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Enhancing visual attribute comprehension of urban heritage landscapes using combined GIS-based visual analysis methods: West Lake as a case study

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ABSTRACT

Urban heritage landscapes, with their layered cultural and aesthetic values, require precise visual analysis to support conservation and planning. However, existing visual analysis methods are often fragmented and fail to fully capture their complex visual-spatial characteristics. To address this gap, this paper proposes a combined visual analysis framework that integrates four GIS-based visual analysis methods—cumulative viewshed (CV), visual magnitude (VM), field of view (FOV) analysis, and street-view image (SVI) segmentation. These methods were applied to the UNESCO World Heritage Site of West Lake in Hangzhou, China, to explore lake–city–landscape relationships, classify lakeside landscape types, and interpret the spatial composition of iconic viewpoints. Findings indicate that: (a) four zones with both high CV and VM values coincide with key architectural and scenic landmarks, suggesting intentional spatial design strategies, while half of the "*Ten Scenic Places*" are influenced by symbolic or experiential factors beyond visibility; (b) 37 landscape types were identified along lakeside roads, revealing areas where vegetation obscures potential lake views and where design trade-offs are evident; (c) only two of ten potential city-to-lake visual corridors remain unobstructed, pointing to unmanaged vegetation as a critical barrier; and (d) these insights inform targeted visual management strategies, including vegetation control, viewpoint activation, and circulation optimization. This study highlights the limitations of single-method approaches, such as SVI's insensitivity to topographic variation, and suggests that a multi-perspective integration of VAMs can yield deeper spatial insights and more actionable guidance for managing urban heritage landscapes.

1. Introduction

Urban heritage landscapes, located at the interface between historical environments and modern urban development, represent a critical category of cultural heritage (Veldpaus, 2015). They preserve tangible and symbolic elements of collective memory, offering aesthetic, cultural, and recreational value to contemporary urban residents (UNESCO). Defined as "*an area, as perceived by people…*" (Déjeant-Pons, 2006), landscapes are inherently shaped by human perception, with vision serving as the dominant sensory modality (Bell, 2012; Liu and Nijhuis, 2020; Nijhuis et al., 2011). In this sense, the visual characteristics of urban heritage landscapes—such as sightlines, spatial layering, and scenic composition—play a fundamental role in their cultural expression and public appreciation. Understanding and managing these visual dimensions is thus essential for preserving both the experiential and symbolic values of heritage landscapes in urban contexts.

The visual management of urban heritage landscapes requires analytical rigor that matches their spatial and cultural complexity (Peng

Abbreviations: GIS, Geographic Information System - A system for managing, analyzing, and visualizing spatial data; VAM, Visual Analysis Method - A research method used for visual analysis to evaluate visibility in landscapes or scenes; FOV, Field of View - The extent of the observable area visible from a specific position, often related to viewing angles; SVI, Street View Image - Images captured through street-view mapping services, used in spatial-visual analysis and related studies; CV, Cumulative Viewshed - An analysis of the cumulative visibility from multiple observation points within a specific area; VM, Visual Magnitude - A measure of the visual prominence or significance of an object or area within a landscape.

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et al., 2024). Unlike ordinary urban spaces, heritage landscapes interweave historical layers, symbolic meanings, and evolving urban dynamics (Bandarin and Van Oers, 2012; Worthing and Bond, 2008). As such, superficial or purely qualitative approaches are insufficient to inform their planning and conservation. Instead, precise visual-spatial analysis is needed to preserve cultural integrity (Sukwai et al., 2022a), optimize scenic environments (Liu et al., 2022; Sarihan, 2021), and enhance visitor experience (Xu et al., 2024). Moreover, detailed analysis can uncover overlooked phenomena—such as vegetation-induced obstructions (Nijhuis, 2015) or degraded view corridors (Sukwai et al., 2022b)—that directly affect landscape legibility and public engagement. These insights not only support scientific landscape governance, but also help interpret spatial functions and cultural logic embedded in heritage sites. In this regard, visual analysis forms an indispensable foundation for sustainable management of urban heritage landscapes (Bandarin and Van Oers, 2012; Worthing and Bond, 2008).

However, despite the growing recognition of the importance of visual analysis in urban heritage landscape management, a critical review of existing literature reveals a persistent methodological constraint: visual landscape research remains fragmented in practice, with limited realization of cross-method integration. While a growing body of studies explicitly advocate for the use of diverse and integrative visual analysis methods (Chamberlain and Meitner, 2013; Domingo-Santos et al., 2011; Ervin and Steinitz, 2003; Inglis et al., 2022; Liu and Nijhuis, 2020; Nutsford et al., 2015; Palmer, 2022), many applications still rely on a single type of VAM or a group of techniques within the same category (e.g., purely viewshed-based or purely reality-based). This gap between methodological aspiration and actual implementation inherently restricts the interpretive depth and range of spatial-visual insights (Chamberlain and Meitner, 2013; Palmer, 2022), particularly in the context of complex cultural heritage environments. Without systematic integration across scales, data structures, and perceptual dimensions, it remains difficult to capture the full spectrum of visual characteristics and their embedded cultural intentions.

This fragmented methodological approach hampers our ability to capture the multi-dimensional and multi-perspective visual attributes of urban heritage landscapes. Therefore, it is necessary to develop integrated methodological frameworks that can synthesize complementary VAMs to improve interpretability and enhance the practical applicability of analysis outcomes for urban heritage landscape planning and management. To bridge this gap, this paper aims to address the following research question: In what ways do combined VAMs outperform single-method approaches in terms of interpretive depth and planning applicability?

To answer this question, we employ a comparative analytical framework using West Lake in Hangzhou, a UNESCO World Heritage Site known for its layered spatial composition and symbolic landscape design—as a representative case (https://whc.unesco.org/en/list/1334/). West Lake exemplifies a complex visual environment where natural, cultural, and urban elements intersect, offering a rich testbed for evaluating the effectiveness of single versus combined VAMs. This paper is structured into three parts: (a) a literature review summarizing existing GIS-based VAMs and their limitations; (b) the application of both single and combined VAMs to the West Lake case; and (c) a comparative analysis of their results, highlighting methodological insights and implications for visual management strategies in urban heritage contexts.

The contributions of this study are threefold: (a) Advancement of visual landscape research: By defining the applicability and limitations of various GIS-based VAMs, this paper highlights the limitations of single VAMs and the potential advantages of combined VAMs, offering theoretical support and practical guidance for improving existing analytical frameworks. (b) Relevance for urban heritage landscapes: Using West Lake as an example, this study reveals the multidimensional visual characteristics of urban heritage landscapes, providing scientific evidence for their visual management and planning. (c) Relevance for West Lake: By uncovering the specific visual characteristics of West Lake, this study offers new perspectives and strategies for its visual preservation and management.

2. Review of GIS-based VAMs

GIS-based VAMs aim to investigate the relationship between landscapes and human perception (Chamberlain and Meitner, 2013; Nijhuis et al., 2011). Based on different application scenarios, analytical focuses, and analysis results, the current VAMs can be categorized into three distinct types, including:

(a) **Vertical VAMs (bird's-eye, digital,** Fig. 1a**)**, a category of methods that encompasses bird's-eye-view visual analysis tools (Liu and Nijhuis, 2020; Nijhuis et al., 2011), like visibility assessment using viewshed-dominant algorithms/methods;
(b) **Horizontal VAMs (eye-level, digital,** Fig. 1b**)**, which analyze visual-spatial features by establishing an eye-level perspective in 3D digital model space (Gill et al., 2013; Labib et al., 2021; Nijhuis, 2014);
(c) **Reality-based VAMs** (Fig. 1c), including (but not limited to) street-view images (SVIs) (Han et al., 2023; Li et al., 2022; O'Regan et al., 2022) and on-site photography with geo-information (Oku and Fukamachi, 2006; Sugimoto, 2018), among others.

2.1. Vertical VAMs

Bird's-eye visibility and spatial configuration.

Vertical visual analysis methods refer to techniques that model and interpret visibility from a top-down (bird's-eye) perspective using digital spatial data. These methods are commonly applied at city or landscape scale and provide insights into large-area visibility, spatial openness, and structural configuration. They can be broadly categorized into three subtypes:

(a) Methods for visibility analysis, such as viewshed (Cervilla et al., 2017; Fisher, 1991, 1992, 1993, 1995) and isovist (Batty, 2001; Benedikt, 1979; Tandy, 1967). Urban applications of these methods encompass the assessment and identification of visual impacts in an urban/suburban environment (Cilliers et al., 2023; Dentoni et al., 2023; Jiang et al., 2015), exposure evaluations for green/blue space (Cimburova and Blumentrath, 2022; Labib et al., 2021; Yu et al., 2016), visibility maps of landmarks (Bartie et al., 2008; Czyńska and Rubinowicz, 2019; Zhang et al., 2023), and the exploration of built environments' spatial-visual characteristics/features (Hilal et al., 2018; Sezer, 2020; Tong, 2011).

(b) Methods for spatial characterization and analysis by using grid cells (Willemen et al., 2008; Woolard and Colby, 2002); The application of such methods extends beyond research on visual-spatial characterization (Van Eetvelde and Antrop, 2009, 2011; Yang et al., 2020), openness/enclosure (Wagtendonk and Vermaat, 2014; Weitkamp et al., 2011), and landscape quality assessment (Hermes et al., 2018; Ramos et al., 1976; Roth et al., 2021).

(c) Using landscape metrics to analyze landscape compositions and configurations (Frazier et al., 2023; Lausch et al., 2015); By focusing on spatial and visual aspects, the application of this category in urban spaces includes predictions of visual-spatial perception (Antrop and Van Eetvelde, 2000; Palmer, 2004; Sang et al., 2008) and landscape aesthetic assessments (Frank et al., 2013; Schirpke et al., 2013).

Together, these vertical methods are effective in modeling abstract spatial structure and predicting large-scale visibility patterns, but often lack the perceptual granularity needed to assess human-scale visual experience.

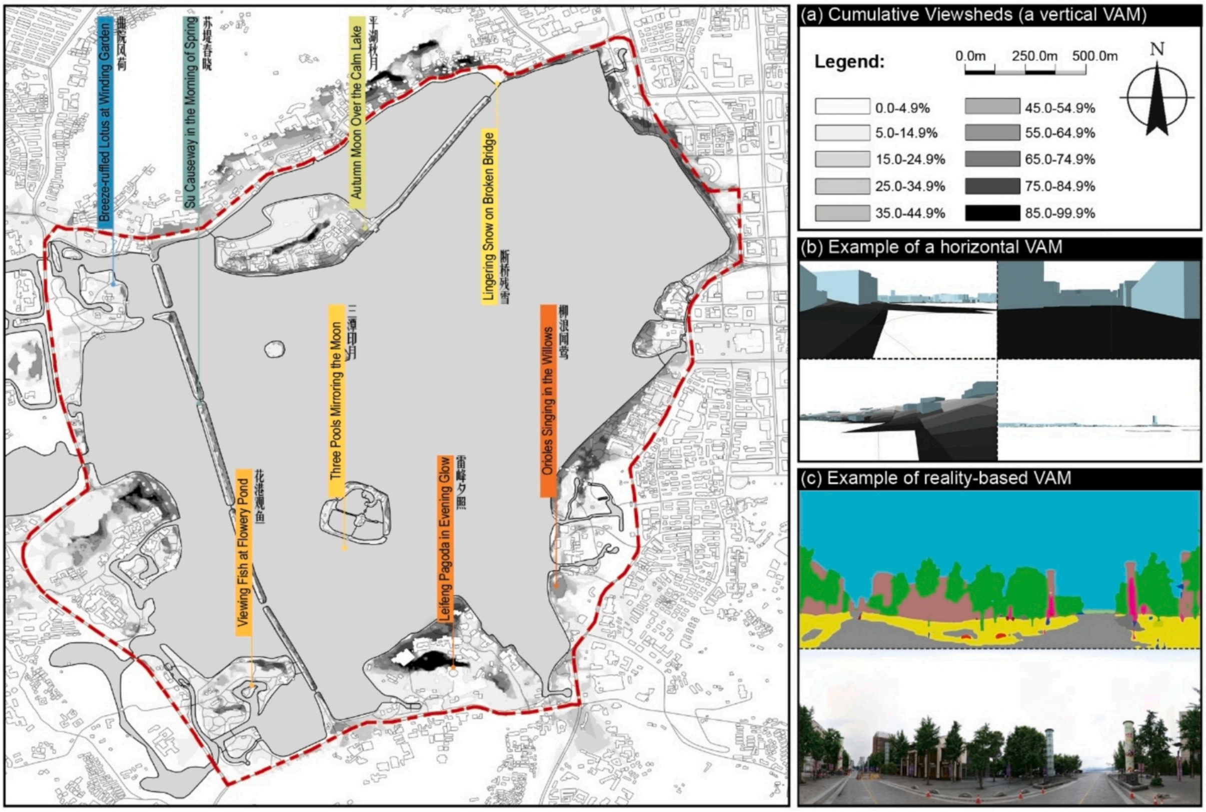


Fig. 1. Explanations for three categories of VAMs: (a) Example of vertical (bird's-eye) VAMs (Cumulative Viewsheds for West Lake, and the locations of the "*Ten Scenic Places*"); (b) example of reality-based VAMs; (c) example of horizontal (eye-level) VAMs.

2.2. Horizontal VAMs: Eye-level simulation of visual experience

Horizontal VAMs refer to methods that simulate human-scale perception by modeling the visible environment from an eye-level perspective within digital 3D environments (Misthos et al., 2023). Unlike top-down viewsheds, these approaches aim to approximate what users would see while standing or walking through a landscape. Horizontal methods are particularly valuable for evaluating visual composition, openness, and experiential quality in designed or historic settings. Two main subtypes can be distinguished:

(a) Monocular view methods simulate directional fields of view (FOV) similar to single-eye vision. For example, the *visual exposure* method projects scene elements onto a retinal-like plane to assess perceptual dominance and spatial hierarchy (Danahy, 2001; Li and Wee, 2009; Peng and Nijhuis, 2021). These methods are often used in assessing focal points, axial depth, and visibility constraints within linear or enclosed spaces.

(b) Panoramic view methods generate 360-degree spherical images to simulate immersive vision (Bischof et al., 2020; Wróżyński et al., 2020). Tools in this category support visual quality evaluation and enclosure index calculation (Susaki et al., 2014), capturing a more complete experiential environment (Pardo-García and Mérida-Rodríguez, 2017; Pardo García and Mérida Rodríguez, 2015; Zhang et al., 2020.

While both subtypes enhance realism in visual analysis, monocular methods are suited to directional attention studies, whereas panoramic methods better support immersive landscape evaluations.

2.3. Reality-based VAM

Reality-based visual analysis methods rely on spatially referenced image data, such as photographs, videos, or street view imagery (SVI), to assess visual characteristics without constructing 3D spatial models. These methods operate from the viewer's eye-level perspective and provide perceptual realism by analyzing scenes as captured in situ. Two subtypes can be distinguished:

(a) Directly captured data, including site photography (Sevenant and Antrop, 2011), video footage (Pardo-García and Mérida-Rodríguez, 2017; Sui et al., 2022), eye-tracking (Dupont et al., 2014; Dupont et al., 2016), and sketch-based analysis (Liu and Nijhuis, 2020), are commonly used for visual perception studies and validation of spatial models. These methods are especially useful in evaluating user attention, scenic preference, and environmental experience.

(b) SVI-based analysis uses panoramic imagery captured by online platforms (e.g., Google Street View, Baidu Maps) and has gained prominence for its accessibility and spatial coverage (Biljecki and Ito, 2021; Rzotkiewicz et al., 2018). With current advancements in computer vision and machine learning technologies, it has become possible to achieve more precise and digitized analyses, such as semantic segmentation (Aikoh et al., 2023; Nagata et al., 2020; Xia et al., 2021a, 2021b) and depth prediction (Micusik and Kosecka, 2009). Applications include the green view index (Li, 2020; Li et al., 2015; Zhu et al., 2023), exposure assessment of urban greenery (Han et al., 2023; Xia et al., 2021a), analysis of colors of facades (Zhong et al., 2021; Zhou et al., 2022), and exposure assessment for blue spaces (Helbich et al., 2019; Labib et al., 2020).

These reality-based VAMs are particularly suited for analyzing streetscapes, vegetation visibility, and user-scale visual aesthetics—making them valuable in heritage settings where public experience and fine-grained visual details matter.

2.4. Summary

The reviewed visual analysis methods (classified as vertical, horizontal, and reality-based) demonstrate distinct perspectives and data foundations (Table 2). Vertical methods offer top-down spatial modeling for large-area visibility analysis; horizontal methods simulate human eye-level perception; and reality-based methods extract visual attributes directly from scene images. While these categories reflect complementary orientations, prior studies have rarely examined their relationships or applied them in combination.

More importantly, current literature tends to apply each method in isolation, often focusing on a single analytical scale, visual dimension, or data source. As a result, it remains unclear how these methods differ in interpretive outcome, or whether their integration could offer enhanced insight, especially in the context of visually complex heritage landscapes.

3. Case study and data

A World Cultural Heritage Site, Cultural Landscape of West Lake, Hangzhou, has been selected as a case study (Fig. 2c). UNESCO (https://whc.unesco.org/) describes the site as follows:

"West Lake is surrounded on three sides by 'cloud-capped hills' and on the fourth by the city of Hangzhou… To make it more beautiful, its islands, causeways, and the lower slopes of its hills have been 'improved' by the addition of numerous temples, pagodas, pavilions, gardens, and ornamental trees…Since the Southern Song Dynasty (thirteenth century), ten poetically named scenic places have been identified as embodying idealized, classic landscapes."

Beyond this historical and aesthetic narrative, West Lake presents a distinct and analytically rich spatial structure. It exemplifies a hybrid heritage landscape that interweaves natural topography (lake and hills), urban interface (the proximity to Hangzhou's historic and modern districts), and constructed cultural features (temples, scenic nodes, and bridges). This layering—comprising water surfaces, built structures, vegetation, and skyline—creates a multidimensional visual hierarchy, offering both vertical and horizontal visibility conditions.

In addition to these structural elements, the site includes designated viewing points (e.g., the "Ten Scenic Places") and dynamic experiential paths. Together, these features enable the study of both static and sequential visual experiences, revealing the interplay between visual framing, cultural symbolism, and spatial configuration. These characteristics position West Lake as a typologically diverse, multi-scalar urban heritage landscape. It typifies issues common to many urban heritage landscapes in Asia and beyond, such as view corridor protection, vegetation-induced occlusion, and the interplay of cultural symbolism with physical space. Therefore, it is particularly well-suited for validating the capacity of combined VAM approaches to capture and interpret the complex visual-spatial characteristics of heritage environments.

3.1. Research questions for the case study

Based on UNESCO's description, the core visual-spatial characteristics and values of West Lake can be summarized as follows: (a) the visual-spatial relationships between the lake, the urban areas, and the cultural landscapes; and (b) the visual arrangement of the scenic sites, reflecting Eastern ideals and traditions. These characteristics reflect a distinctive cultural logic in which spatial design, rather than individual monuments, functions as the primary medium for expressing heritage value. In other words, the cultural significance of West Lake is embedded in the spatial interplay between water, terrain, vegetation, pathways, and urban features (including buildings), forming an experiential structure that encodes and conveys cultural meaning.

To investigate these core visual-spatial characteristics in detail, three specific research questions are proposed:

- **RQ1: What are the visual-spatial connections between the lake, the city, and the surrounding cultural landscapes?** This question

Table 2
Summary of the three VAM categories.

Categories	Approaches	Scenarios	Perspectives	Descriptions
Horizontal VAMs	Visibility	Digital	Bird's-eye	Mainly, it involves establishing lines of sight (LoSs) to detect the visual relationships between the viewed object and the surrounding grid. This is primarily divided into the isovist method (often applied in urban and architectural spaces) and the viewshed method (commonly used in natural landscape environments).
	Landscape metrics	Digital	Bird's-eye	These methods typically model landscapes into patches, corridors, matrices, and mosaics.
	Grid cell analysis	Digital	Bird's-eye	These methods overlay multiple factors by distinguishing visual feature differences among grids and polygons.
Vertical VAMs	One-eye methods	Digital	Eye-level	These methods attempt to understand landscape spaces' compositional elements or spatial characteristics through visualization or the visual analysis of monocular views.
	Panoramic methods	Digital	Eye-level	These methods attempt to understand landscape spaces' compositional elements or spatial characteristics through visualization or the visual analysis of panoramic views.
Reality-based VAMs	SVI-based	Reality	Eye-level	This type of method often involves crawling and analyzing large-scale SVI data. The main methods include semantic segmentation and image depth prediction.
	On-site photography/ video footage/ sketching	Reality	Eye-level	This method relies on these on-site tools to summarize and analyze landscape features or validate the results of digital calculations.

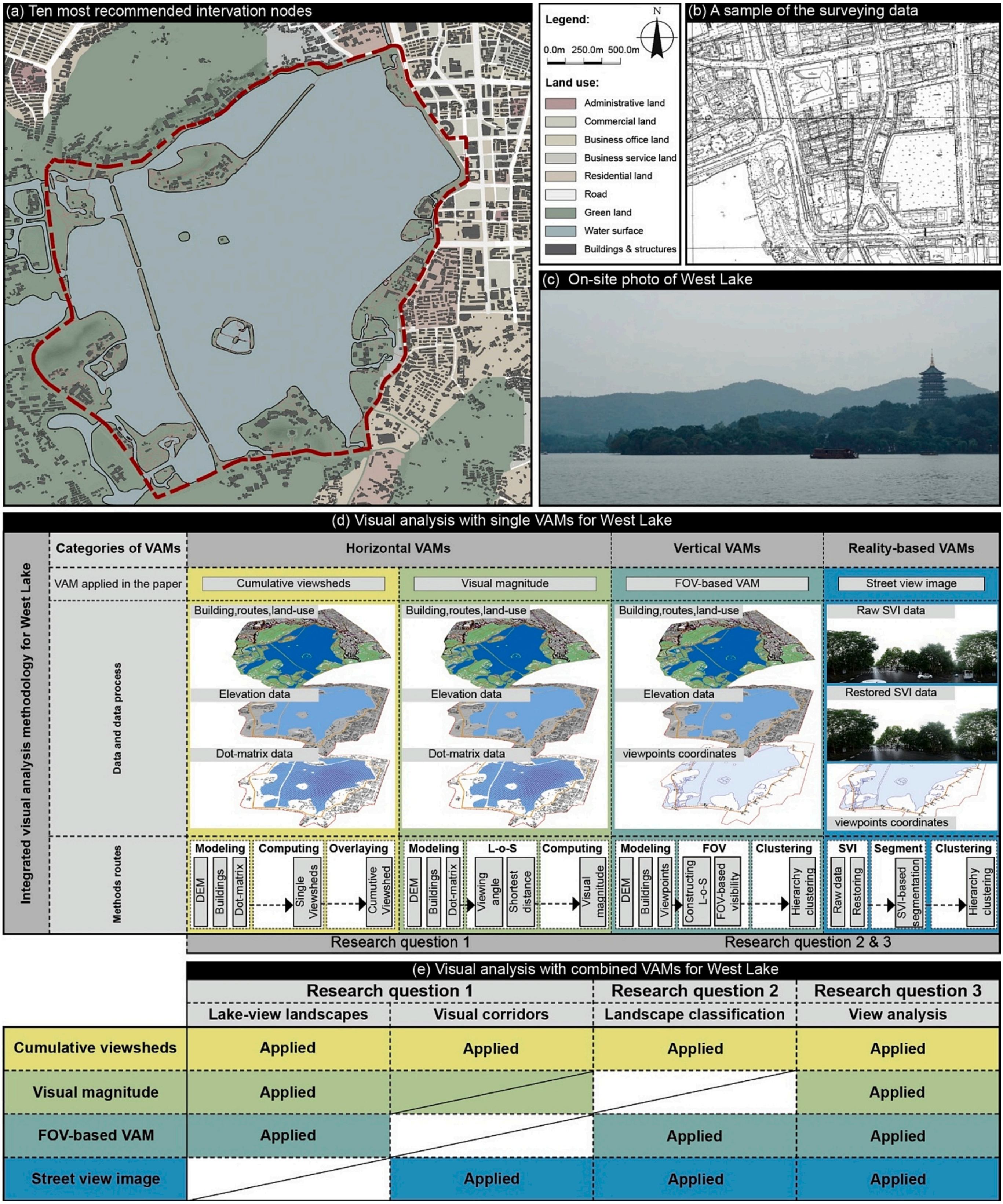


Fig. 2. Research data and methodology: (a) research site and classification of the DEM surface; (b) mapping and surveying data of the research site; (c) landscape view of West Lake (personal source); (d) research methods with single VAMs for West Lake; (e) research methods with combined VAMs for West Lake.

explores the spatial configuration and visibility patterns that define how the lake interacts visually with its broader context, including viewsheds, corridor alignments, and adjacency relationships.

- **RQ2: How can viewing spaces around the lake be classified based on their visual-spatial characteristics?** Building on RQ1, this question seeks to define discrete types of viewing experiences, providing a basis for spatial planning and tailored management strategies.
- **RQ3: How are the viewing points and spaces within and around West Lake designed and arranged to achieve visual and spatial harmony?** This final question addresses the intentional composition of scenic viewpoints, including the strategic use of placement, framing, and sightline alignment to construct meaningful views.

This study therefore adopts a spatial-cultural perspective, treating the visual structure of the landscape itself as a key carrier of cultural value. The research questions do not attempt to decode symbolic meaning directly, but rather aim to uncover the spatial mechanisms that support cultural perception and experiential engagement.

3.2. Research area and data

To address the above research questions, the lake's surface, lakeside urban areas, and some adjacent mountainous areas have been selected as the research area. The data used for the study area comprises three types:

(a) **SVIs:** The SVI data utilized in this paper were sourced from Baidu Maps (https://map.baidu.com/) as panoramic views at various viewpoints on the roads near/surrounding West Lake (the coordinate data for each viewpoint has also been extracted, and the distance between two adjacent points is approximately 5 m, totaling 2140 panoramic images, in detail: 103 from May 2014, 20 from April 2015, 1020 from August 2017, 822 from September 2017, and 175 from June 2020).

(b) **Elevation data (Fig. 2b):** These data consist of elevation points (approximately 100 points per hectare) and contour lines (with a contour interval of 1 m). The lowest point in the study area is at an elevation of 3.8 m, while the highest point is at a height of 48.3 m, resulting in a vertical difference of 44.5 m.

(c) **Open-source data (Fig. 2a) (https://lbsyun.baidu.com/):** These data pertain to building/structure data, including information on the number of floors, building types (commercial, residential, public administration, mixed-use, etc.), and the construction years of the buildings, route data, including the mid-line, width, and type of the routes, and land use data, including the borders and types for each piece of land.

Regular square grids have been used to model the elevation data (b) as a bare-earth model with 1 m and 5 m grid resolutions. Subsequently, the modeling of the study site was completed by integrating information from open-source data (c). Finally, the model's surfaces were segmented into five types: green land, lake surface, non-lake water surface, paved ground, and buildings/structures. Additionally, the main roads surrounding West Lake (four drivable urban roads) were selected as research segments, corresponding to the roads covered by street-view scanning points. In addition, data from Dianping (http:/www.dianping.com/) and historical photographs are also referenced as supplementary data for further explanation.

4. Methods

To address the above research questions and to compare the interpretability of results between single VAMs and combined VAMs, two categories of approaches were constructed to respond to RQ1 through RQ3 (Fig. 2d, Fig. 2e).

4.1. Visual analysis with single methods

Four VAMs have been selected and appropriately adapted for this study: CV, VM, FOV-based method, and SVI-based method (Fig. 2d). Specifically, CV and VM are independently applied to examine the visual and spatial connections between West Lake, its surrounding cultural landscapes, and adjacent urban areas, addressing **RQ1**. The FOV and SVI methods are utilized to classify the landscape types of roads and viewing spaces around West Lake, contributing to the exploration of **RQ2**. Furthermore, these two methods are employed to analyze the visual composition of lake-view sites, offering insights into **RQ3**.

4.1.1. Cumulative viewshed

The lake surface of West Lake serves as a pivotal visual focal point within this heritage landscape. Consequently, an adapted CV method is utilized for the visibility assessment of extensive surface areas, such as the lake surface. A 30-m grid of "dots" is established throughout the lake. The viewsheds for each "dot" are produced using the standard algorithm provided by ArcGIS version 10.2. The individual viewsheds are subsequently superimposed to generate a CV map. The frequency of visible dots correlates with the overlay count, where increased overlays signify a greater proportion of visible lake surface, thereby indicating enhanced lake visibility.

4.1.2. Visual magnitude

The lake's visibility and its proportion within the field of vision are crucial visual attributes of the viewing experience. Consequently, an altered VM method is employed to forecast the lake's significance within the visual perspectives of various viewpoints. In the cultural landscape area, characterized by sloped terrain and an expansive lake surface, the modified VM method integrates three variables: the distance from the viewpoint to the nearest "dot" on the lake, the vertical difference between the maximum and minimum viewing angles, and the horizontal difference between the maximum and minimum horizontal viewing angles. The VM values for various regions can be derived by overlapping these factors.

4.1.3. FOV-based method for lakeside main roads

A novel FOV-based method is implemented in a digital space. This method computes the proportion of each landscape element within the FOV. Four types of landscape elements around West Lake are considered: paved ground, unpaved ground, buildings/structures, and lake surface. The main steps of this horizontal VAM include:

(a) Placement of viewpoints: Points are placed along roads based on coordinates obtained from SVIs and elevated by 1.6 m.

(b) LoS construction: For each viewpoint, lines of sight (LoS) are constructed at 5-degree intervals horizontally within a 360-degree range and vertically between 30 and 175 degrees relative to the ground, with a line length of 5000 m.

(c) Calculating the ratios of different landscape compositions: When a LoS encounters an obstacle, feedback is provided based on the type of grid cell it intersects. If no obstacles are encountered, the cell corresponds to the "sky." This process is repeated for all viewpoints, allowing for the calculation of the proportions of four surface types (paved ground, buildings/structures, unpaved ground, and lake surface) and the sky within each FOV.

(d) Clustering: Hierarchical clustering in IBM SPSS Statistics is used to differentiate landscape types associated with the viewpoints. Clustering is based on the proportion data of different landscape elements, a method applied in visual studies such as research on greenway landscapes and urban visual characteristics (Liang et al., 2023; Liu et al., 2022).

4.1.4. SVI-based method for lakeside main roads

A novel SVI-based method is employed to analyze the landscape composition along the lakeside main roads. SVIs from the same season are restored by removing pedestrians and vehicles. The PSPNET model is used to segment the SVIs, with the reliability of the data sourced from Baidu Map (Sun et al., 2023; Yue et al., 2022). Based on the composition around West Lake, SVIs are classified into six categories: sky, buildings/structures, unpaved ground, paved ground, lake surface, and vegetation. The proportion of each landscape element is statistically compiled, and clustering is performed using the same method as in the FOV-based method (Liang et al., 2023; Liu et al., 2022).

4.2. Visual analysis with combined VAMs

This section employs four combined approaches to address the three research questions proposed in the previous chapter. Specifically, the VAMs in Section 4.2.1 address **RQ1**, the VAM in Section 4.2.2 responds to **RQ2**, and the VAM in Section 4.2.3 answers **RQ3**.

4.2.1. Analyzing the visual relationship between West Lake and its surrounding environment

The analysis of the relationship between West Lake and its surrounding environment will be conducted using two combined VAMs:

(a) Analysis of the visual-spatial relationship between the lake and surrounding cultural landscapes: By integrating CV and VM analyses, regions with high CV values (indicating significant lake visibility) and high VM values (indicating substantial lake presence within the visual field) are identified. These results are compared with the distribution of cultural landscapes and lake-view buildings to reveal how the lake's visual attributes influence their siting. Representative cultural landscapes and buildings are selected for detailed analysis of visual composition using FOV data, validating the findings and providing insights into the visual-spatial dynamics between the lake and its surrounding cultural landscapes.

(b) Analysis of the visual-spatial relationship between the lake and urban areas: The urban area of Hangzhou is situated on the eastern bank of West Lake, comprising ten urban roads, including three main roads that extend toward the lake. The procedure begins with a CV evaluation to ascertain the theoretical visibility of the lake from these roads. Thereafter, SVI data are employed to assess the present state of these prospective corridors.

4.2.2. Classification of landscape types along the lakeside roads

This paper utilizes a combination of CV, FOV, and SVI to classify the landscape types along the lake-circling roads near West Lake. This integrated analysis aims to provide more comprehensive information to support subsequent visual management efforts. The specific classification steps are as follows:

(a) Lake visibility classification (based on CV): Using the CV map, the visibility levels of the lake surface were categorized into three levels: non-visible areas (N), low-visibility areas (L), and high-visibility areas (H).

(b) Classification without vertical elements (based on FOV): FOV analysis was used to identify landscape types that do not include vertical elements such as vegetation, dividing them into four categories: F1, F2, F3, and F4.

(c) Classification with vertical elements (based on SVI): SVI analysis focused on identifying landscape types containing vertical elements such as vegetation, further dividing them into five categories: S1, S2, S3, S4, and S5.

(d) Overlaying the three approaches: the results of FOV and SVI analyses were superimposed onto the CV map to create an integrated classification of landscape attributes along the lake-circling roads.

This method has the potential to identify up to 60 distinct comprehensive landscape types. For example, "F3-S4-H" represents a specific landscape type characterized by an FOV classified as F3, an SVI classified as S4, and high lake visibility (H).

4.2.3. Analysis of visual composition at viewing points

Taking "*Broken Bridge in the Snow*" and "*Leifeng Pagoda at Sunset*," two of the "*Ten Scenic Places of West Lake*", as examples, the visual composition of these iconic viewing points are analyzed using combined VAMs. CV and VM methods provide insights into the spatial relationships and visual connections between the lake and the viewing sites. Meanwhile, SVI and FOV analyses offer detailed insights into the visual composition strategies, such as framing and sightline guidance, offering an understanding of their design strategies.

5. Results

This chapter consists of three sections: the analysis results of single VAMs, the analysis results of combined VAMs, and a comparison between the two approaches.

5.1. Results from single VAMs

5.1.1. Visual-spatial relationship between the lake and its surrounding environment

The single VAM analysis applies CV and VM to explore the visual-spatial connections between West Lake and its surrounding environment. The results from these VAMs exhibit certain similarities and are presented as follows:

(a) Analysis results of CV: The CV map depicts differing degrees of lake visibility within the study area (Fig. 3a). The color gradient on the map signifies visibility, with the darkest regions denoting the highest visibility and the lightest regions indicating the lowest. More than 60 % of the lake's surface is observable from the adjacent mountainous areas (dark gray). Other regions of significant visibility are predominantly located near the lake's surface. Urban regions demonstrate restricted visibility of West Lake.

(b) Analysis Results of VM: The VM values indicate the probable visibility of the lake within visual fields in different regions (Fig. 3b). The visualization employs a color gradient, with the darkest regions signifying the highest prominence and the lightest regions denoting the lowest. The VM map indicates that the lake is visually conspicuous on slopes facing the lake and in nearshore regions. In contrast, flat areas far from water display comparatively lower VM values.

5.1.2. Landscape types classification of lakeside roads

The analysis employs FOV and SVI to answer the research question. The following section presents and interprets the results of each method individually. Overall, the analysis results from these two methods exhibit certain differences.

(a) Analysis Results of SVI: The columns containing five colors indicate the proportion of each landscape component within the field of view (Fig. 3c). Hierarchical clustering revealed four distinct landscape types along the main roads surrounding West Lake (Fig. 3d): **Type F1** represents urban roads dominated by a substantial percentage of buildings. **Type F2** comprises densely constructed lakeside thoroughfares offering a mix of buildings and lake views. **Type F3** is characterized by undulating mountainous road segments with a high proportion of unpaved terrain. **Type F4** includes prime lake-viewing locations with the greatest percentage of the lake surface, primarily along northern and partially southern road segments.

(b) Analysis Results of SVI: Six columns of colors represent the proportion for each landscape component within the SVI (Fig. 3c). Hierarchical clustering method identifies five landscape types along the lakeside main roads (Fig. 3e): **Type S1** represents areas with a high proportion of buildings, predominantly situated on the eastern shore of the lake with smaller roadside trees. **Type S2** features substantial vegetation and large sky proportions, located on the eastern shore along broader thoroughfares with shorter edifices. **Type S3** is characterized by significant vegetation interspersed with unpaved terrain, primarily found in urban areas with integrated structures and landscapes. **Type S4**

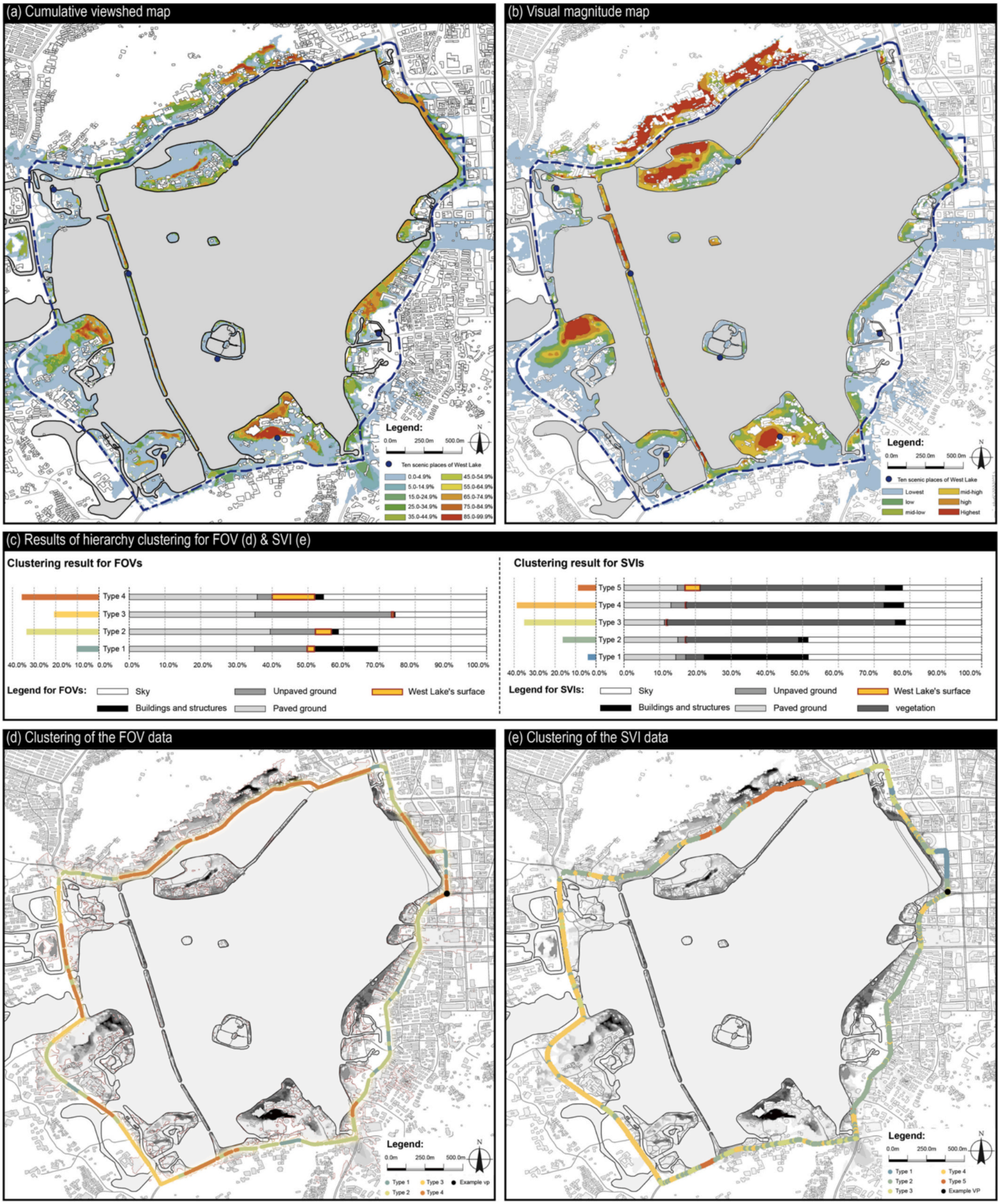


Fig. 3. Research findings of single VAMs: (a) CV maps; (b) VM maps; (c) clustering analysis for FOV and SVI; (d) FOV clustering; (e) SVI clustering. Note: The continuous CV and VM values were classified by equal range of values between the observed minimum and maximum.

includes regions with less vegetation but more unpaved ground, typically found in natural mountainous terrain. **Type S5** denotes areas with excellent lake-view visibility, concentrated on the northern and partially southern shores.

5.1.3. Visual characteristics analysis of lake-view sites

To further explore the visual structure at key lake-viewing locations, an example viewpoint located on the eastern edge of the lake was selected for detailed comparison using FOV and SVI methods. The two approaches yielded markedly different visual outcomes.

(a) Results from FOV Analysis: The proportions of five landscape elements identified through the FOV method are as follows: the lake accounts for 12.3 %, buildings for 5.2 %, soft surfaces for 7.2 %, hard surfaces for 38.2 %, and the sky for 37.1 %. These results indicate that the viewpoint provides a relatively open view of the lake and is situated along the urban interface.

(b) Results from SVI Analysis: The semantic segmentation of SVI data reveals the proportions of six landscape elements as follows: the lake accounts for 0 %, vegetation for 33.2 %, buildings for 2.2 %, soft surfaces for 4.1 %, hard surfaces for 14.3 %, and the sky for 46.2 %. These findings indicate that the lake is not visible from this viewpoint. The area is surrounded by street trees, which obscure the road, and buildings are largely concealed by vegetation.

This comparison highlights the contrasting perspectives provided by FOV and SVI methods, emphasizing the influence of different analytical approaches on understanding the visual characteristics of lake-view points.

5.2. Results from combined VAMs

5.2.1. Visual-spatial relationship between the lake and its surrounding environment

The results in this section focus on two aspects: (a) the relationship between the lake and the surrounding cultural landscapes, particularly in terms of location selection and viewshed, and (b) the visual-spatial connection between the lake and the urban areas, specifically through visual corridors.

(a) Location selection of surrounding cultural landscapes and buildings: By overlaying CV and VM analysis results, four areas with both high visibility and high VM values were identified (Fig. 4a). These areas correspond closely to the locations of significant cultural landscapes and buildings around the lake, such as *Leifeng Pagoda*, *Zhongshan Park* (the site of Emperor Kangxi's temporary palace in Hangzhou), *Xizi Hotel*, and several buildings of the *West Lake State Guesthouses* (Fig. 4b). These findings affirm the high landscape value of areas with both high visibility and high VM values, underscoring their suitability as lake-viewing sites. For example, the visual field surrounding *Leifeng Pagoda* offers exceptional lake views in three directions, validating its designation as a prime viewing location. At the same time, these locations also function as iconic visual focal points within the landscape, meaning that the buildings themselves are not only platforms for viewing, but also key components being viewed—framing and enriching the overall visual narrative of the lake. The visual overlays (Fig. 4a) further exemplify how combining CV and VM yields complementary insights and directly supports the identification of visually significant zones, thus enhancing the interpretability and applicability of combined VAMs in practical heritage management scenarios.

In addition, an analysis of the "*Ten Scenic Places of West Lake*" reveals that their site selection does not fully align with high visibility or high VM values. Among the ten sites, only one is in a high-visibility zone, four are located in high VM value areas but lack high visibility, and two are situated in low visibility and low VM zones (Fig. 4b). This suggests that the site selection of these cultural landscapes is influenced by factors beyond visibility or VM values, such as historical and cultural considerations.

(b) Urban lake-view corridors: The CV analysis identifies ten roads with the potential to establish lake-view corridors, connecting the city to the lake (Fig. 4c). However, SVI data reveals that most of these corridors are obstructed by vegetation. Among the three primary roads, two are partially obstructed, and one is entirely blocked. Of the seven secondary streets, three are obstructed, and two are partially blocked. Only two streets provide unobstructed views of the lake despite not being explicitly designed for this purpose. Furthermore, the extensive canopies of the trees obscure the adjacent hills of West Lake in the SVI images. This complicates the capacity of people to recognize their presence within an urban heritage landscape, thereby undermining their connection to the surrounding natural landscape. This indicates that strategic vegetation management may improve urban lake-view corridors, thereby enhancing visual access and connectivity between urban areas and the cultural landscape.

5.2.2. Landscape types classification results of the lakeside roads

Thirty-seven different integral landscape types have been identified (Fig. 5a, Fig. 5b). The landscape category with the greatest proportion is F3-S4-L, comprising 12.383 % of the total. This category denotes perspectives where the FOV reveals a significant extent of unpaved terrain (in mountainous regions), the spectral vegetation index reflects a substantial amount of vegetation (characterized by dense roadside trees), and there is comparatively limited visibility of the lake (with the possibility of observing the lake). The landscape type with the second highest proportion is F4-S5-H, comprising 8.318 % of the total. This category denotes road segments accessible for lake viewing. The subsequent category is F2-S3-L, comprising 7.757 %. This type depicts the terrain in a semi-urban region characterized by limited lake visibility and dense roadside vegetation. Furthermore, F4-S3-H (6.308 %) indicates significant visibility, though the lake surface is partially concealed by dense vegetation. Another category, F1-F4-H (6.308 %), denotes road segments in urban settings where vegetation conceals buildings, thereby offering significant potential for lake visibility. In addition to the aforementioned prevalent and comprehensible landscape types, some are more anomalous. For instance, F2-S5-N, which constitutes merely 0.187 % of the total, exhibits a degree of inconsistency: it lacks visibility in the CV yet possesses a comparatively high lake proportion in the SVI. This results from the inadequate density of the dots employed to replicate the lake surface for CV computation.

From the findings of the classification, several critical insights can be deduced, primarily encompassing the elements listed below:

(a) Visual arrangement of the lakeside roads: Initially, concerning the lakeside main roads, viewpoints exhibiting a significant proportion of lake surface visibility in the field of view (F4) constitute over 36 % of the total. Nevertheless, merely 8.3 % of these perspectives (F4-S5) maintain elevated lake visibility in the SVI data. The predominant landscape types among these road segments are F4-S4 and F4-S3, characterized by vegetation-dominant FOVs. This suggests that the designers deliberately concealed the lakeside main road from lake views using vegetation. This arrangement aims to mitigate the visual and auditory impact of lakeside main roads on heritage landscapes. Meanwhile, designers created lakeside pedestrian pathways in regions with higher CV and VM values, offsetting the lack of high-quality scenic experiences along main roads. The results corroborate design principles that have gained extensive application and acceptance (Lynch and Hack, 1984; Simonds, 1983).

(b) The variation of landscape types: By overlaying FOV, SVI, and CV, the variation of landscape is as follows: the northern section of the lakeside road has the slightest variation in landscape and the highest lake-view quality. The western section of the lakeside road shows relatively low variation, where the landscape is mainly dominated by roadside trees, with variation coming from lake visibility and topographical changes. The eastern and southern sections of the lakeside road exhibit more landscape variation, generally including vegetation-dominant segments, building-dominant segments, and segments with high-quality lake views.

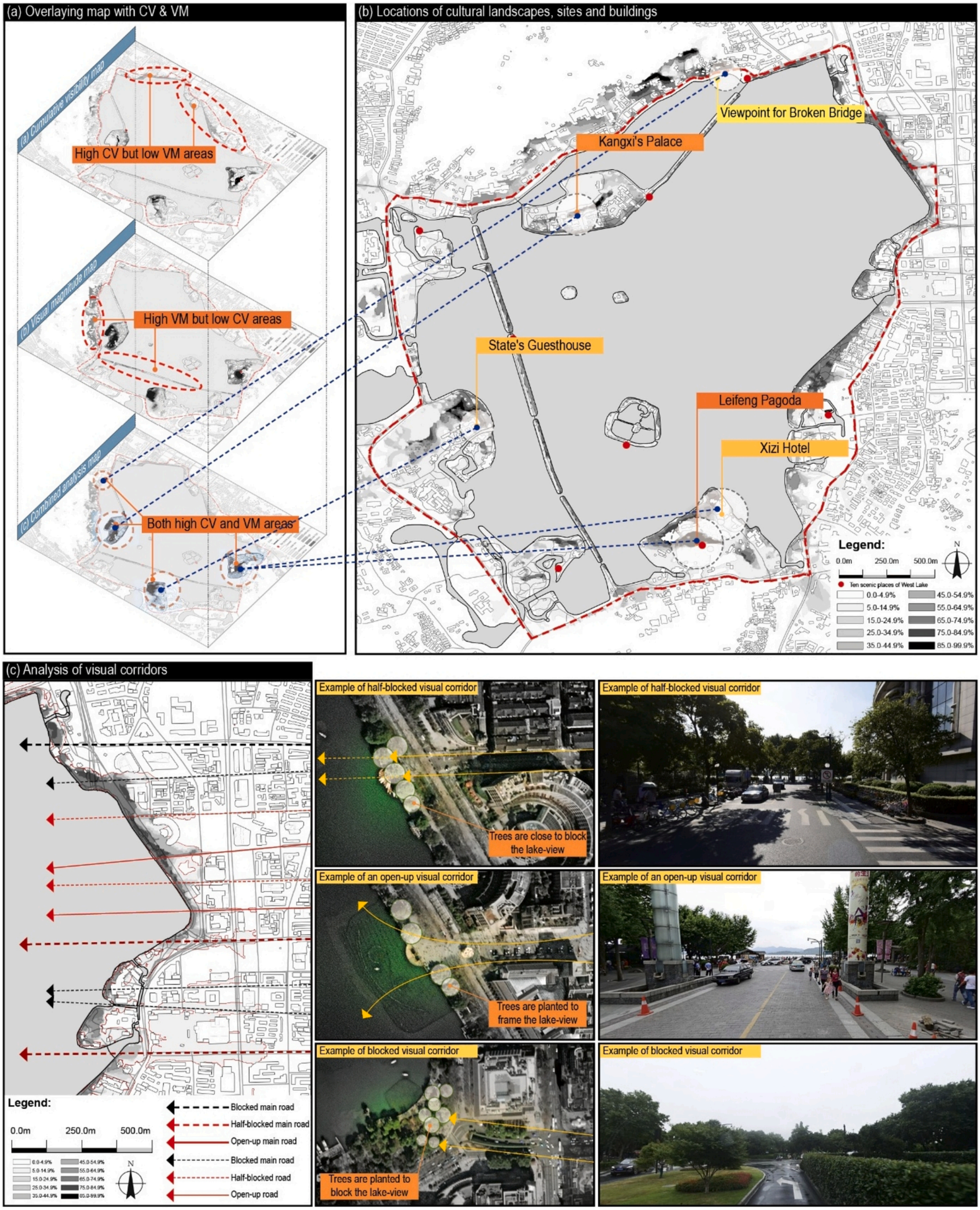
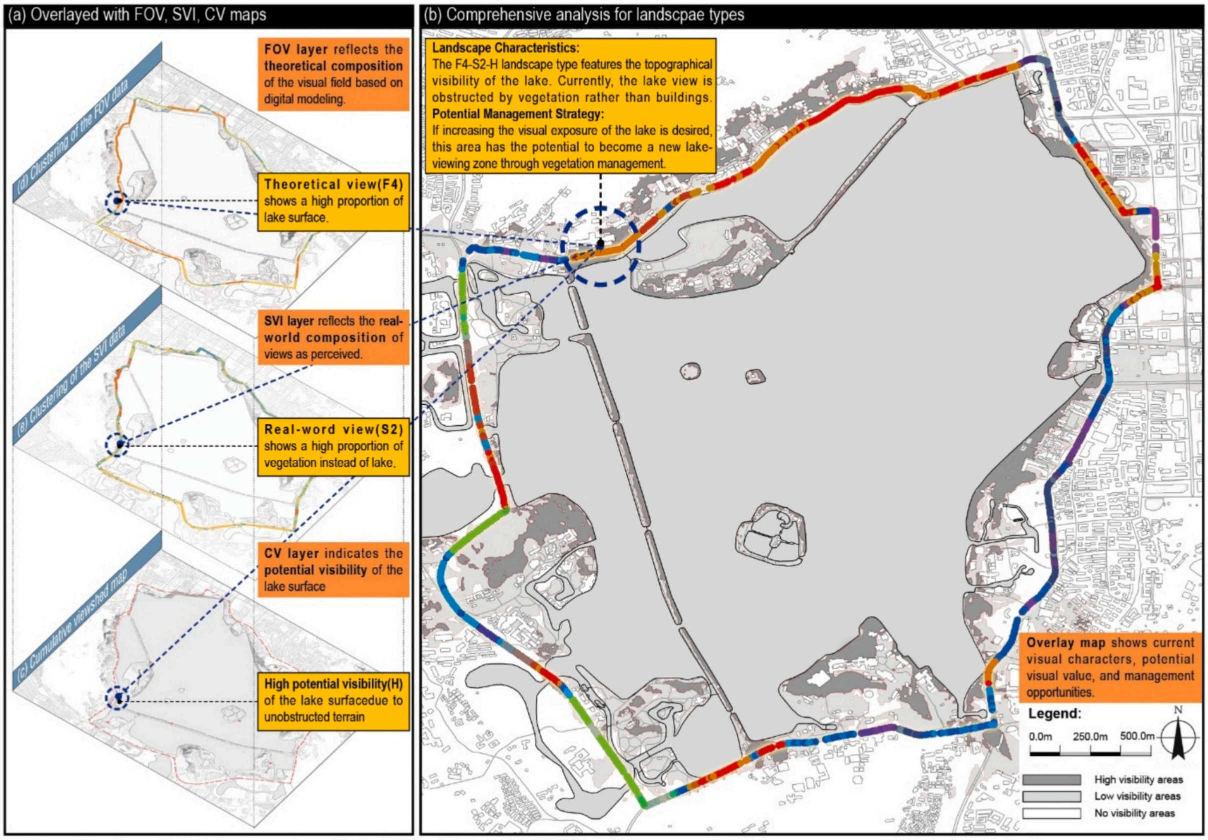


Fig. 4. The analysis results of the visual-spatial relationship between the lake and its surrounding environment using combined VAMs include: (a) overlaying CV and VM maps to identify high-quality lake-viewing spaces; (b) the spatial relationship between high-quality lake-view spaces and cultural landscapes/buildings; (c) visual corridors: visual and spatial connections between the city and the lake.



(c) Comprehensive analysis for landscpae types: N=No visibility, L=low visibility, H=high visibility

SVI / FOV	Type: S1			Type: S2			Type: S3			Type: S4			Type: S5		
	Type	Number	Proportion	Type	Number	Proportion	Type	Number	Proportion	Type	Number	Proportion	Type	Number	Proportion
Type F1	F1-S1-N	11	0.514%	F1-S2-N	29	1.355%	F1-S3-N	57	2.664%						
	F1-S1-L	27	1.262%	F1-S2-L	45	2.103%	F1-S3-L	45	2.103%						
	F1-S1-H	3	0.140%							F1-S4-H	135	6.308%			
Type F2	F2-S1-N	12	0.561%	F2-S2-N	44	2.056%	F2-S3-N	68	3.178%	F2-S4-N	103	4.813%	F2-S5-N	4	0.187%
				F2-S2-L	32	1.495%	F2-S3-L	166	7.757%	F2-S4-L	44	2.056%			
	F2-S1-H	18	0.841%	F2-S2-H	28	1.308%	F2-S3-H	46	2.150%						
Type F3				F3-S2-N	12	0.561%	F3-S3-N	35	1.636%	F3-S4-N	74	3.458%			
				F3-S2-L	19	0.888%	F3-S3-L	35	1.636%	F3-S4-L	265	12.383%			
				F3-S2-H	7	0.327%									
Type F4							F4-S3-N	57	2.664%	F4-S4-N	55	2.570%			
	F4-S1-L	7	0.327%	F4-S2-L	55	2.570%	F4-S3-L	87	4.065%	F4-S4-L	6	0.280%			
	F4-S1-H	2	0.093%	F4-S2-H	66	3.084%	F4-S3-H	135	6.308%	F4-S4-H	128	5.981%	F4-S5-H	178	8.318%

Fig. 5. Classification of lakeside road landscape types using combined VAMs: (a) Integration of FOV, SVI, and CV methods; (b) classifications of the lakeside main roads; (c) classifications of landscape types of the lakeside main roads.

The combined VAM helps to identify areas of consistent high visibility and locations where vegetation/structures obstruct otherwise strong visual potential. This tri-layered approach supports more precise classification and informs landscape management strategies aimed at enhancing the visual environment.

5.2.3. Visual composition analysis of lake-view sites

This section uses two examples (Fig. 6) to reveal the visual composition techniques employed at lake-view points. Both examples are selected from the "*Ten Scenic Places*":

(a) *Lingering Snow on Broken Bridge* (Fig. 6a**):** The viewpoints designed to view the "Broken Bridge" are on the north side of the lake. The viewshed analysis demonstrates that this area belongs to a continuously mid-visibility region of the lake surface, but with a notably high ratio of the lake surface in the visual field. With the lake surface as a contrasting background, the "Broken Bridge" on the lake becomes particularly conspicuous in lake views along the road. Plants do not obstruct this part, unlike most main road segments, with lake surface visibility, providing open and wide-ranging lake views. SVI observations show that the Platanus trees' distant trunks and drooping canopies act as a natural frame for viewing the "Broken Bridge" and the lake.

(b) *Leifeng Pagoda at Sunset* (Fig. 6b**):** As previously identified, *Leifeng Pagoda* is situated in an area with both high visibility and VM values. In comparison to historical photographs, FOV more accurately reflects the original condition at the time of the building's site selection, which showcased an unobstructed, expansive lake vision from the hilltop. However, SVI indicates that the lake view is primarily hindered by vegetation at this location. This makes the area surrounding Leifeng Pagoda no longer an optimal zone for viewing the lake.

In conclusion, scenic-view locations exhibit a weaker direct correlation with lake surface visibility and are more associated with the composition of elements within the visual field. The findings also indicate that vegetation significantly influences viewing perspectives: it can enhance the scenic frame, or conversely, it can obstruct or conceal the scenic views.

5.3. Comparison between single and combined VAMs

In addressing the three research questions, combined VAMs provided a deeper understanding of visual information compared to single VAMs, as detailed below (Table 3):

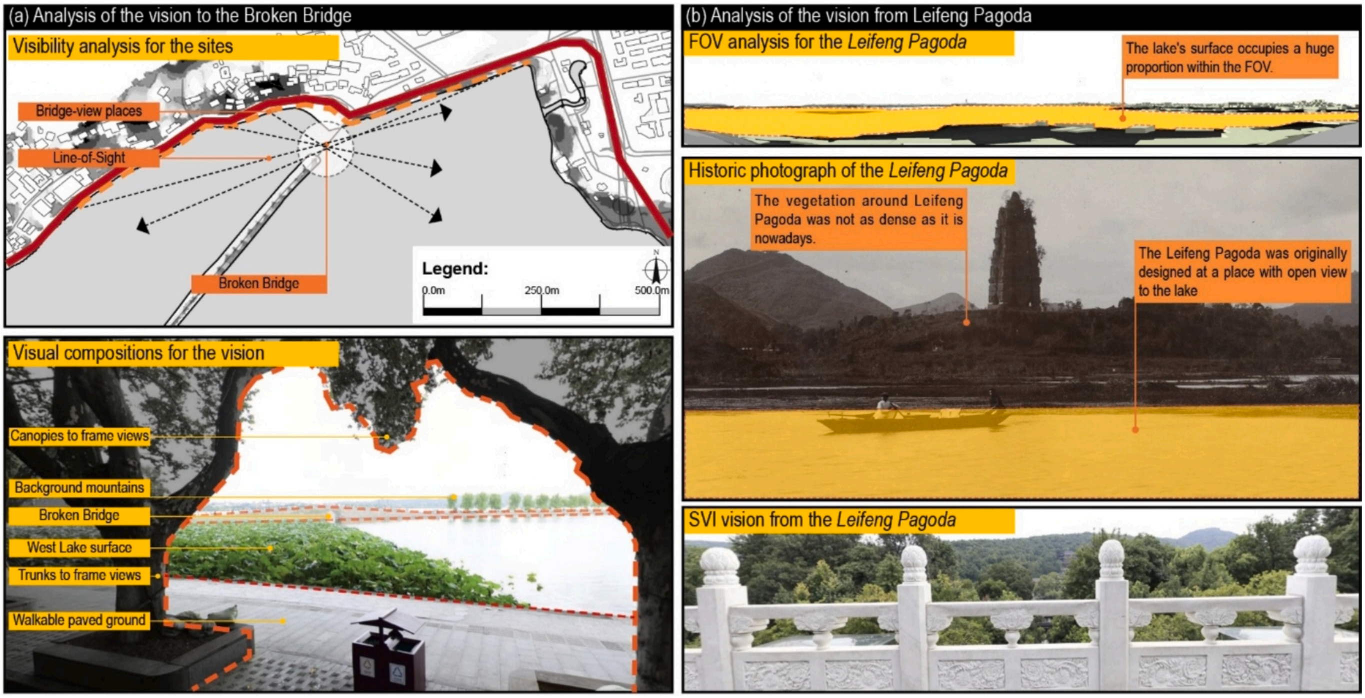


Fig. 6. Visual composition analysis of lake-view sites using combined VAMs: (a) the framing effect of vegetation in "Lingering Snow on the Broken Bridge"; (b) the complete obstruction of lake views by vegetation at the base of Leifeng Pagoda.

5.3.1. RQ1-Visual relationship between the lake and its surrounding environment

Single VAMs primarily reveal the lake's viewshed range and visual prominence distribution, but fail to identify the visual connectivity between the city and the lake. They also do not uncover the rationale behind the siting of cultural landscapes and lake-view structures or their complex relationship with the lake's visual characteristics. Combined VAMs elucidate the logic behind the placement of cultural landscapes, such as *Leifeng Pagoda*, which is situated in areas of high visibility and visual prominence, emphasizing their role as core viewing structures. Furthermore, the *scenic places* are shown to be located in areas influenced more by non-visibility factors, a relationship that single VAMs cannot capture. Additionally, single VAMs fail to recognize the role of vegetation in obstructing visual corridors and diminishing the visibility of cultural landscapes. Combined VAMs explicitly highlight how strategic vegetation management can optimize visual corridors and enhance the visual connectivity between the city and the lake.

5.3.2. RQ2-Classification of lakeside roads landscape types

FOV and SVI classify lakeside roads based on the proportion of view elements or street-level imagery, revealing basic types and spatial distributions. However, these VAMs operate independently and lack the ability to reflect the relationships between types. This refined classification by combined VAM not only provides a more complete depiction of road landscapes but also reveals design intentions. Additionally, combined VAMs reveal the dynamic variations in landscape types, particularly as they adapt to topographical changes (e.g., mountainous versus urban areas). Single VAMs are incapable of capturing these variations or the design trade-offs between lake views and vegetation distribution, whereas combined VAMs analyze these dimensions and offer actionable insights for optimizing and managing road landscapes.

5.3.3. RQ3-Visual characteristics of lake-view sites

FOV and SVI independently reveal the visual composition at the lake-view site, displaying the proportions of different landscape elements. However, these single VAMs do not uncover the deeper logic of visual design. Combined VAMs illuminate the composition's impact on lake views and design strategies of lake-view sites. For instance, in the two lake-view sites, the dual role of vegetation is highlighted. In summary, single VAMs only reveal the static visual composition of viewpoints, while combined VAMs establish connections between visual characteristics and design intentions, offering a deeper understanding of the relationship between visual characteristics and management strategies.

In conclusion, combined VAMs, through multidimensional overlay analysis, provide a better understanding of the complexity of visual-spatial information and the underlying design intentions (Fig. 7).

6. Discussions

This study demonstrates that integrating multiple GIS-based VAMs provides a more complete understanding of spatial visibility and enables a quantifiable interpretation of landscape composition and design strategies in urban heritage contexts. Compared to single-method results, the combined VAM approach revealed previously unnoticed patterns, such as the intentional concealment of lakeside roads through vegetation, the spatial logic behind scenic site placements, and the regional variations in visual accessibility around West Lake. This framework aligns with contemporary calls in landscape research for more holistic, multi-perspective approaches to visual analysis (e.g., Chamberlain and Meitner, 2013; Palmer, 2022). The following sections explore how the findings inform visual management strategies for West Lake and other urban heritage landscapes, and further discuss the strengths and limitations of the individual and combined VAMs, evaluating their applicability to heritage landscape analysis.

6.1. Visual management strategies: From West Lake to generalizable principles

Based on the combined VAM analysis of West Lake, a series of management strategies have been proposed that not only address local visual-spatial challenges but also offer transferable insights for other urban heritage landscapes. These strategies are grouped under four key themes:

(a) Enhancing visual corridors (red box in Fig. 8a): The spatial

Table 3
Comparison between single and combined VAMs.

Research question	Insights from single VAMs	Additional insights from combined VAMs
RQ1: Visual-spatial relationship between the lake and Its surrounding environment **(dark orange and yellow boxes in** Fig. 7**)**	- Reveal the lake's viewshed range and visual prominence distribution. - Cannot identify the visual connectivity between the city and the lake.	- Identify the logic behind cultural landscape siting, such as *Leifeng Pagoda* and *Zhongshan Park* being in high-visibility and high-prominence areas. - Highlight that the "*Ten Scenic Places*" are influenced more by non-visibility factors. - Show how strategic vegetation management improves visual corridors and enhances city-lake connectivity.
RQ2: Classification of lakeside road landscape types **(light orange boxes in** Fig. 7**)**	- Classify roads based on the proportion in FOV or SVI. - Reveal basic landscape types but operate independently.	- Provide a more detailed classification with 37 refined types. - Reveal design intentions, such as using vegetation to shield lake views from roads while enhancing scenic experiences via lakeside pathways. - Capture dynamic changes in landscape types with topography and buildings.
RQ3: Visual characteristics of lake-view sites (Fig. 6)	- Show the proportions of the scenic-view visions. - FOV-based and SVI-based methods exhibit huge contradictions.	- Uncover the dual role of vegetation in enhancing depth through natural framing or obstructing scenic quality. - Connect visual composition with design strategies, such as in "*Lingering Snow on the Broken Bridge.*"

and visual linkage between the city and West Lake is critical, yet often obstructed by vegetation. In West Lake, approximately 15 obstructing trees could be selectively transplanted or pruned to restore lake visibility **(**Fig. 8b**)**. This recommendation is informed by the integrated results of CV and SVI analyses, which revealed that 6 high-potential corridors (CV range from 3 % to 10 %) were currently occluded by vegetation belts detected in SVI segmentation. This minimal intervention approach can be generalized: in urban heritage landscapes, vegetation-based obstructions can be identified through integrated VAMs and addressed via targeted ecological management, enhancing the spatial legibility of the heritage setting.

In many historic urban areas, such visual corridor obstructions accumulate over time due to unmanaged planting or redevelopment. A replicable strategy involves conducting a corridor inventory aligned with key heritage sightlines, then overlaying it with VAM results to identify conflict zones and prioritize targeted ecological interventions. These corridors serve not only as spatial connectors, but also as cultural devices to reveal or conceal specific elements (e.g., buildings, monuments, natural elements) at critical moments, echoing classical viewing practices.

(b) Managing and activating scenic-viewing points (orange boxes in Fig. 8a**):** The spatial arrangement of key viewing sites at West Lake, such as *Leifeng Pagoda* and *Broken Bridge*, reflects a nuanced interplay between visual prominence, compositional framing, and cultural symbolism. These sites offer panoramic or symbolic value, but the VAM analysis reveals a mismatch between potential visibility and actual design use: some areas with high VM remain underutilized, while others, historically significant, now suffer from visual obstruction due to vegetation overgrowth. According to the VM distribution results (Fig. 9), area near *Leifeng Pagoda* exhibit both top VM and CV, yet their current visibility has been degraded due to increased vegetation density (SVI, tree coverage >40 %). To address this, scenic-viewing points should be periodically reassessed based on updated visual metrics (e.g., CV, VM, and field composition). Underperforming sites can be reactivated through small-scale interventions, such as pruning, adjusted viewing platforms, or the introduction of interpretive cues that draw attention to framed elements in the view **(**Fig. 8c**)**.

At a broader level, viewpoint systems in urban heritage landscapes should be understood as distributed networks rather than isolated nodes. By creating multiple, layered viewing experiences, including distant (e.g., viewpoints beside *Leifeng Pagoda*), framed (e.g., viewpoints near *Broken Bridge*), elevated (e.g., viewpoints around *Kangxi's Palace*), and immersive perspectives, designers can accommodate diverse user preferences and spatial dynamics. Strategic layering also builds resilience into the landscape experience, ensuring visual continuity despite vegetation growth or urban change. More importantly, such viewpoint systems function as narrative devices in heritage landscapes, offering staged revelations of culturally significant elements. Managing and activating these systems is therefore essential for preserving the intended sequence and symbolism embedded in the spatial design.

(c) Structuring and managing route systems (yellow box in Fig. 8a**):** At West Lake, the circulation system reflects a layered spatial strategy: main vehicular roads are intentionally screened from lake views by dense vegetation, while pedestrian pathways are aligned with zones of high visibility and VM value, offering more direct scenic engagement. This separation helps mitigate the visual and acoustic impacts of traffic while preserving immersive experiences along the lakefront. However, field analysis reveals that some lakeside roads, especially those traversing hilly terrain, are excessively enclosed by roadside vegetation, leading to monotony and a loss of spatial rhythm. To improve visual legibility and experiential quality, it is advisable to selectively thin or prune vegetation along terrain-facing edges of these roads. Doing so would restore alternating patterns of openness and enclosure, allowing for glimpses of undulating hills without compromising the heritage landscape's serenity **(**Fig. 8d**)**.

In general, enhancing circulation systems in urban heritage landscapes requires both macro-scale design logic (e.g., route hierarchy and path alignment with visual potential) and micro-scale interventions (e.g., pruning, view corridor framing) to ensure spatial coherence and visual richness. Monitoring tools such as FOV-based simulations and updated SVI can guide adaptive maintenance strategies over time. This layered approach to circulation design does more than improve spatial coherence: it also preserves the movement-based experience that many heritage landscapes rely on to unfold meaning. Routes in such settings are not merely functional paths, but orchestrated cultural journeys shaped by changing visibility and spatial transitions.

(d) Vegetation as both structure and constraint: Vegetation plays a dual and sometimes conflicting role in the visual-spatial configuration of heritage landscapes. It can enrich visual composition through deliberate framing and layering, yet may also obstruct designed view axes when left unmanaged. At West Lake, this tension is evident in the contrast between intentionally framed lakefront perspectives and visually compromised heritage nodes. This duality reflects a broader management challenge identified in previous studies: vegetation contributes to spatial character and ecological value, but risks visual enclosure, fragmentation, and experiential degradation when overly dominant or poorly maintained (Ciaffi et al., 2018; Nijhuis, 2015; Tomao et al., 2015). Rather than treating vegetation as static background, visual management should regard it as an active design element: requiring periodic assessment, typological classification (e.g., framing vs. obstructing), and adaptive intervention cycles.

In heritage contexts, where visual legibility is essential for interpreting cultural meaning, vegetation must be continuously monitored and adjusted to maintain a dynamic balance between ecological

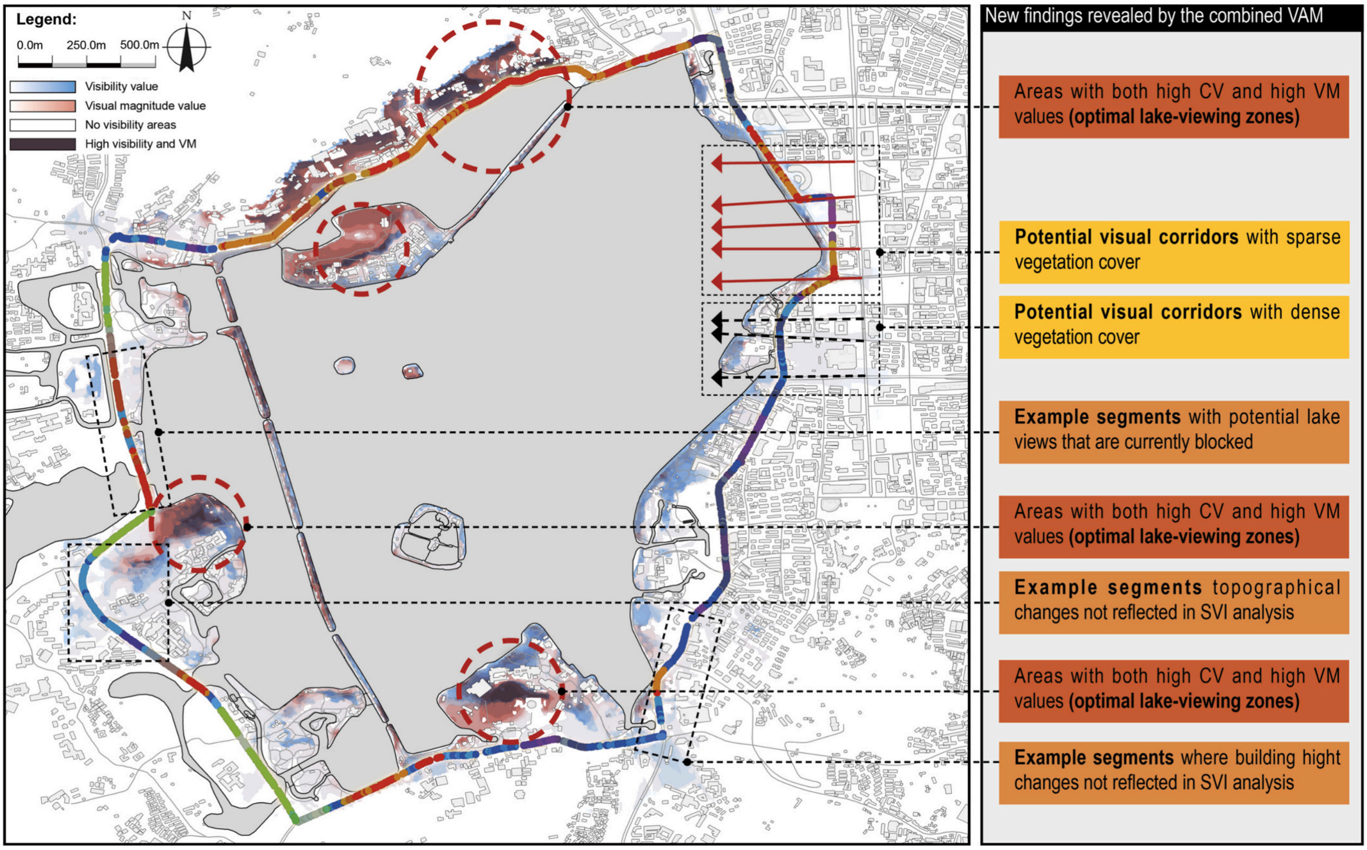


Fig. 7. The new findings derived from the combined VAMs.

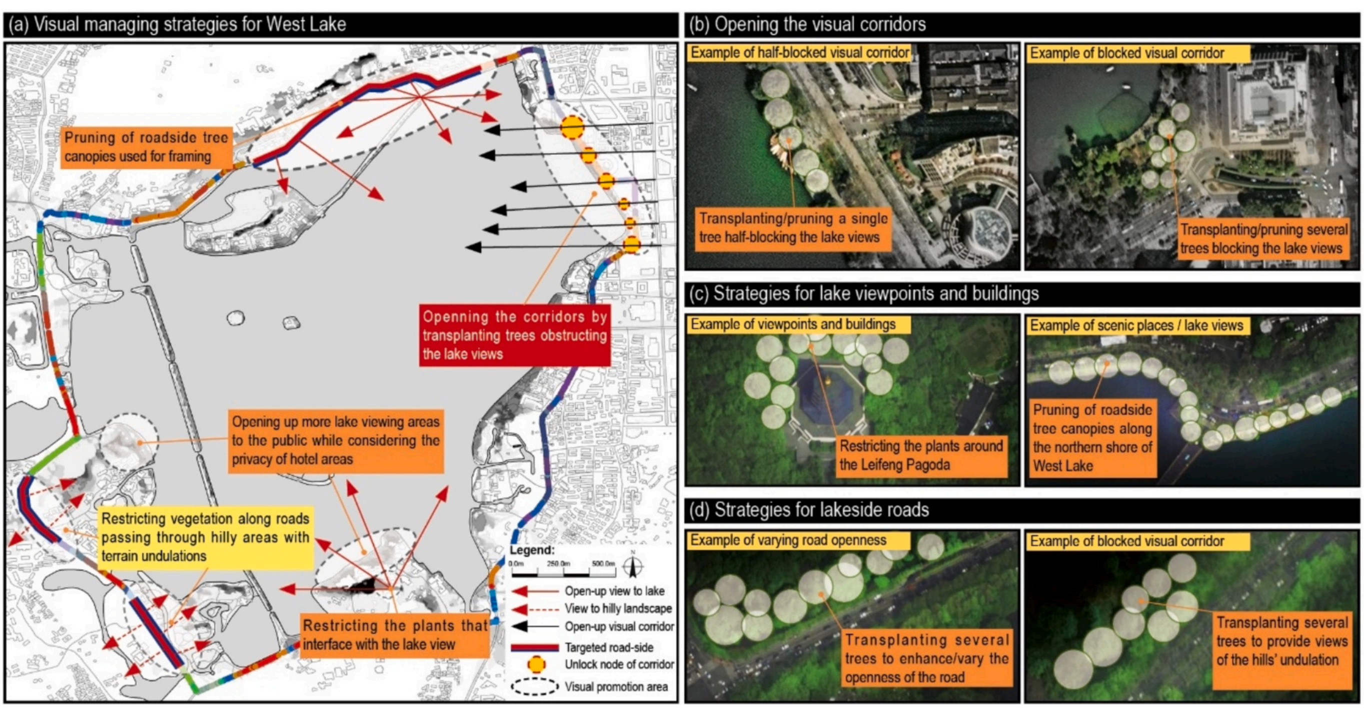


Fig. 8. Visual management strategies for West Lake: (a) overview of the strategies; (b) opening the visual corridors facing the lake; (c) strategies for managing the lake views from the scenic places and buildings; (d) strategies for managing the visual environments along the routes.

performance and visual clarity. In this sense, vegetation should be managed not only as a physical element but as a cultural interface. Its presence shapes what is revealed or concealed, when and how, thus playing a vital role in sustaining the intended experiential narrative of the heritage landscape.

In summary, the visual management strategies derived from West

Fig. 9. The limitations of SVI-based methods: (a) The SVI can be far different from human perception; (b) an example of a junction node choosing preference; (c) trees block the buildings.

Lake demonstrate how combined VAMs can move beyond analysis to directly inform actionable planning in urban heritage landscapes. From restoring blocked view corridors to structuring circulation routes and adapting vegetation dynamics, these strategies illustrate how visual-spatial data can translate into site-specific and transferable design responses.

6.2. Strengths and limitations of single VAMs

The comparison provides a deeper understanding of the four VAMs applied in the paper. The following summarizes the advantages and limitations of VAMs based on their actual performance in the West Lake case study.

6.2.1. Cumulative viewshed (CV)

The strength of this method lies in its broad applicability (Inglis et al., 2022; Wheatley, 2022). It is versatile in overlaying viewsheds from multiple distinct "point" elements (e.g., cultural sites) and calculating their visibility variations (Lake et al., 1998; O'Driscoll, 2017). It also applies to evaluating the visibility of extensive surface objects (e.g., mountains, lakes, building complexes) by employing "points" to describe these surfaces (Alphan and Aşur, 2021; Chamberlain and Meitner, 2013). However, a limitation of this method lies in its disregard for factors such as viewing angle and distance, which influence the exposure of "viewed objects" in human visual fields (Chamberlain and Meitner, 2013; Palmer, 2022).

This limitation became evident in West Lake where the CV values were high along certain lakeside road segments, yet the proportion of visible lake surface within the actual field of view was minimal. For instance, two integral landscape types, F1-S4-H (6.308 %) and F3-S2-H (0.327 %), together accounting for 6.635 % of the total, exhibited minimal lake surface in view despite being located in high-CV areas. This reflects a misalignment between vertical visibility metrics and human-eye-level experience. Furthermore, we observed that the CV method inadequately captured surface areas due to trade-offs in sampling resolution. For example, landscape types F4-S3-N (2.664 %) and F4-S4-N (2.570 %) displayed significant lake surface in FOV, yet CV analysis returned no visibility. This discrepancy, specific to the West Lake terrain and vegetation setting, illustrates how algorithmic simplifications can exclude key views.

6.2.2. Visual magnitude (VM)

The strength of this method lies in its ability to rapidly assess areas where the "viewed object" occupies a significant portion of the observer's visual field (Chamberlain and Meitner, 2013; Iverson, 1985). In the West Lake case, the method effectively highlighted sloped terrain with potential visibility advantages. However, the lack of perceptual precision became apparent when VM returned high scores in locations like the base of *Leifeng Pagoda* where tree cover blocked the view entirely. The method's insensitivity to vertical occlusion and visual layering reduced its reliability in heavily vegetated areas. By overlaying VM with CV, we found that the VM method tended to overestimate the visibility of core features in areas where steep slopes and close proximity to the lake result in narrow or constrained water views (dark red areas Fig. 7).

6.2.3. FOV-based visual analysis

This method's advantage is to address the limitations of vertical VAMs, which may not intuitively reveal the composition of the human visual field (Misthos et al., 2023). However, our application in West Lake highlighted several constraints. First, the computational demand of FOV modeling made it less suitable for wide-area heritage studies. Second, and more importantly, the omission of vegetation data during model generation led to substantial interpretive errors. Specifically, FOV analysis suggested that over 36 % of viewpoints had clear views of the lake, while SVI results indicated only 8.3 %, revealing a major overestimation caused by the lack of obstruction modeling. This discrepancy illustrates the risk of applying FOV-based analysis independently in vegetated contexts.

6.2.4. SVI-based visual analysis

SVI is one of the most widely used data types in contemporary urban visual research, especially in studies that incorporate computer vision (Han et al., 2023; Li et al., 2022; O'Regan et al., 2022). However, its limitations became evident in this study:

(a) Technical distortions resulted in significant perceptual mismatch. In West Lake, SVI overstated the presence of sky, 139 viewpoints registered sky proportions over 50 %, which is rarely true from a pedestrian perspective. This is due to sensor height and angle. The discrepancy between paved surface in FOV (36.1 %) and SVI (13.2 %) further confirmed this divergence. These errors, though consistent with prior studies (Xia et al., 2021a), were particularly problematic in heritage contexts where skyline and horizon perception play symbolic roles (Fig. 9a).

(b) The method was unable to detect buildings or terrain behind vegetative cover, even when clearly visible to human observers (Fig. 9b, Fig. 9c). In West Lake, this caused important scenic layers, like undulating hills or distant towers, to be misrepresented. Given that spatial legibility is key in heritage visual design, this limitation suggests that SVI should not be used in isolation when assessing cultural landscapes.

6.3. Advantages of combined VAMs

In visual landscape research, previous studies have increasingly advocated for combining multiple VAMs to enhance interpretive robustness (Palmer, 2022). However, such approaches often remain conceptual or limited to two-method combinations, typically integrating viewshed simulations with photographic assessments (Bishop and Miller, 2007; Wróżyński et al., 2020). This study advances these efforts by proposing and implementing a tri-layered integration framework that incorporates vertical VAMs (CV, VM), horizontal VAM (FOV-based), and reality-based VAM (SVI-based). Applied to the complex visual environment of West Lake, this integrated approach offers clear advantages in both analytical reliability and practical landscape planning.

First, the combined VAMs demonstrate methodological complementarity across data, perspective, and verification levels (Fig. 10). On the data level, digital simulations such as CV and VM effectively model topography and elevation, but fail to capture obstructions from vegetation. In contrast, SVI provides realistic street-level imagery that highlights these omissions. This data complementarity enables cross-checking and correction of visibility errors, particularly where FOV analysis significantly overestimated lake openness (36 %) compared to SVI validation (8.3 %). On the perspective level, vertical methods offer macro-scale spatial overviews useful for regional visibility corridors, while horizontal methods capture human-scale visual compositions critical for local landscape design. While Palmer (2022) emphasized the need to bridge these perspectives, our study operationalizes this integration to uncover spatial mismatches, such as high CV-FOV zones with low experiential visibility. Furthermore, by layering these methods, we establish an analytical loop where digital outputs can be verified, adjusted, or contextualized by reality-based results. Few prior studies have implemented such semantic segmentation-based validation.

Second, the combined approach supports detailed quantitative classification and targeted visual management. Through the integration of CV, VM/FOV, and SVI, this study classifies 37 distinct landscape types

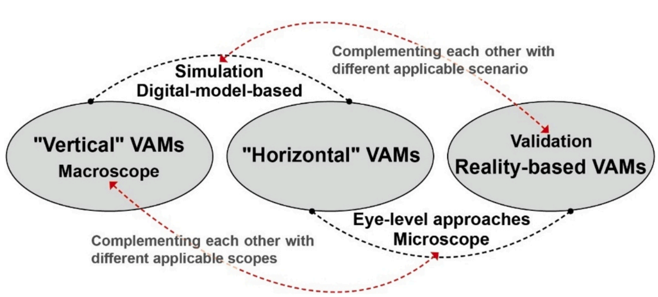


Fig. 10. Complementarity among different VAMs.

(Fig. 5), each characterized by specific combinations of ground type, vegetation coverage, and lake visibility. These types allow for precise spatial diagnosis: identifying road segments with blocked scenic potential, areas suitable for viewpoint interventions, and zones requiring vegetation adjustment. This contrasts with earlier studies such as Chamberlain and Meitner (2013) or Ioannidis et al. (2022), where visual assessments often focused on exposure magnitude or isolated elements without producing actionable spatial typologies. In the West Lake case, the derived categories directly inform design and management strategies—for instance, adjusting vegetation to restore blocked lake views. The method thus moves beyond general visual assessment toward an integrated planning tool, capable of bridging perceptual data and spatial interventions.

Overall, this study demonstrates that combining VAMs not only enhances visual interpretation but also creates a structured, verifiable basis for managing visibility in complex landscape contexts. By building upon and extending previous dual-method applications, the approach provides both analytical depth and practical utility in heritage landscape planning.

6.4. Limitations

Previous discussions have already demonstrated that the accuracy of the digital model significantly affects the precision of visual landscape research (Klouček et al., 2015). Notably, the model employed in this study is based on high-precision surveying maps. Despite this, differences remain between the generated DEM and the actual terrain, resulting in computational errors. Additionally, the DEM used in calculations does not include data on vegetation, service facilities, and many landscape structures, although these vertical elements greatly influence the computational outcome. Therefore, there are substantial differences from the actual conditions when calculating viewshed, VM, and FOV. Furthermore, due to data availability issues, the study area does not include the entire visible range of the lake surface, neglecting the visual space characteristics of many distant visible areas. In addition to errors generated in the digital modeling space, there are also limitations in real-world SVI-based visual analysis. First, the quality of SVI is generally adequate, but there are some technical defects, such as overexposure and underexposure. Second, irrelevant objects (e.g., people and vehicles in the images) can interfere with the accuracy of semantic segmentation. Additionally, the model used for semantic segmentation could also impact the results. Despite the limitations of each VAM, this paper attempted to employ multiple VAMs simultaneously to form a combined approach for visual landscape research to minimize these limitations.

In addition to these spatial and data-related constraints, the current methodology also faces challenges in accounting for culturally driven spatial logics that are not directly observable through visual metrics. For example, the analysis reveals that several iconic sites, such as those from the "*Ten Scenic Place*," do not align with zones of highest visibility or optimal visual composition as defined by the applied VAMs (Fig. 4). This suggests that cultural landscapes often embed layered meanings beyond spatial-optical logic, shaped by poetic traditions, symbolic narratives, or political intent. As such, while VAMs provide valuable quantitative insights into visual structure, they may overlook cultural rationales unless supplemented by historical and symbolic data. Future research could address this by incorporating historical maps or archival landscape documentation into the analytical process, enabling a more culturally informed interpretation of visual patterns in heritage landscapes.

7. Conclusions

This paper applies both single and combined VAMs to West Lake, highlighting the combined VAMs' effectiveness in identifying the visual characteristics of urban heritage landscapes. The contributions of this paper mainly cover three aspects:

(a) **Insights into the methodologies of visual landscape research:** Building on the case study of West Lake, this paper's contribution lies in constructing an integrative framework where multiple VAMs are strategically combined to reveal layers of meaning and managerial insights that are inaccessible through any single VAMs (which has not been systematicly discussed in the former literature).
(b) **Insights into the visual analysis and design/planning principles of urban heritage landscapes:** The paper reveals the multidimensional visual characteristics of urban heritage landscapes, providing scientific evidence for their visual management and planning. The combined VAM approach offers a practical framework for assessing view quality, identifying obstructed visual corridors, and informing vegetation management strategies. This supports more evidence-based decision-making in design, planning, and day-to-day maintenance of heritage landscapes with complex spatial-visual structures.
(c) **Insights on the visual features and visual management for West Lake:** The paper emphasizes the (i) significance of visual attributes, (ii) actionable strategies for vegetation and accessibility management, and (iii) maintaining visual connectivity for the preservation and planning of West Lake's visual environment.

In conclusion, this paper highlights the necessity of employing combined VAMs for an exhaustive visual analysis of urban heritage landscapes, supporting evidence-based design and maintenance decisions in heritage landscape contexts. The case study of West Lake in Hangzhou is representative yet lacks wide elements of the urban heritage landscape. Consequently, additional research is required to implement the combined VAM methodologies for the analysis of other instances of urban heritage landscapes.

CRediT authorship contribution statement

Yuyang Peng: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Steffen Nijhuis:** Conceptualization, Supervision, Writing – review & editing. **Mingwei Geng:** Methodology, Software. **Yingwen Yu:** Visualization.

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.

Data availability

The authors do not have permission to share data.

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