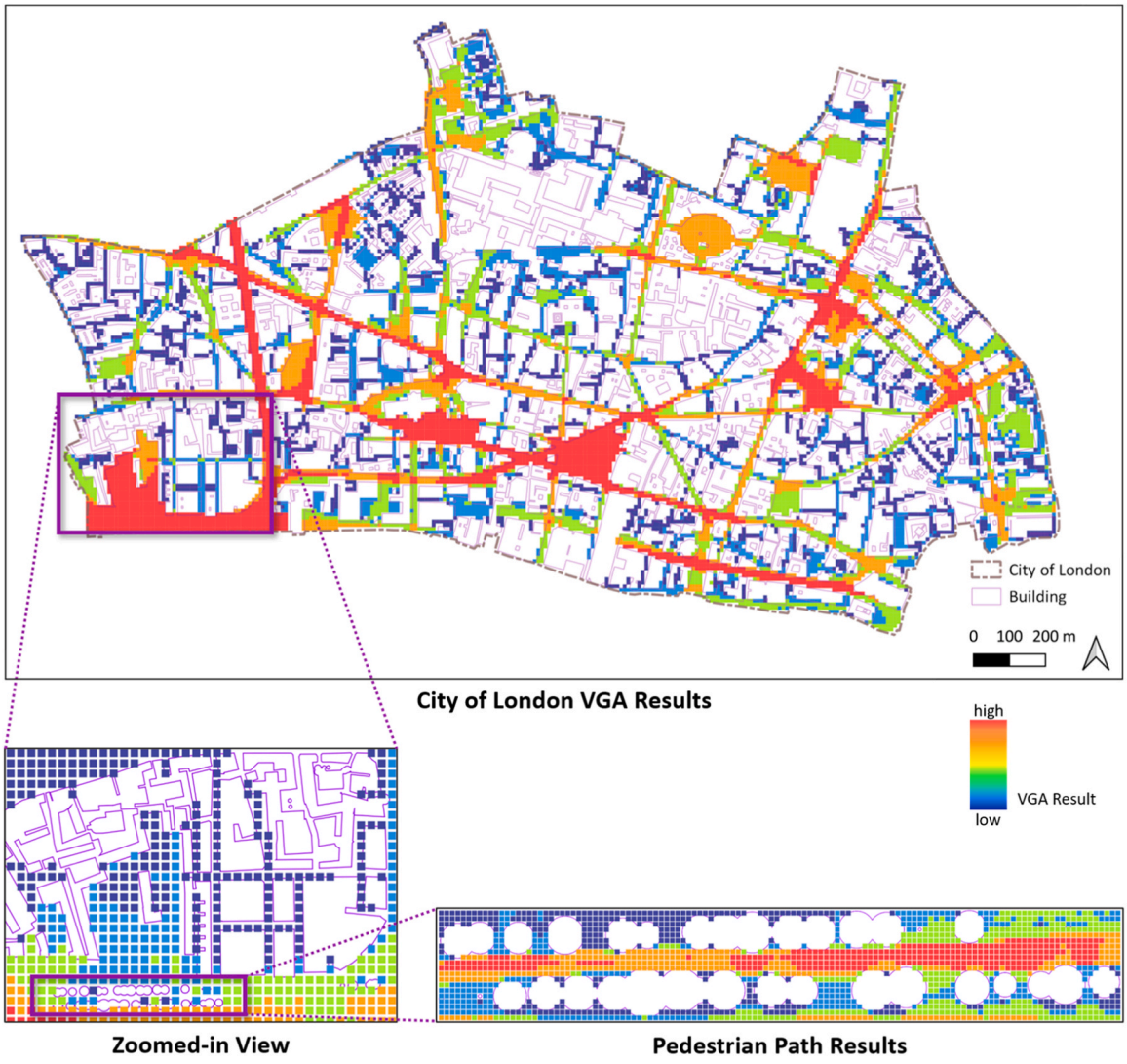


Fig. 5. VGA Analysis.

of greenery may not be particularly strong, the primary reason for incorporating this analytical dimension is that VGA allows for the precise calculation of the maximum visible range from a normal human perspective when obstacles are present. By overlaying this analysis with green view index data (i.e., the proportion of green vegetation within the field of view), we can accurately measure the actual area of greenery visible to individuals, taking into account the influence of obstacles. This methodological approach not only offers a new perspective on assessing the impact of street trees on visual accessibility but also provides a scientific basis for considering the layout of green spaces in urban planning and design.

Given that VGA computation results are planar data, the calculation of the VGA Green View Index (VGA-GVI) considered all green data at the planar level. The green data at this level consists of two parts: urban green spaces and the area covered by tree canopies, where urban green spaces include categories such as allotments, farms, forests, grasslands,

parks, and scrubs. After remodeling the trees in the city, cross-sections are generated from the perspective of human height, capturing data at the eye level. This data is then overlapped with data on urban green spaces. Subsequently, city roads are segmented by selecting center points within a planar grid according to VGA calculation principles, and calculations are conducted in DepthmapX to determine the visible range from a human perspective at these points. Then, we trim and cut the visible range calculated by DepthmapX with the planar level green data to derive the green view index area within the visible range of each point (Fig. 6). Finally, by utilizing GIS to perform spatial linking, we calculate the average for each road, resulting in the VGA-GVI data.

$$VGA - GVI = \sum_{i=1}^{n} A_i$$

where A_i represents the planar area of the i-th type of green space (e.g., allotments, farms, forests, grasslands, parks, and scrubs) visible from the given point; n is the total number of different types of green spaces considered in the calculation.

2.5. Volunteer participation scoring

In this section, we employed a stratified sampling framework to ensure demographic representativeness and spatial diversity in both participant recruitment and street segment selection, thereby mitigating potential sampling biases. Participants (n = 183) were recruited across Greater London through a hybrid purposive-snowball sampling approach, with stratification criteria aligned to the city's adult population demographics: age distribution (18–25: 32 %; 26–40: 41 %; 41–60: 20 %; >60: 7 %), gender balance (52 % female, 46 % male, 2 % non-binary), and residential diversity (68 % urban core vs. 32 % suburban residents across 12 boroughs). Professional backgrounds were deliberately varied, with 45 % from non-design occupations, 35 % urban planning/design professionals, and 20 % students, ensuring multi-perspective evaluations. Exclusion criteria included uncorrected visual impairments and residency in London for less than one year, while post-hoc power analysis confirmed adequate statistical power (88.2 %, α = 0.05) to detect medium effect sizes.

Street segments were systematically selected to represent nine typologies derived from spatial clustering of the City of London's street network attributes, including green infrastructure density, road width (6–30 m), pedestrian flow, and urban functional mix. To enhance generalizability, the selected segments were geographically distributed across six wards, with green coverage deviating by no more than 10 % from the borough-wide average. Each segment was documented using standardized 360° photographic sequences, capturing front, back, left, and right perspectives.

In our questionnaire design, seven indicators were selected for investigation: greenness, walkability, safety, imageability, enclosure, complexity, human scale, and transparency (Buttazzoni & Minaker, 2023; Ewing & Handy, 2009; Qiu et al., 2023). The psychological and social benefits of green spaces have been extensively documented in the environmental psychology literature pertaining to urban planning and design. Greenness plays a pivotal role in providing psychological restoration, reducing stress, and promoting physical and mental health (Geary et al., 2023). Furthermore, Walkability is considered a crucial factor in enhancing resident activity and health; well-designed walkable spaces can foster social interaction and reduce the prevalence of diseases (Baobeid et al., 2021). The perception of Safety is directly linked to the frequency of use and resident satisfaction (Turkseven Dogrusoy & Zengel, 2017). As demonstrated by Fisher & Nasar (1992), an environment perceived as safe can significantly elevate the willingness of residents to utilize the space and enhance their quality of life. Imageability is closely associated with the concept of urban imagery; environments with distinct identifiers and conspicuous landmarks provide a stronger sense of direction and memory cues (McCunn & Gifford, 2017). Enclosure affects individual perceptions of spatial boundaries and privacy, where an appropriate level of enclosure can increase feelings of security and comfort (Shi et al., 2014). Complexity relates to the level of environmental stimuli (Cassarino & Setti, 2016); either excessive or insufficient complexity may adversely affect psychological well-being. Human Scale and Transparency are directly related to the individual's experiential feeling within the environment, and human-centric design is critical in supporting user behavior and experience (Buttazzoni & Minaker, 2023). After providing demographic data, participants evaluated nine street segments through a structured protocol: four directional views per location were presented sequentially with a 30-second minimum observation period to prevent rapid-response bias, followed by 10-point perceptual scoring (1 = "strongly disagree" to 10 = "strongly agree") and randomized paired comparisons to elicit preferential choices.

Finally, participants were asked to compare two images side-by-side and select the one they preferred, further enriching our data set. This comprehensive process aims to understand the public's perception of urban street design elements and contributes valuable insights for urban planning and design.

2.6. Data statistics: Pearson correlation analysis

The statistical relationships between computational green visibility indices—Pedestrian Green Visibility Index (PGVI), streetscape Green View Index (GVI), and Visibility Graph Analysis-derived GVI (VGA-GVI)—and human-perceived green visibility ratings were rigorously examined using Pearson correlation analysis. This method was selected for its ability to quantify both the strength and direction of linear associations between continuous variables, providing a robust framework to evaluate the alignment between objective metrics and subjective human perceptions (Mukaka, 2012). Prior to analysis, all variables were



Fig. 6. VGA Green View Index (VGA-GVI) generation process.

standardized to a 0–1 scale via min-max normalization to mitigate potential biases arising from disparate measurement units. Pairwise Pearson's correlation coefficients (r) were then calculated to assess linear dependencies across variable pairs, with coefficient magnitudes interpreted as follows: $|r| \geq 0.5$ indicating strong associations, 0.3–0.5 moderate associations, and < 0.3 weak associations (Schober et al., 2018). Statistical significance was evaluated through two-tailed hypothesis testing at $\alpha = 0.05$, with p-values adjusted for multiple comparisons using the Bonferroni correction to minimize Type I errors. By focusing on correlation rather than causal inference, this approach effectively maps synergies and discrepancies between computational indices and ground-truthed perceptual data, offering critical insights into the validity of multi-method visibility assessments for human-centric urban greenery planning.

3. Result

3.1. Comparing results of PGVI and GVI

Based on the comparison of the PGVI and GVI results in Table 2 and Table 3, it can be seen that among the nine types of greening structures from T1 to T9, the results of green visibility from the pedestrian viewpoint and green visibility from the motorized vehicle viewpoint differ significantly, except for T5. However, the special one is the green structure of type T5 (grass/shrub on both sides), which has the highest similarity between the results of PGVI and GVI.

In addition, the green structure type T7 has a value of 0 for GVI and a non-zero value for PGVI; in fact, the green structure type T7 is flanked by tall trees, which means that the area of greenery that pedestrians can see is very much related to where they are standing.

Of the nine types, T1-T9, the highest PGVI values were found in types T6 (trees on one side, shrubs + grass on the other) and T9 (grass/shrubs + trees on both sides) and T8 (grass/shrubs and trees on one side, trees on the other side), indicating that pedestrians are able to see a larger area of green when both sides of the roadway have landscaping and there are shrubs or grasses on at least one side.

3.2. The result of VGA-GVI

After conducting a Visibility Graph Analysis on the overall urban architecture and tree modeling, as well as cross-sections derived from a human eye-level perspective, we compiled Visibility Graph Analysis data for each road. Due to the diversity and complexity of urban built environments and tree distributions, we reselected roads with similar built environments and tree distribution conditions within each road type and used the average of their Visibility Graph Analysis results as the visibility outcome data for that road type. Table 2 presents the Visibility Graph Analysis data results for each type of road.

The results of green visibility based on spatial syntax for plane viewpoints calculated according to our formula are shown in Table 2. We found by comparison that type T8 has the richest variety of vegetation and the highest visibility. The values show that the combination of trees and grasses tends to have higher visibility than the combination of a single type of vegetation.

Table 2
Comparison of the three methods (PGVI / VGA-GVI / Green Visibility).

Type	PGVI	GVI	VGA	VGA-GVI	Green Visibility
T1	0.0004	0.003	8179.33	315.50	6.46
T2	0.0240	0.000	6389.57	2221.70	6.08
T3	0.1334	0.017	9189.60	1609.65	6.48
T4	0.2223	0.319	6706.12	1402.20	6.70
T5	0.2344	0.216	31811.62	9722.30	7.08
T6	0.3724	0.072	7987.11	3545.91	6.79
T7	0.0748	0.000	3817.14	530.85	6.83
T8	0.3190	0.197	10199.65	4118.86	6.83
T9	0.5014	0.193	15477.29	8407.44	6.79

As seen in Table 2, types T5 (grass/shrubs on both sides) and T9 (grass/shrubs + trees on both sides) have the highest visibility values, which have in common that both types have lawns or shrubs on both sides. Types T1 (no greenery, buildings on both sides) and T7 (trees on both sides) have the smallest green visibility values based on VGA. From a data point of view, trees cannot contribute in the green visibility calculation, yet this is contrary to our real life experience. So this confirms to some extent the limitations of the planar perspective in this research area.

In addition to this, we found that T9 is characterized by mixed greenery with a high spatial syntax value (49034.049), suggesting that it may be located in highly connected urban areas. Interestingly, T5 demonstrates two rows of grasses or shrubs, also with high spatial syntax values, suggesting that these types of greenery may be common in urban areas with good transportation access.

3.3. The result of volunteer participation scoring

From the questionnaire results, T5, T6, and T7 have high green visibility values of 6.883 6.99, and 6.91, respectively, and these three types of roadway greenery share the common characteristic of having greenery on both sides of the road. The highest visibility value is for type T5, which has a green structure with extreme planar extensibility. The next type, T7, also has a high visibility value and its green structure is characterized by a strong three-dimensional space occupation.

By observing and comparing the values of the seven indicators corresponding to several greening types with higher green visibility, we found the commonality that higher green visibility tends to correspond to higher walkability, safety, and imaginability. T7, which is covered by two rows of trees, scored high in these variables, suggesting that dense tree cover may enhance perceptions of safety and walkability in addition to increasing green visibility. T3 and T7 introduced green and forested environments, respectively, and scored highest in imaginability, suggesting that the presence of green elements may enhance the imaginative appeal of urban spaces.

In addition to this, other indicators show some specific characteristics in different types of greening structures. For example, T4 and T5, characterized by trees and shrubs, scored the highest on the human scale, suggesting that such greening may make the urban environment more suitable for human presence. Enclosures with more greenery scored lower (T5 and T7), suggesting that green spaces may give a more open feel. Complexity did not show a clear trend with the presence of greenery, but T4, featuring a single row of trees, had the highest complexity score, which may be due to the trees adding visual complexity to the streetscape. Visual transparency is highest in types with diverse or dense greenery (T5 and T9), suggesting that different green elements can enhance the visual openness of a space.

3.4. Comparison and data statistics

In order to compare the degree of correlation between PGVI and VGA-based visibility values and the real perception of pedestrians in a more scientific and precise way, and in order to understand which indicators are most closely related to green visibility, this paper analyzes the statistical results of questionnaires on PGVI, GVI, VGA-based visibility, green visibility, and other variables (e.g., walkability, safety, imaginability, enclosure, complexity, human scale and visual transparency) correlations between them, revealing the complex interactions between urban design elements that affect the quality of urban space, the results of which are shown in Fig. 7.

The results indicate that PGVI, GVI, and VGA-GVI all demonstrate significant correlations with perceived green visibility, with PGVI showing a slightly higher coefficient. However, given the close values of the correlation coefficients (0.59, 0.56, and 0.57, respectively), it is important to interpret these findings cautiously. Each metric offers

Table 3
Mean value of seven streetscape indicators from the survey.

Type	Walkability	Safety	Imaginability	Enclosure	Complexity	Human Scale	Visual Transparency
T1	6.7389	6.6278	6.5778	6.6667	6.6389	6.5833	6.6667
T2	6.5833	6.3667	6.6389	6.5333	6.5278	6.6556	6.5333
T3	6.7056	6.9222	7.0278	6.5389	6.3944	6.6556	6.8333
T4	6.6556	6.6722	6.7944	6.5889	6.4111	6.9722	6.9778
T5	6.8833	6.9167	6.9444	6.2444	6.2944	6.7333	7.0111
T6	6.9889	6.7944	6.5333	6.6556	6.6000	6.8722	6.6889
T7	6.9056	6.8111	7.0667	6.2000	6.6556	7.0000	6.7833
T8	6.6389	6.6667	6.6333	6.5944	6.5222	6.5667	6.7111
T9	6.6111	6.7278	6.8056	6.2667	6.4833	6.8278	6.8056

unique insights into green visibility assessment, and their complementary use can provide a more comprehensive understanding of pedestrian-level experiences.

Although it is not possible to achieve complete consistency, the correlation values show that it is the PGVI from the sidewalk perspective that is closer to the real walking experience. Admittedly, PGVI is the only measurement that stands in the pedestrian perspective and is bound to be closer to the real human experience.

In addition to the above measurements from different perspectives, the indicators related to the pedestrian's walking experience also influence the magnitude of green visibility. As shown in Fig. 7, from the correlation analysis, the seven metrics with the highest correlation with pedestrian-perceived green visibility are safety, visual transparency, and walkability, with correlation values of 0.72, 0.69, and 0.53, respectively. The metrics with the least correlation with pedestrian-perceived green visibility are Complexity and Imaginability, with correlation values of only −0.27 and 0.31, respectively.

We further examine the correlation between the three visibility measures and streetscape indicators. PGVI moderately correlates with safety ($r = 0.31$) and visual transparency (0.29). GVI positively correlates with visual transparency (0.69) while negatively correlating with complexity (-0.60). VGA-GVI also positively correlates with visual transparency (0.41) and safety (0.31) while negatively correlating with complexity (-0.58) and enclosure (-0.52). Other indicators, including walkability, imageability, and human scale, show low level of associations with the three visibility measures.

4. Discussion and conclusions

4.1. Summary of the key findings

This study has addressed three primary research questions, offering a nuanced understanding of how green visibility can be quantified and optimized for pedestrian experiences through the combined use of space syntax and Street View Imagery.

4.1.1. Measurement of green visibility benefits

This study proposes measuring the visibility of street greenery through two different methods: SVI-derived PGVI and space syntax-based VGA-GVI. PGVI offers a pedestrian-centric perspective by utilizing street-level imagery, capturing the actual views experienced by individuals as they navigate the city. This method excels at representing the qualitative aspects of greenery perception, such as the visual impact of different vegetation types and arrangements (Zhang & Zeng, 2024). However, PGVI's reliance on available street-level imagery may limit its applicability in areas with sparse or outdated image coverage.

In contrast, VGA-GVI provides a more comprehensive, top-down understanding of green visibility by considering the spatial configuration of the urban environment. This approach can identify areas with high or low visibility based on factors like street network layout and building geometry, making it useful for citywide planning and identifying priority sites for greening interventions. However, VGA-GVI may not fully capture the nuances of human-scale perception and can be sensitive to the accuracy and detail of the input spatial data.

Practical considerations for using these methods include the availability and quality of input data (street-level imagery for PGVI, detailed spatial models for VGA-GVI) (Páez & Scott, 2005), computational requirements, and the need for technical expertise. Combining PGVI and VGA-GVI offers a promising way to leverage their complementary strengths – the former's ability to represent the pedestrian experience and the latter's spatial analytical power. An integrated approach could involve using VGA-GVI to identify areas with low overall visibility, then applying PGVI in those areas to diagnose specific issues and design targeted interventions.

By validating PGVI and VGA values against volunteer assessments, this study contributes a practical approach to aligning computational methods with human perception. Results indicate a significant correlation between PGVI and human ratings, suggesting that PGVI can serve as a reliable proxy for pedestrian experiences. This validation approach could be extended to integrate human feedback more systematically into urban planning tools, ensuring that these tools capture the multidimensional nature of urban greenery visibility and address the limitations identified in existing methods. While PGVI exhibited the highest correlation with perceived green visibility, the relatively small differences among the correlation values suggest that all three methods provide valuable perspectives. Future research could further validate these results through qualitative assessments or alternative quantitative approaches, such as direct pedestrian surveys or eye-tracking studies.

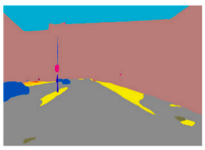
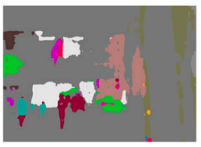
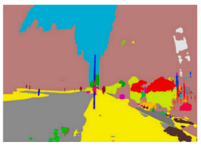
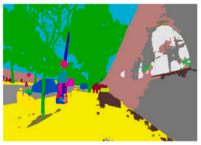
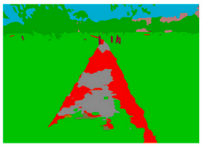
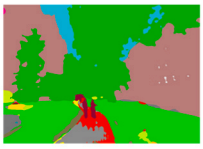
Findings suggest that the height and type of greenery influence perceived green visibility from a pedestrian viewpoint. For instance, relatively low vegetation, such as shrubs or grass along sidewalks, enhances pedestrian green visibility more effectively than tall trees, especially on streets with greenery on both sides. These findings have practical implications for urban planners and landscape designers by underscoring the importance of considering not only the aesthetic and ecological attributes of greenery but also the optimal plant height and arrangement to maximize pedestrian visibility.

4.1.2. Comparison of space syntax and SVI measurements

The study confirms that SVI-derived PGVI, which accounts for a pedestrian's actual viewpoint, aligns more closely with human perception than road-based GVI or VGA-based measurements. By capturing the street-level perspective, PGVI provides a more accurate representation of how individuals experience urban greenery in their daily lives. This finding underscores the importance of considering the pedestrian perspective in street greenery analysis, as it can yield insights that may be overlooked by top-down, spatial approaches alone.

However, the study also reveals that both PGVI and VGA-based methods have limitations in fully capturing the complexity of green visibility. Factors such as road width, orientation, and the presence of obstructions like buildings or street furniture can significantly impact the visibility of greenery, and these elements are not always adequately represented in either approach (Lu et al., 2023). For instance, wide streets may result in lower PGVI scores even if there is ample greenery, as the vegetation may be visually distant from the pedestrian. Similarly, VGA-based measurements may overestimate visibility in areas with

Table 4
Vehicle-level and pedestrian-level image segmentation results.

Type	Google Street View images	GVI segmentation result	Pedestrian perspective original images	PGVI segmentation result images
T1				
T2				
T3				
T4				
T5				
T6				
T7				
T8				
T9				

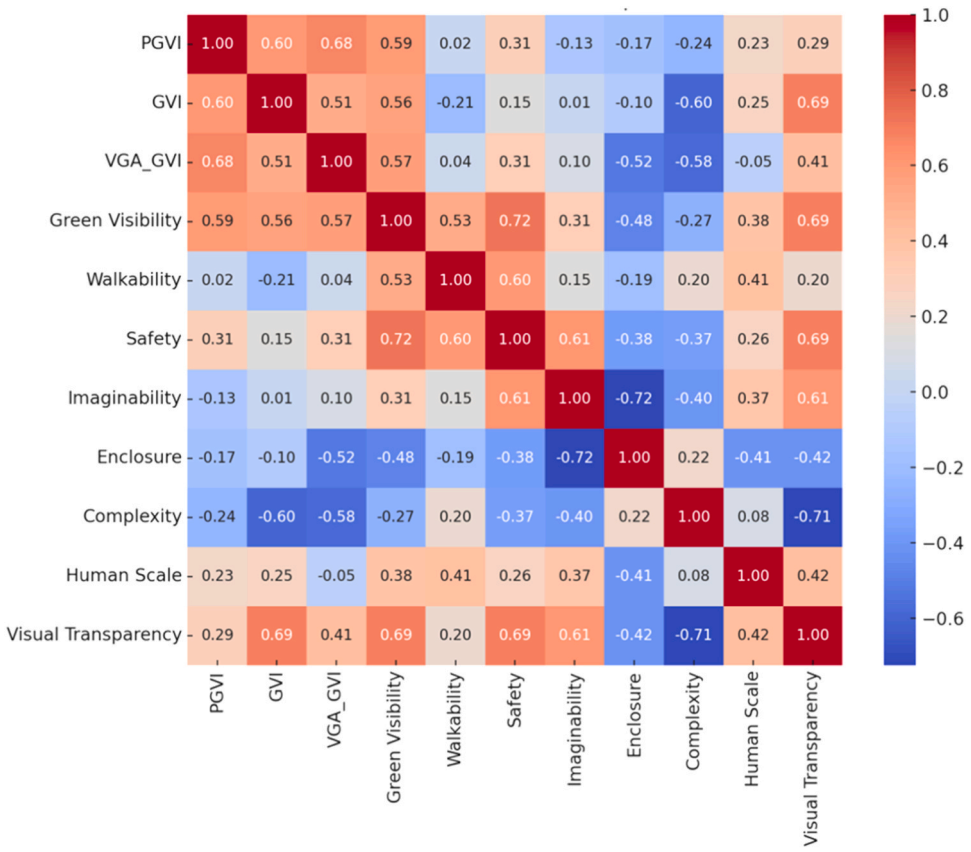


Fig. 7. Correlation Plot: Correlation between PGVI, VGA-GVI, and other factors.

open spatial configurations but limited actual vegetation.

4.1.3. *Parameters for a comprehensive green visibility model*

The study reveals that perceived green visibility is influenced by a complex interplay of factors beyond just the physical presence of vegetation. Statistical analysis indicates that seven key parameters (Ewing & Handy, 2009)—Safety, Visual Transparency, Walkability, Imaginability, Complexity, Human Scale, and Enclosure—significantly contribute to how individuals perceive and experience urban greenery. Safety and Visual Transparency emerge as the most critical factors, suggesting that pedestrians are more likely to notice and appreciate greenery in environments that feel secure and visually open. Walkability is also closely linked to green visibility, highlighting the importance of creating pedestrian-friendly spaces that encourage exploration and engagement with the natural surroundings.

Integrating these parameters into a comprehensive green visibility model offers several advantages. First, it allows for a more accurate understanding of how individuals perceive and interact with urban greenery. Second, this multi-dimensional approach can inform the design of urban spaces that optimize both green visibility and pedestrian comfort. Third, a comprehensive model can serve as a valuable tool for evaluating and comparing the performance of different green infrastructure proposals or existing spaces. To operationalize this approach, planners could develop a green visibility index that integrates PGVI and VGA-based measures with ratings for the seven key parameters identified in this study, providing a standardized metric for assessing the quality and impact of urban green spaces from a pedestrian perspective.

4.2. *Practical applications in urban planning and design*

The findings of this study have direct implications for urban planning and design practices. By understanding the factors that influence pedestrians' perception of green visibility, planners and designers can create more effective and engaging green spaces in cities (Endalew Terefe & Hou, 2024; Ugolini et al., 2022; Yan et al., 2023). The study suggests that incorporating a mix of vegetation types, such as low-lying shrubs and grass alongside trees, can enhance the visibility of greenery from the pedestrian perspective. Additionally, ensuring that greenery is present on both sides of the street can further improve the visual experience for pedestrians. While previous studies have suggested the intuitive benefits of diverse vegetation types, this study provides quantitative evidence to support strategic planting decisions. The combined use of PGVI and VGA-GVI enables a more granular assessment of how different vegetation compositions contribute to pedestrian experiences in varied urban contexts. Such data-driven insights can inform targeted interventions that optimize both aesthetic and functional aspects of urban green spaces.

The study also highlights the importance of considering the pedestrian perspective when planning and designing urban green spaces. Planners should prioritize the creation of safe, visually transparent, and walkable environments that encourage pedestrians to explore and engage with the natural surroundings. By focusing on these key factors, as well as incorporating elements that enhance imaginability, complexity, human scale, and enclosure, planners can create green spaces that are not only visually appealing but also welcoming for pedestrians.

Furthermore, the proposed comprehensive green visibility model, which integrates PGVI, VGA-based measures, and the seven key parameters identified in the study, can serve as a valuable tool for urban planners and designers. By using this model to assess and compare different green infrastructure proposals or existing spaces, planners can make more informed decisions and prioritize interventions that maximize the benefits for pedestrians. This approach can lead to the development of a standardized green visibility index, which can be used to

evaluate and monitor the performance of urban green spaces over time, ensuring that they continue to meet the needs and preferences of the local community.

4.3. Limitations and future research directions

While this study provides valuable insights into green visibility assessment, several limitations must be acknowledged. The findings may not be directly generalizable to cities with varying tree species, street layouts, or pedestrian behaviors. Additionally, reliance on Google Street View and the crowdsourced Mapillary platform introduces potential biases due to the frequency of image updates, seasonal variations, and image quality discrepancies. These factors could affect the comparability of PGVI scores and highlight the need for caution when applying these findings in contexts where SVI data may not fully represent the current urban environment.

4.3.1. Data availability and quality constraints

One of the key limitations of the study is the dependence on available street view imagery, which may not always reflect the current urban landscape accurately. Differences in image collection frequency across different regions introduce inconsistencies in data coverage, making it challenging to perform longitudinal analysis or cross-city comparisons. Future research should explore integrating real-time data collection methods, such as drone imagery (Choi et al., 2024) and crowdsourced mobile applications (Kong et al., 2019), to enhance the accuracy and timeliness of green visibility assessments.

Furthermore, while photographs provide an efficient means to assess perceptions across diverse street types, they may not fully capture the immersive experience of being in the actual streetscape (Kim & Lee, 2022; Ogawa et al., 2024). The static nature of images may not account for dynamic elements such as moving pedestrians, changes in lighting conditions, or seasonal variations. Future studies should consider combining SVI-based assessments with in-situ observations and sensor-based monitoring to better reflect real-world experiences (Alahacoon & Edirisinghe, 2022; Behifar et al., 2023; Van Leeuwen & Orr, 2006).

4.3.2. Methodological limitations in green visibility assessment

Both PGVI and VGA-GVI methods have inherent limitations. PGVI, while providing pedestrian-scale visibility assessments, is highly dependent on the availability of street-level imagery, which may not always be up-to-date or comprehensive in covering all pedestrian pathways. On the other hand, VGA-GVI offers a broader, top-down perspective but may not fully capture pedestrian-scale nuances such as obstacles, elevation changes, and human perception of greenery. Combining these approaches remains a promising direction, but challenges remain in terms of data integration and validation.

In addition to the insights already provided, we acknowledge the potential of VGA-GVI to identify visibility hotspots and gaps across urban environments. While this aspect was not fully explored in our study, its importance for practical urban planning, particularly in identifying priority sites for greening interventions, is recognized. The ability to incorporate factors such as street network layout and building geometry makes VGA-GVI a valuable tool for citywide green visibility assessments.

4.3.3. Challenges in implementing green visibility strategies in dense and historical Cities

Implementing green visibility optimization strategies in historical urban areas presents unique challenges that require careful consideration. Historical districts are often subject to strict preservation regulations, which can limit modifications to streetscapes and building facades (Vafaie et al., 2023). Additionally, the narrow street layouts and densely built environment characteristic of historical areas may pose physical constraints, making it challenging to incorporate greenery without compromising the cultural integrity of the space (Li et al., 2022; Zhang et al., 2022).

Heritage conservation policies often restrict physical alterations to historical structures, limiting the scope of green interventions such as tree planting, green facades, and vertical gardens (Aslanoğlu et al., 2025; Blavier et al., 2023). These constraints necessitate innovative, reversible, and non-invasive solutions that align with preservation guidelines while enhancing green visibility for pedestrians

Implementing green infrastructure in historical cities can be costly due to the need for specialized materials and maintenance practices that do not compromise the integrity of heritage buildings (Hunt et al., 2023; Vafaie et al., 2023). Long-term financial sustainability remains a key concern, and future research should explore cost-effective solutions, such as modular green installations and public-private partnerships (Koppenjan, 2015), to facilitate the implementation of greening initiatives in such areas. Future research should also focus on assessing the economic feasibility of these strategies through detailed cost-benefit analyses and exploring funding mechanisms that can support sustainable urban greening efforts in heritage districts.

4.4. Future research directions

Future studies should aim to refine the integration of VGA and PGVI by incorporating temporal dynamics and seasonal variations, allowing for a more comprehensive understanding of green visibility that captures changes over time. Expanding the dataset to include diverse urban contexts and greenery types will improve the model's generalizability.

Additionally, exploring interactions between green visibility and other urban environmental variables—such as air quality, noise pollution, and pedestrian traffic—could provide further insights into the role of greenery in enhancing urban living environments (Dzhambov et al., 2023; Dzhambov & Dimitrova, 2015; Lyu, 2024; Margaritis & Kang, 2016; Rey-Gozalo et al., 2023). A multidimensional approach that considers ecological, aesthetic, and social aspects of urban greenery could lead to more effective and inclusive urban greening policies.

To ensure that the proposed methods align with human perceptions and behaviors, future research should incorporate participatory approaches, engaging local communities in the assessment and design of green visibility interventions (Barendregt et al., 2024; Burrage, 2011). By integrating feedback from diverse stakeholders, urban planners can develop more context-sensitive and sustainable solutions for enhancing green visibility in cities worldwide.

Author Statement

During the preparation of this work, the author(s) used ChatGPT (GPT-4) for checking grammar and spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2025.128725.

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