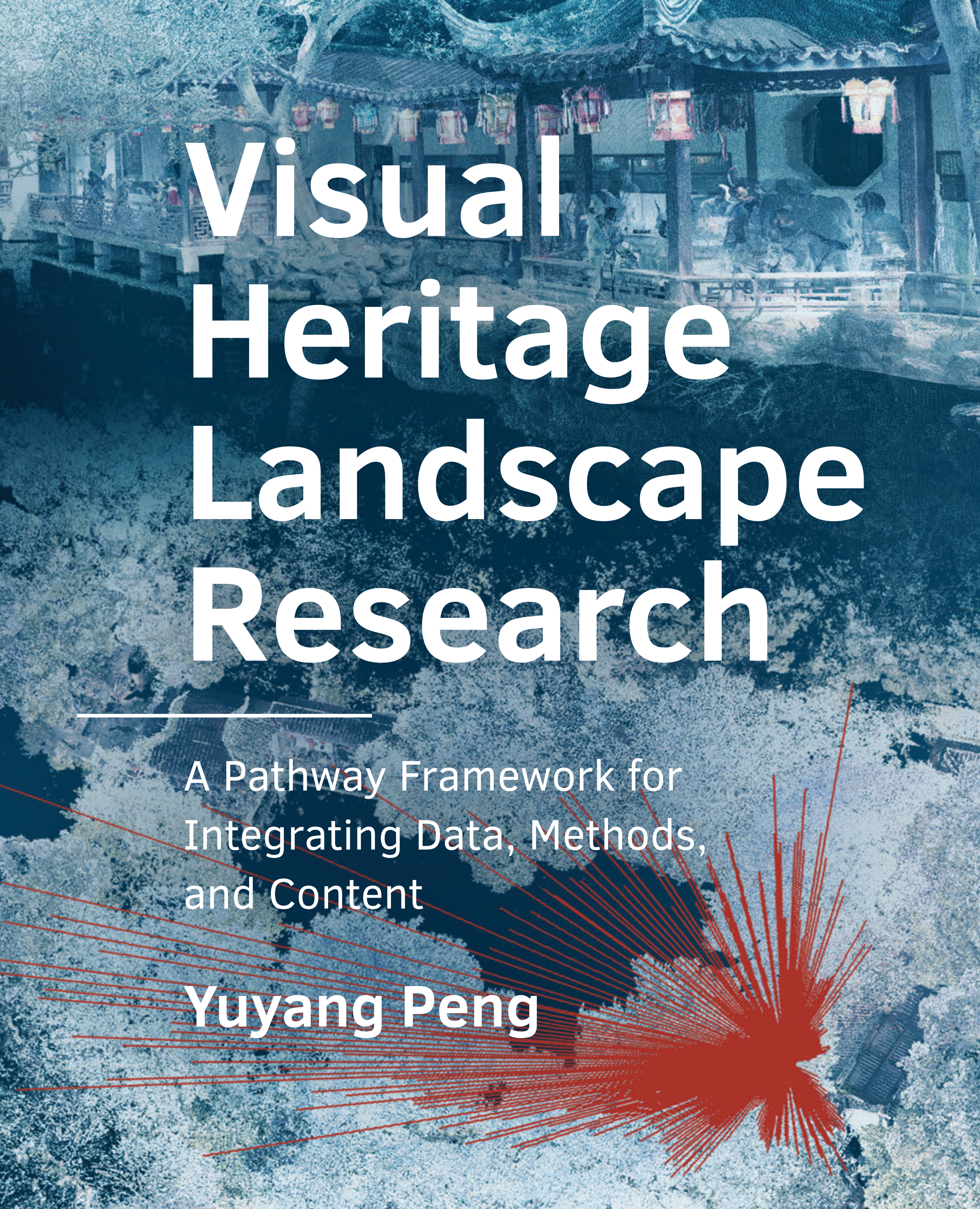

Visual Heritage Landscape Research

A Pathway Framework for Integrating Data, Methods, and Content

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Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus,
Prof.dr.ir. H. Bijl,
chair of the Board for Doctorates
to be defended publicly on
Monday, 1 June 2026 at 12:30

by

Yuyang PENG

TOC

This dissertation has been approved by the promotors and the copromotor.

Composition of the doctoral committee:

Rector Magnificus,	chairperson
Prof.dr.ing. Steffen Nijhuis	Delft University of Technology, promotor
Prof.dr. J.E. Stoter	Delft University of Technology, promotor
Dr. G. Agugiaro	Delft University of Technology, copromotor

Independent members:

Prof.dr. A.R. Pereira Roders	Delft University of Technology
Prof.Dr.-Ing. U. Pottgiesser	Delft University of Technology
Prof.dr. X. Wang	Beijing Forestry University
Prof.dr. O.G. Schroth	Hochschule Weihenstephan-Triesdorf
Prof.ir. E.A.J. Luiten	Delft University of Technology, reserve member

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TOC

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Contents

PART I Literature-grounded mapping, and framework construction

List of Tables

List of Figures

TOC

Summary

Heritage landscapes are experienced, interpreted, and governed through what people see. Visual qualities such as skyline continuity, landmark prominence, enclosure, openness, and view accessibility influence how heritage value is perceived and how spatial interventions are accepted. Meanwhile, urbanization, tourism development, and infrastructure expansion increasingly reshape visual environments, making visual governance a central concern in heritage conservation and landscape planning. Although visual heritage landscape research has grown rapidly, it often remains fragmented: studies tend to privilege either spatial-technical modelling or perception-based evaluation, and the connections between data, methods, and research aims are frequently implicit. This fragmentation limits cross-case comparability, weakens methodological accumulation, and reduces the usability of research outputs for practice. Therefore, the main objective of this thesis is to establish a pathway-oriented framework that links data-method-content configurations, enabling visual evidence to be translated into structured knowledge and practical guidance for spatial decision-making.

A pathway-oriented framework for visual heritage landscape research

This thesis conceptualizes visual heritage landscape research as a set of pathways that integrate three core components: the data used to describe visual environments, the methods used to analyze them, and the content outcomes expected for interpretation and decision support. Instead of treating methods as isolated techniques, the framework emphasizes how different components can be assembled in coherent sequences to match research purposes, spatial scales, and heritage contexts. Based on this logic, four expanded pathway types (EP-1 to EP-4) are proposed to bridge commonly separated approaches and to support more systematic, integrative study designs. Each pathway highlights a distinct integration focus, but collectively they provide a transferable structure for organizing visual research questions, selecting appropriate evidence, and producing outputs that are both analytically rigorous and implementation-oriented.

Pathway implementation through four case studies

The framework is implemented through four case studies that test the expanded pathways across diverse heritage landscape contexts and multi-scale conditions. EP-1 demonstrates an integrated spatial-perceptual pathway that connects spatial structure with perceptual evidence, enabling the interpretation of visual mechanisms and the validation of experienced visual qualities. EP-2 develops a digitally supported perception evaluation pathway that extends visual assessment to larger spatial coverage and multiple viewpoints through digital capture and modelling, providing scalable insight into visual quality and environmental preference. EP-3 proposes a multi-source visual-spatial pathway that integrates heterogeneous geo-data and multi-view analyses to strengthen interpretation across viewpoints and spatial levels, supporting a richer understanding of how visual patterns emerge from landscape structure. EP-4 advances a perception-informed decision pathway that couples perceptual evidence with visibility modelling to generate threshold-style rules and decision-ready outputs for visual impact assessment, planning control, and governance. Across cases, the thesis produces reusable indicators, spatial typologies, and pattern-based knowledge that can inform conservation strategies, design interventions, and management priorities.

Synthesis, navigation, and contributions

Building on cross-case synthesis, the thesis develops a navigational model that supports pathway selection and configuration according to objectives, constraints, data availability, and implementation needs. This model encourages modular entry points, allowing studies to begin from data constraints, methodological strengths, or governance questions, while still remaining comparable within a shared pathway system. Overall, the thesis contributes by structuring a fragmented field into a coherent framework of pathways, offering modular workflows that connect data acquisition-computation-assessment, and translating visual heritage landscape research into evidence-informed, interpretable, and actionable tools. These contributions aim to strengthen the integration of visual evidence into heritage landscape conservation, planning, and design, and to support more transparent and robust decision-making in visually sensitive heritage contexts.

Samenvatting

Erfgoedlandschappen worden ervaren, geïnterpreteerd en bestuurd via wat mensen zien. Visuele kwaliteiten zoals de continuïteit van de skyline, de zichtbaarheid van herkenningspunten, mate van beslotenheid of openheid, en de toegankelijkheid van uitzichtpunten beïnvloeden hoe erfgoedwaarden worden waargenomen en hoe ruimtelijke ingrepen worden geaccepteerd. Tegelijkertijd veranderen verstedelijking, toeristische ontwikkeling en infrastructuurprojecten in toenemende mate het visuele landschap, waardoor visuele sturing een kernvraagstuk wordt binnen erfgoedbescherming en landschapsplanning. Hoewel onderzoek naar visuele erfgoedlandschappen sterk is toegenomen, blijft het vaak gefragmenteerd: studies benadrukken doorgaans óf ruimtelijk-technische modellering óf perceptie-gebaseerde evaluatie, terwijl de relaties tussen data, methoden en beoogde onderzoeksuitkomsten vaak impliciet blijven. Deze fragmentatie beperkt de vergelijkbaarheid tussen casussen, belemmert methodologische cumulatie en vermindert de toepasbaarheid van resultaten in de praktijk. Het centrale doel van dit proefschrift is daarom het ontwikkelen van een pathway-georiënteerd raamwerk dat data-method-content configuraties expliciet verbindt, zodat visueel bewijs kan worden omgezet in gestructureerde kennis en toepasbare ondersteuning voor ruimtelijke besluitvorming.

Een pathway-georiënteerd raamwerk voor onderzoek naar visuele erfgoedlandschappen

Dit proefschrift benadert onderzoek naar visuele erfgoedlandschappen als een set van pathways die drie kerncomponenten integreren: de data waarmee visuele omgevingen worden beschreven, de methoden waarmee deze worden geanalyseerd, en de inhoudelijke uitkomsten die nodig zijn voor interpretatie en besluitondersteuning. In plaats van methoden te behandelen als losse technieken, benadrukt het raamwerk hoe verschillende componenten in samenhangende sequenties kunnen worden geconfigureerd, passend bij onderzoeksdoelen, ruimtelijke schaalniveaus en erfgoedcontexten. Op basis van deze logica worden vier uitgebreide pathway-typen (EP-1 tot en met EP-4) voorgesteld om vaak gescheiden benaderingen te overbruggen en om meer systematische, integratieve onderzoeksontwerpen mogelijk te maken. Elk pathway-type legt een ander accent in integratie, maar gezamenlijk vormen zij een overdraagbare structuur om visuele onderzoeksvragen te ordenen, passend bewijs te selecteren en uitkomsten te produceren die zowel analytisch robuust als praktijkgericht zijn.

Toepassing van de pathways via vier casestudies

Het raamwerk wordt operationeel gemaakt via vier casestudies die de uitgebreide pathways toetsen in uiteenlopende erfgoedlandschappen en op verschillende schaalniveaus. EP-1 laat een geïntegreerde ruimtelijk-perceptuele pathway zien die ruimtelijke structuur koppelt aan perceptueel bewijs, waardoor visuele mechanismen kunnen worden geïnterpreteerd en ervaren visuele kwaliteiten kunnen worden gevalideerd. EP-2 ontwikkelt een digitaal ondersteunde perceptie-evaluatie pathway die visuele beoordeling opschaalt naar grotere ruimtelijke dekking en meerdere perspectieven via digitale vastlegging en modellering, en zo schaalbare inzichten levert in visuele kwaliteit en omgevingsvoorkeur. EP-3 stelt een multi-source visueel-ruimtelijke pathway voor die heterogene geo-data en multi-view analyses integreert om interpretatie over verschillende gezichtspunten en schaalniveaus te versterken, en om beter te begrijpen hoe visuele patronen voortkomen uit landschapsstructuur. EP-4 werkt een perceptie-gedreven besluitvormingspathway uit die perceptueel bewijs koppelt aan zichtbaarheidmodellering, met als doel drempel-achtige regels en besluitklare outputs te genereren voor visual impact assessment, planningssturing en governance. Over de casussen heen levert het proefschrift herbruikbare indicatoren, ruimtelijke typologieën en patroon-gebaseerde kennis op die kunnen bijdragen aan conserveringsstrategieën, ontwerpinterventies en beheerprioriteiten.

Synthese, navigatie en bijdragen

Op basis van een synthese over de casestudies heen ontwikkelt dit proefschrift een navigatiemodel dat de selectie en configuratie van pathways ondersteunt, afhankelijk van doelen, randvoorwaarden, databeschikbaarheid en implementatiebehoeften. Dit model stimuleert modulaire instappunten: studies kunnen starten vanuit databeperkingen, methodologische sterktes of governance-vragen, terwijl zij toch vergelijkbaar blijven binnen een gedeeld pathway-systeem. In totaal draagt het proefschrift bij door een gefragmenteerd onderzoeksveld te structureren tot een samenhangend raamwerk van pathways, modulaire workflows te bieden die data-acquisitie-berekening-beoordeling verbinden, en onderzoek naar visuele erfgoedlandschappen te vertalen naar evidence-informed, interpreteerbare en toepasbare instrumenten. Deze bijdragen beogen de integratie van visueel bewijs in erfgoedlandschapsbescherming, planning en ontwerp te versterken en transparantere en robuustere besluitvorming te ondersteunen in visueel gevoelige erfgoedcontexten.

1 Introduction

This chapter introduces heritage landscapes as culturally constructed and physically formed environments where visual experience plays a central role in interpretation, conservation, planning, and communication. It outlines the core research problem: although visual heritage landscape research is methodologically rich, it remains structurally fragmented, with data sources, analytical methods, and research contents often developing in parallel rather than as integrated configurations. To address this gap, the chapter defines the overall objective of the thesis, formulates three research questions, and explains why a pathway-oriented perspective is needed to connect emerging data, hybrid methods, and diverse visual tasks. Finally, it presents the thesis structure across three parts, clarifying how the literature-grounded mapping, case-based pathway exploration, and cross-case synthesis jointly contribute to a structured, adaptable framework for visual heritage landscape research.

1.1 Background

Heritage landscapes are the result of long-term interactions between human societies and the natural environment (Crumley et al., 2017; Tengberg et al., 2012). They reflect how people have shaped, adapted to, and assigned meaning to their surroundings over time, giving rise to landscapes that are both physically formed and culturally constructed (Aplin, 2007; Greider & Garkovich, 1994). Due to this intricate composition, heritage landscapes hold both cultural and ecological value (Farina, 2000). Culturally, they preserve historical narratives and act as repositories of shared memory; ecologically, many contribute to biodiversity, microclimate regulation, and sustainable land use (Leifeste & Stiefel, 2018; Wall, 2014). Their dual significance positions them as critical subjects in both cultural heritage conservation and environmental planning (Kalman & Létourneau, 2020; Mason & Avrami, 2002).

Visual analysis and management have long been central concerns in the study of heritage landscapes, as vision mediates how visual-spatial features are perceived and how symbolic meanings are conveyed and interpreted (Peng et al., 2025a). Effective visual landscape research supports diverse functions, including landscape evaluation, conservation planning, visualization, and public communication (Lovett et al., 2015; Metze, 2020). Such research can be understood through a “conceptual triangle” composed of three interdependent components **(FIG. 1.1)**:

a) **Contents**: the specific heritage objects and landscape elements under investigation, as well as the thematic concerns they raise, whether for management (e.g., utilization or protection), analytical understanding, or visual archiving (Howard, 2003; Letellier & Eppich, 2015);

b) **Methods**: the tools and techniques applied to process, interpret, simulate, or intervene in visual qualities, ranging from GIS-based visibility analysis and spatial metrics to participatory mapping and immersive modeling (Wróżyński et al., 2024);

c) **Data**: the representational formats and sources used to document, analyze, and manage visual experience, including images, point clouds, eye-tracking data, and 3D polygonal models (Rodríguez-Gonzálvez et al., 2017; Y. Yu et al., 2025).

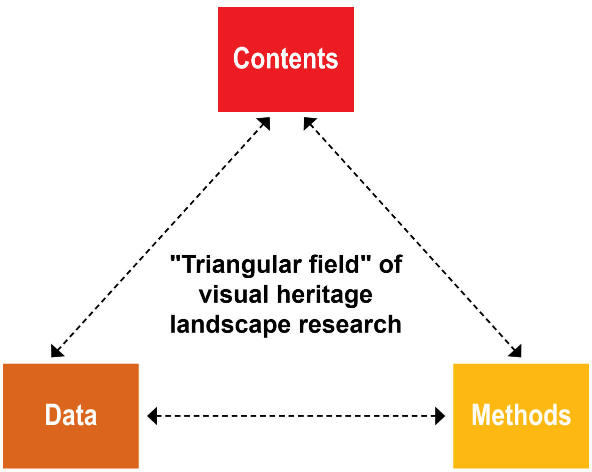

FIG. 1.1 Conceptual triangle: Representing the interdependent relationship among contents, data, and methods in visual research on heritage landscapes.

These components define a “conceptual triangular field” in which each dimension informs and constrains the others. Existing studies have often approached this “triangle” from different angles: whether emphasizing thematic content, advancing data acquisition and application, or focusing on methodological innovation, resulting in distinct research clusters and relatively fixed analytical pathways. Despite growing academic interest, however, the full potential of this conceptual space remains underexplored. There is a clear need to expand the possible combinations of contents, data, and methods in ways that respond to emerging challenges in both research and practice. At the same time, researchers require clearer strategies for navigating this “conceptual triangular field” and constructing context-sensitive, integrative visual research pathways. This thesis responds to these gaps by using the “conceptual triangle” as a conceptual framework to identify, organize, and extend the methodological and thematic configurations of visual heritage landscape research, with the goal of supporting more adaptive and practically meaningful future directions.

1.1.1 Contents: heritage landscapes and thematic concerns

This section addresses the content dimension of visual heritage landscape research, which includes two closely connected aspects. On one hand, heritage landscapes exist in diverse forms and spatial scales: from small-scale historic gardens and urban fragments to large-scale rural systems and natural-cultural hybrids (Ashrafi & Shokrani, 2019; Papageorgiou, 2016). These differences shape the physical visual-spatial features of landscape environment and the interpretive depth and perceptual experience they afford (Shao et al., 2024) . On the other hand, such variability gives rise to a wide range of visual research and application concerns, including how to preserve visual continuity, enhance cultural legibility, evaluate change, or support public engagement (Bell, 2019). But as a basis of the further discussions, the definition of “heritage landscape” need to be stabilized in this thesis.

1.1.1.1 Definition of heritage landscape

Heritage landscapes have been defined in multiple ways, reflecting diverse disciplinary traditions and policy frameworks. Under the World Heritage Convention, UNESCO cultural landscapes are described as “combined works of nature and humankind,” grouped into designed, organically evolved (continuing or relict), and associative types (Rössler, 2006). The European Landscape Convention (ELC) adopts a broader formulation, defining landscape as “an area, as perceived by people,” whose character results from the interaction of natural and/or human factors (Bell, 2012; Zube & Pitt, 1981). The former provides a legal and administrative basis for inscription and monitoring, whereas the latter offers a conceptual and policy foundation that highlights perceptibility as a condition for recognition. McDowell (2016) views heritage as an accumulated record of cultural and ecological processes over time. Tengberg et al. (2012) emphasize heritage as a source of cultural ecosystem services (CES), including aesthetics, identity, and spirituality. Heras et al. (2019) focus on governance and the integration of expert and community perspectives. Approaches such as the *Historic Urban Landscape* (HUL) and the *Faro Convention* further integrate spatial and visual attributes with social practices and community values. More recently, researchers have drawn attention to “everyday,” vernacular, or ordinary heritage landscapes that may lack formal designation but are meaningful to communities through identity, memory, and belonging, expressed both through visible cues and through daily practices (Jones, 2016; Waterton & Watson, 2010).

This thesis adopts a pragmatic and operational definition: **a heritage landscape is any landscape-scale entity that carries heritage significance by virtue of either formal designation** (such as UNESCO, national, or local listings) or explicit community recognition. We take a balanced position between expert assessment and community claims. Community recognition deserves serious consideration, while expert validation against widely accepted criteria, such as integrity, authenticity, and historical continuity, helps safeguard the essential attributes that support conservation and international comparability (Arriaza et al., 2004; Deacon & Smeets, 2013). This dual pathway (formal designation or community recognition) constitutes the operational basis for our literature selection and coding in subsequent analyses, ensuring consistent use of the term “heritage landscape.” Given the contested nature of definitions and the stance adopted here, the scope of heritage landscape spans a wide range of types and spatial scales.

1.1.1.2 Heritage landscape as research objects

Heritage landscapes are formed through the long-term interaction of natural processes and human activities, rather than being solely the result of cultural creation or reactive adaptation (Dastgerdi et al., 2019; Plieninger & Bieling, 2012). They emerge from the co-evolution of ecological dynamics, spatial transformations, and sociocultural practices over time (Veldpaus, 2015). The relative degree of human involvement in shaping these landscapes varies significantly, and this variation provides a meaningful basis for classification (Turner, 1989). The UNESCO World Heritage Convention categorizes heritages into three major types (Rössler, 2006), and we can also broadly group heritage landscapes into these categories in lines with this logic:

a) **Heritage landscape as cultural heritage**: These landscapes result from the interaction between human activities and the natural environment, reflecting the historical evolution of human-environment relationships. They fall under the category of cultural heritage, including traditional agricultural landscapes, historic gardens, and designed parks (Aplin, 2007; Farina, 2000). In 1992, UNESCO officially recognized "cultural landscapes" as a distinct category of World Heritage, defining them as "the combined works of nature and humankind", illustrating the adaptation and transformation of human societies under environmental and sociocultural influences (Rössler, 2006; Titchen, 1996). Cultural landscapes are further classified into: *(i) Designed landscapes,* intentionally created for aesthetic, functional, or symbolic purposes (e.g., historic gardens); *(ii) Organically evolved landscapes***,** shaped by socio-economic or environmental processes over time, which can be continuing landscapes (still evolving) or relict landscapes (preserved in their historical form); and *(iii) Associative cultural landscapes*, strongly linked to cultural or religious traditions, even if they lack significant physical modifications.

b) **Heritage landscape as natural heritage:** Primarily formed by natural processes, these landscapes are recognized for their exceptional natural beauty, geological significance, or ecological value. Examples include ancient forests, canyons, coral reefs, and mountain ranges.

c) **Heritage landscape as mixed heritages:** These landscapes hold both cultural and natural significance. According to the World Heritage Convention Operational Guidelines, a landscape that meets the criteria for both cultural and natural heritage is classified as "mixed heritage", highlighting its dual value in cultural and ecological preservation.

In addition to typological distinctions, heritage landscapes can be differentiated based on spatial scale, which significantly influences both their visual-spatial characteristics and the ways in which they are perceived and experienced. These scales form a continuum ranging from localized sites to broad territorial systems. By synthesizing various classification schemes from landscape planning (Antrop, 2000; Taylor, 2017), heritage typology (Organisation, 2008), and visual analysis (Nijhuis, Van Lammeren, & van der Hoeven, 2011), the following seven categories are used in this thesis **(FIG. 1.2)**:

a) **Site**: Single, spatially defined heritage elements such as an imperial garden or a monumental building.

b) **Cluster**: A group of related but spatially distributed heritage features, forming a unified conceptual or functional whole (e.g., architectural ensembles, monastic networks).

c) **Area**: Contiguous urban or rural sections characterized by shared identity or function, such as a historic urban core or a traditional village.

d) **Landscape**: Visually or ecologically coherent units shaped by long-term human-nature interaction, such as terraced agricultural systems or cultural river valleys.

e) **Regional**: Larger governance-defined zones encompassing multiple landscape units, often associated with planning policies or conservation frameworks (e.g., heritage buffer zones, cultural eco-regions).

f) **National**: Near-complete country-scale heritage systems, often symbolic or unifying at the national level.

g) **International**: Transboundary or cross-country landscapes jointly recognized for their shared heritage value (e.g., Silk Road corridors, mountain ranges with shared cultural symbolism).

The typological and spatial diversity of heritage landscapes provide a foundation for their classification and a basis for understanding their distinct visual conditions and research needs (Sowińska-Świerkosz, 2017). Whether at the scale of a single site or across transboundary systems, each type and scale of landscape brings with it specific challenges and opportunities for visual engagement (Arts et al., 2017), ranging from the preservation of sightlines and spatial composition, to the interpretation of symbolic meaning and experiential quality.

TOC

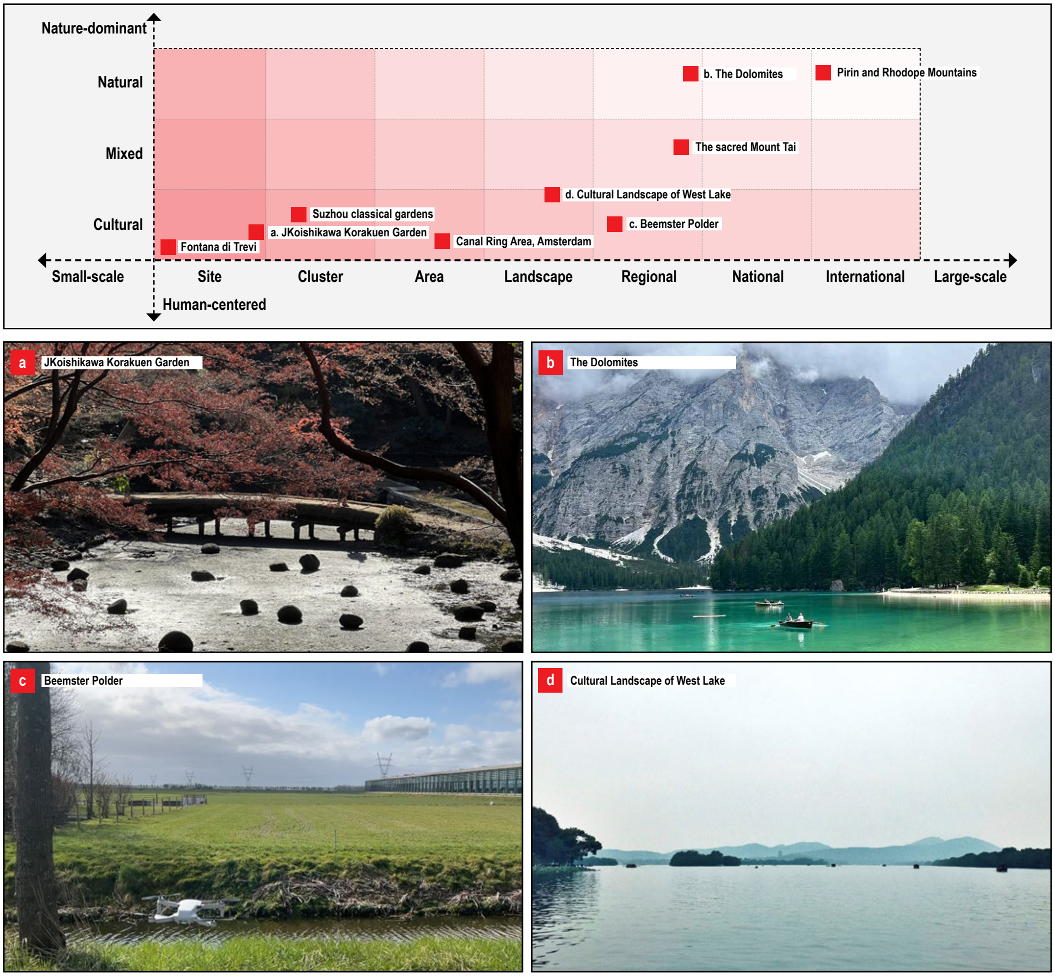

FIG. 1.2 Typological positioning of heritage landscapes based on their cultural-natural attributes and spatial scales: (a) Japanese Okayama Korakuen Garden (cultural, site scale, by Z. Wu); (b) The Dolomites (natural, national-scale, by F. Tang); (c) Beemster Polder, the Netherlands (cultural, regional scale, by author); (d) Cultural Landscape of West Lake, China (cultural, landscape scale, by Z. Wu).

1.1.1.3 Thematic concerns on visual heritage landscape research

Building upon the diversity of heritage landscape types and spatial scales discussed above, it becomes clear that visual research in this context must respond to distinct thematic challenges (Inglis et al., 2022; Windhager et al., 2019). Unlike ordinary landscapes, heritage landscapes are marked by their exceptional cultural and/or ecological value, often carrying symbolic meanings, historical narratives, and strong associations with collective identity (Tengberg et al., 2012; Whelan, 2016). Their visual character is not merely aesthetic, it serves as a medium through which authenticity, continuity, and place-based meaning are perceived and interpreted (Kopec & Bliss, 2020).

At the same time, heritage landscapes tend to be visually fragile and highly sensitive to change. Even small-scale visual disturbances, such as alterations in skyline, material texture, vegetation structure, or view corridors, can undermine their perceived authenticity, dilute their cultural resonance, or trigger the loss of identity (Deghati Najd et al., 2015; Fang et al., 2021). This heightened sensitivity demands special attention to how heritage landscapes are visually assessed, protected, and communicated (Ashrafi et al., 2021). Accordingly, thematic concerns in visual heritage research often concentrate on the following key issues:

a) **Conservation of heritage landscape:** Heritage landscapes are increasingly threatened by a variety of pressures in contemporary society, including urban encroachment, infrastructure development, climate change, and tourism-related impacts. In response to these challenges, international organizations such as UNESCO, ICOMOS, and IFLA have issued a series of charters and guidelines aimed at safeguarding the visual, ecological, and cultural integrity of heritage landscapes **(TABLE 1.1)**. These include foundational documents such as the *Athens Charter* (1931) and *Venice Charter* (1964), as well as more targeted frameworks like the *Florence Charter* (1981) for historic gardens, the *Lisbon Charter* (2016) for agricultural landscapes, and the *Recommendation on the Historic Urban Landscape* (2011), which integrates visual, social, and ecological aspects into urban heritage management (Deghati Najd et al., 2015). Notably, many of these frameworks, particularly those that address historic urban areas, gardens, rural systems, and cultural-natural interfaces, emphasize the importance of visual-spatial features in maintaining landscape authenticity and identity (Nezhad et al., 2015; Nitavska, 2020). The protection of view corridors, material coherence, and symbolic visibility is increasingly recognized as integral to heritage conservation (Lopes et al., 2019; Sukwai et al., 2022). Therefore, visual analysis and monitoring are not only tools for documentation but also essential strategies for ensuring the continued legibility and value of heritage landscapes under pressure (Pietroni & Ferdani, 2021; Sarihan, 2021).

TABLE 1.1 Summaries of the charters for heritage landscape conservation and management

No	Charter Name	Issuing Organization	Year	Descriptions
1	Athens Charter[1]	International Conference on Historic Monuments	1931	The first international charter on heritage protection, emphasizing scientific conservation, authenticity preservation, and international cooperation.
2	Venice Charter[2]	ICOMOS	1964	Protects the authenticity and integrity of historic buildings, opposes excessive reconstruction, and emphasizes minimal intervention and environmental conservation.
3	Florence Charter[3]	ICOMOS & IFLA	1981	Specifically focuses on the protection of historic gardens, emphasizing the integrity of gardens, plants, and spatial layout.
4	Nairobi Recommendation[4]	UNESCO	1976	Protects historic urban areas, preserving their social, cultural, and economic functions, and encourages integration into urban planning.
5	Washington Charter[5]	ICOMOS	1987	Concerns the protection of historic towns, emphasizing the holistic preservation of buildings, public spaces, and social structures.
6	Madrid-Toledo Document[6]	ICOMOS	2011	Introduces the Historic Urban Landscape (HUL) concept, promoting the balance between heritage conservation and urban development.
7	Lisbon Charter[7]	ICOMOS & IFLA	2016	Focuses on the protection of agricultural cultural landscapes, emphasizing sustainable management and community involvement.
8	Recommendation on Historic Urban Landscape[8]	UNESCO	2011	Establishes the HUL concept, integrating planning, ecology, and social aspects for comprehensive heritage management.
9	Principles for Rural Landscape as Heritage[9]	ICOMOS & IFLA	2017	Highlights the cultural and ecological value of rural landscapes, promoting sustainable management and community participation.

1 First International Congress of Architects and Technicians of Historic Monuments. (1931). *The Athens Charter for the Restoration of Historic Monumen*ts.
2 International Council on Monuments and Sites. (1964). International charter for the conservation and restoration of monuments and sites (The Venice Charter).
3 International Council on Monuments and Sites. (1982). *Charter of Historic Gardens (The Florence Charter)*.
4 United Nations Educational, Scientific and Cultural Organization. (1976). *Recommendation concerning the safeguarding and contemporary role of historic* areas.
5 International Council on Monuments and Sites. (1987). *Charter for the conservation of historic towns and urban areas (Washington Charter)*.
6 ICOMOS International Scientific Committee on 20th Century Heritage (ISC20C). (2*011). Madrid Docu*ment 2011.
7 ICOMOS–IFLA. (2017). Principles concerning rural landscapes as heritage.
8 United Nations Educational, Scientific and Cultural Organization. (2011). *Recommendation on the Historic Urban Lan*dscape.
9 International Council on Monuments and Sites, & International Federation of Landscape Architects. (2017). *Principles concerning rural landscape*s *as heritage*.

b) **Analysis and interpretation:** These theoretical frameworks support the identification and analysis of a wide range of visual features, such as spatial layout, openness, visibility, skyline composition, and the proportions of natural and built elements, as well as more abstract attributes like mystery, harmony, or atmosphere. Importantly, these features are not only descriptors; they are carriers of meaning, linking tangible forms with intangible heritage values such as memory, identity, and cultural continuity. As a result, visual analysis has become a core theme in heritage landscape research. Recent studies increasingly focus on visual characterization and aesthetic quality assessment, not only to document landscape conditions but to inform decision-making, design guidelines, and value-based planning. Other critical concerns include public perception and well-being, exploring how landscape features support emotional resonance, place attachment, and psychological health. Moreover, visual methods are used to assess heritage values, environmental impacts, and landscape transformation across ecological, cultural, and social dimensions.

c) **Management, planning, and sustainable use:** Heritage landscapes demand not only preservation but also effective management, forward-looking planning, and meaningful integration into contemporary life. Visually, this includes maintaining spatial coherence, controlling intrusive changes, and ensuring the continuity of landscape character. At the same time, heritage landscapes are increasingly seen as active resources, supporting functions such as cultural tourism, regional identity building, and sustainable development. These dual demands highlight the need to balance visual continuity with adaptive use, making visual research central to both regulation and transformation in heritage planning.

d) **Communication and engagement across audiences:** Effective communication is essential for sustaining the value of heritage landscapes. These landscapes carry meanings that must be interpreted, shared, and made accessible to diverse audiences, including local communities, residents, visitors, heritage professionals, planners, policymakers, land managers, educators, creatives, and underrepresented groups. Visual communication plays a central role in this process, shaping how different stakeholders perceive, remember, and emotionally connect with heritage. Engagement strategies should therefore be audience-specific and multimodal, such as exhibitions and signage, maps and digital storytelling, virtual or augmented reality experiences, participatory mapping, co-design workshops, and citizen science. Tailoring content, language, and media to each audience while enabling two-way dialogue enhances awareness, strengthens stewardship, and builds a shared yet plural heritage identity.

While the above themes represent key areas of focus, they do not cover the full range of concerns in visual heritage research. Many studies engage with multiple themes simultaneously, and new thematic directions continue to emerge. As societal values evolve and new challenges arise, the scope and complexity of visual research in heritage landscapes will require continuous review and expansion.

1.1.2 Methods: Visual landscape research for heritage landscapes

Visual landscape research provides essential methodological tools to understand how heritage landscapes are perceived, evaluated, and managed. It bridges the physical configuration of space with the perceptual responses it evokes. As summarized by Nijhuis et al. (2011), this field integrates three complementary components: *(a) Geographic Information Science (GISc)-based spatial analysis*, *(b) perception-oriented approaches*, and *(c) planning, design, and management frameworks*. Each plays a distinct but interconnected role in revealing and sustaining the visual values of heritage landscapes (Nijhuis & de Vries, 2019; Nijhuis & Reitsma, 2011; Peng et al., 2024).

a) **GISc-based methods and techniques**: These methods form the analytical backbone of visual landscape research. They focus on simulating and quantifying spatial visibility, terrain structure, and land use configuration (Liu, 2020; Nijhuis, van Lammeren, & Antrop, 2011). Common tools include viewshed analysis, spatial overlays, and landscape metrics, which enable researchers to model visual exposure, detect visual-spatial patterns, and support scenario analysis (Fisher, 1996). Importantly, GIS platforms also function as integrative environments, facilitating the combination of spatial data with perceptual and planning inputs (Llobera, 2003).

b) **Landscape perception approaches**: This component investigates how individuals and groups perceive and interpret visual landscapes. Rooted in environmental psychology and behavioral geography, such methods include surveys, interviews, field observations, and participatory mapping (Llobera, 2003; Misthos et al., 2023). They capture aesthetic preferences, emotional resonance, and place attachment: dimensions often overlooked in purely spatial analyses (Brown & Raymond, 2007; Jaśkiewicz, 2015). Recent advances such as eye-tracking and immersive techniques further enrich understanding of attention, affect, and engagement, particularly relevant in heritage contexts (Rusnak et al., 2025).

c) **Landscape planning, design, and management concepts**: The third strand connects visual insights to planning and action (López Sánchez et al., 2020). This includes tools for visual sensitivity mapping, heritage zoning, and impact assessment, as well as broader design strategies and scenario-building methods (Ahern, 1999; Tress & Tress, 2003). These approaches support decision-making across scales (from site-specific interventions to regional conservation frameworks), ensuring visual coherence, authenticity, and adaptability in the face of change (Jassim et al., 2025). They often synthesize analytical outputs and perceptual feedback into implementable strategies (Bell, 2012).

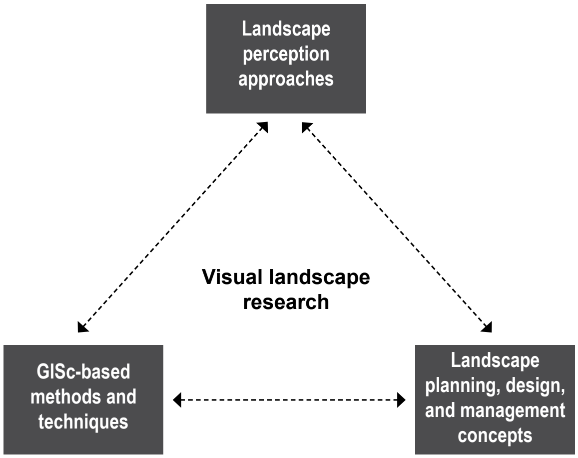

FIG. 1.3 Visual landscape research: Characterized by the integration of landscape planning, design and management, landscape perception and GISc-based methods and techniques (adapted from Nijhuis, 2015).

While the above three categories provide a foundational structure for visual landscape research, the field is far from static. In practice, methodological boundaries often blur: studies increasingly employ hybrid strategies that combine spatial modeling, perceptual analysis, and planning frameworks. Moreover, new challenges, ranging from climate adaptation to participatory governance, continue to reshape research priorities and methodological demands. In response, emerging technologies, shifting societal concerns, and the growing availability of high-resolution spatial and sensory data have driven the development of new methods or reconfigured traditional approaches. For instance, immersive visualization, machine learning (ML)-based interpretation, and user-generated content (UGS) are not just tools but methodological enablers, expanding how visual perception and spatial dynamics can be studied (Lian & Xie, 2024; Y. Yu et al., 2025). As such, methods are expanding in number and evolving in function, thus becoming more integrative, adaptive, and data-responsive.

1.1.3 Data: Sources for capturing spatial-perceptual information

Visual landscape research increasingly relies on multi-source and multi-scale data to capture the complexity of heritage landscapes (Peng et al., 2025b). As research methods and technologies continue to develop, the types, amount, and functions of data also expand. These data serve both as analytical inputs and as representations of perception, memory, and cultural meaning (Walliss & Rahmann, 2016). Based on their roles and applications, the data sources can be broadly grouped into three interrelated categories:

a) **Spatial-structural data**: These data underpin spatial analysis in visual research. They include high-resolution imagery, digital elevation models (DEMs), topographic maps, and 3D models, as well as spatial parameters such as viewpoint coordinates, viewing directions, and terrain configuration (Boulton & Stokes, 2018; Poli et al., 2004). Emerging acquisition techniques such as UAV photogrammetry, LiDAR scanning, and image-based point cloud reconstruction (e.g., dense image matching, Structure-from-Motion) enhance the accuracy and richness of visual modeling (Pepe et al., 2022). This category of data supports visibility simulation, spatial hierarchy analysis, and structural mapping of heritage landscapes (Hu & Minner, 2023).

b) **Perception and behavior data:** This category addresses how individuals and groups experience, interpret, and evaluate heritage landscapes. It includes survey results, interview transcripts, and participatory mapping outputs that reflect aesthetic judgments, emotional responses, and cultural meanings (Ginzarly & Teller, 2018). Behavioral data such as GPS movement paths or gaze sequences from eye-tracking experiments offer insight into spatial interaction and attention distribution (Wang et al., 2021). In many cases, these data are supplemented by contextual narratives from local communities, expert commentaries, or semantic interpretations drawn from textual sources (Ginzarly et al., 2019; Nowacki, 2021). Such integration enriches the understanding of landscape perception, especially in relation to symbolic and intangible values.

c) **Historical-institutional and design data**: This category consolidates archival records, planning and design drawings, and semantic/institutional sources (e.g., charters, inventories, management plans, regulations, typologies, ontologies), together with communication and visualization media used for interpretation and public engagement (e.g., signage systems, exhibitions, maps, digital storytelling). Linked with spatial measurements and perception findings, these datasets inform buffer-zone delineation, viewpoint protection, and heritage-compatible interventions (Fang et al., 2025).Coding frameworks and text-analysis tools are used to extract meanings from these materials, align terminology with spatial features, and trace change over time (Veldpaus, 2015).

These data categories establish a comprehensive foundation for visual analysis, perception studies, and planning actions. As technologies advance and societal expectations evolve, the data landscape will continue to expand, supporting more nuanced, inclusive, and adaptive approaches to visual heritage research.

1.2 Problem statement

Compared to ordinary landscapes, heritage landscapes are often more sensitive and fragile, requiring higher levels of precision, contextual awareness, and methodological rigor in visual research (Misthos et al., 2023). At the same time, the growing diversity of data sources and analytical techniques has expanded what researchers *could* do, but it has also intensified a recurring practical difficulty: researchers often struggle to justify *why* a certain dataset and method are appropriate for a given heritage question, *under what conditions* they remain valid, and *how* they should be combined into a coherent workflow.

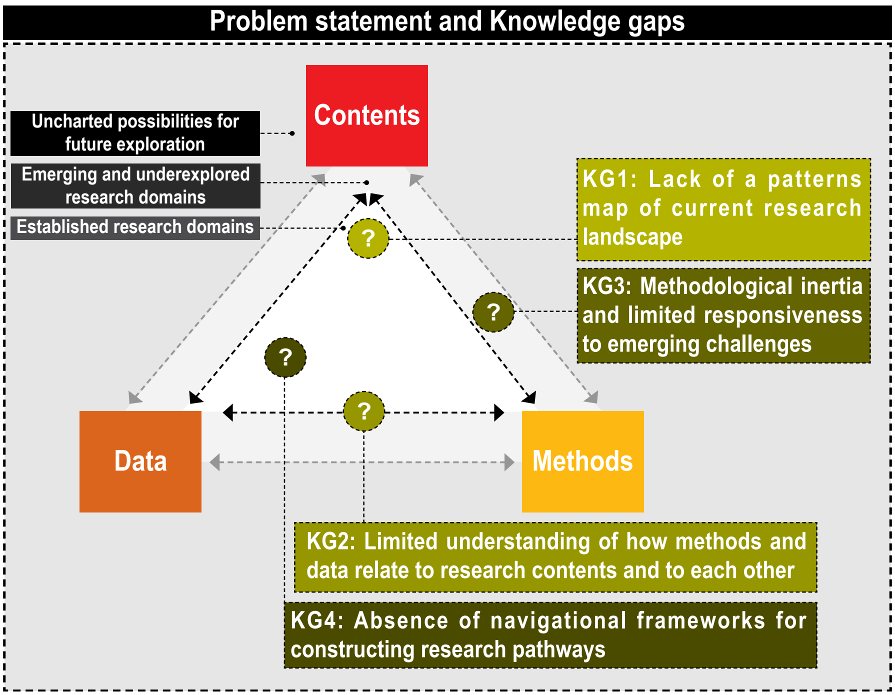

FIG. 1.4 Problem statement and knowledge gaps: Four knowledge gaps in visual heritage landscape research.

TOC

Crucially, this difficulty is not merely a matter of “having too many tools,” but rather a problem of insufficiently articulated linkages between research contents, data practices, and analytical methods **(FIG. 1.4)**:

- **KG1-Fragmented content-data-method linkages and weak transferability (core gap):** Despite the breadth of visual heritage studies, there is limited synthesis of how particular research tasks and heritage subjects map onto specific data types and analytical strategies, and how these components relate to one another across contexts (Antrop, 2000). Many studies report what data and tools were used, but rarely explain the selection rationale and compatibility conditions, such as task-fit, scale and resolution requirements, method- and data-driven assumptions and uncertainties, and validation or triangulation strategies. Integrative practices including multimodal fusion, cross-scale linkage, and iterative loops between quantitative analysis and contextual interpretation are often presented as case-specific pipelines rather than reusable design patterns. As a result, content-data-method relationships remain fragmented, constraining methodological innovation, reproducibility, and cross-context application.

- **KG2-Lack of a comprehensive map of current research patterns:** There is no systematic and up-to-date overview of how existing studies are distributed across different types of heritage landscapes, research themes, spatial scales, methodological strategies, and data practices. This absence makes it difficult to understand the overall research landscape of the field, trace its developments, or position new research in relation to established directions.

- **KG3-Methodological inertia and limited responsiveness to emerging challenges:** Many studies continue to follow conventional research pathways, despite the increasing availability of advanced tools, new data formats, and evolving societal demands. This persistence reflects insufficient responsiveness to emerging issues such as shifts in heritage value orientations, the growing importance of public engagement and participatory approaches (Ke & Mustafa, 2024), and the expanding use of digital analysis techniques and immersive technologies. Without critical methodological adaptation and openness to innovation, research risks becoming disconnected from the current and future priorities of heritage landscape practice.

- **KG4-Absence of navigational frameworks for constructing research pathways:** Researchers often lack guidance when designing research workflows, especially when working in unfamiliar or interdisciplinary domains. There is a need for conceptual tools that support the construction of coherent research pathways: linking research questions to appropriate methods and data, and adapting workflows to different heritage contexts and goals.

1.3 Research objective and questions

The core objective of this thesis is to **advance visual heritage landscape research by expanding the potential of data, methods, and research contents, and by developing a structured system to navigate integrated research pathways that connect them (FIG. 1.5).**

- **RQ1:** What types of research pathways currently exist in visual heritage landscape studies, and what emerging trends can be identified in how data, methods, and research contents are combined within these pathways? **(Chapter 2-3)**

- **RQ2:** How can emerging methods, data types, and research contents be practically combined to develop new research pathways in visual heritage landscape studies, and how can these be tested through case-based applications? **(Chapter 4-7)**

- **RQ3:** How can researchers and practitioners navigate the complexity of available methods, data sources, and research contents to make case-sensitive and goal-oriented choices in visual heritage landscape research? **(Chapter 8)**

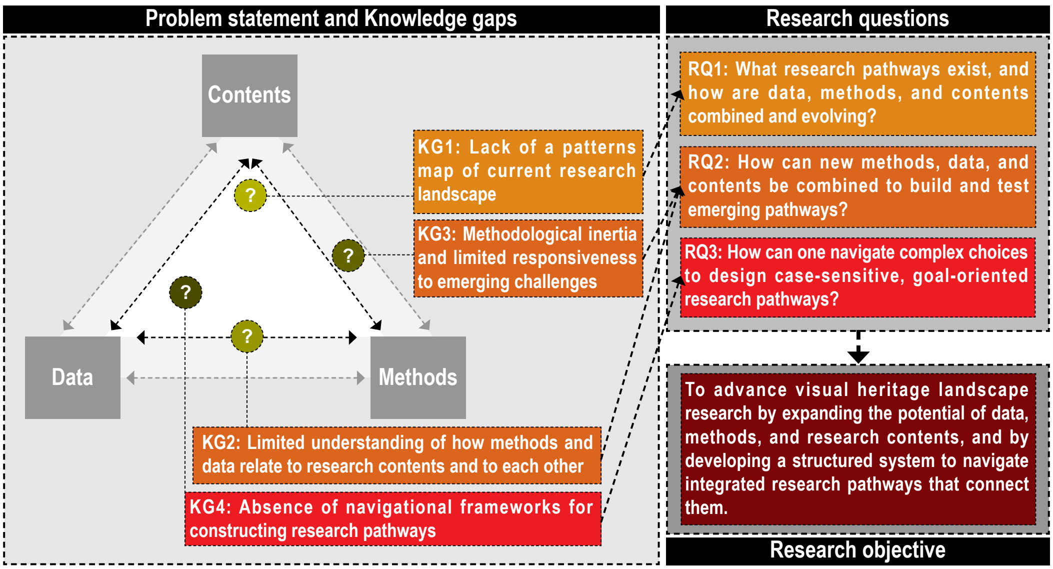

FIG. 1.5 Framework linking knowledge gaps, research questions, and objectives in visual heritage landscape studies.

1.4 Research methodology

To fulfill this aim, this research adopts an exploratory and structure-oriented approach. The focus is not on isolated procedures, but on constructing adaptive pathways that reflect how different components can be meaningfully combined in various research scenarios. Therefore, this thesis adopts a multi-stage methodological structure to address the complexity of visual heritage landscape research in a systematic yet adaptive manner.

The **first stage** focuses on identifying the current landscape of visual research related to heritage. It addresses **KG2** by drawing upon a systematic literature review to map existing data types, analytical methods, thematic orientations, and case typologies, and to examine how these elements are combined in practice. This stage provides both the conceptual foundation and the empirical reference framework for the subsequent inquiry.

The **second stage** addresses **KG3** by exploring new possibilities for combining and expanding data, methods, and research contents. It selects a set of representative case studies to test these pathways in diverse real-world conditions, encompassing a range of landscape types, research themes, analytical techniques, and datasets—such as UAV photogrammetry, point clouds, image-based modeling, and participatory tools. This stage aims to evaluate the applicability and adaptability of emerging approaches across different heritage contexts.

The **final stage** solves **KG4** by synthesizing the findings and derives broader insights into how visual research in heritage landscapes can be structured, adapted, and scaled. Through inductive reflective generalization, it proposes a flexible, non-linear mode of methodological design—one that acknowledges variation in research intent, site specificity, and technical affordances, and treats research pathways as strategically navigable rather than prescriptively defined.

1.5 Research relevance

This research holds significance in both academic and societal contexts, addressing key challenges in visual-spatial analysis and interpretation of heritage landscapes. It aims to support the development of structurally informed research pathways by clarifying how data, methods, and research contents can be combined to meet evolving demands in heritage research and practice.

1.5.1 Scientific relevance

This research advances theoretical understanding in visual heritage landscape studies by addressing the structural disconnect between data types, methodological approaches, and research contents. While various techniques have been applied to analyze visual characteristics, existing studies often treat data and methods in isolation, lacking clarity in how these components relate to one another or to specific research objectives. This leads to fragmentation in methodological reasoning, limited comparability across studies, and difficulty in adapting methods to different contexts.

By proposing a pathway-oriented perspective, this study introduces a structural approach that supports the construction, evaluation, and adaptation of method and data configurations based on specific visual research goals. Rather than focusing on any single technique, the study contributes a conceptual system that clarifies the connections among data availability, analytical capacity, and heritage-specific tasks. This approach facilitates more transparent research design, enhances methodological comparability, and enables reflection on research logic and field development.

In addition, the thesis contributes an empirical and typological overview of visual research in heritage landscapes. Through a systematic review, it identifies patterns of thematic focus, case types, data usage, and methodological application. This overview not only informs the framework and case design in this study, but also provides a reusable foundation for future work aiming to identify underexplored areas or assess disciplinary development. The case-based exploration of emerging and underutilized pathways further supports practical experimentation and theoretical generalization.

1.5.2 Societal relevance

This study is also practically relevant for professionals involved in heritage conservation, planning, and design. In both urban and rural settings, heritage landscapes are increasingly threatened by visual disruption resulting from development, environmental change, and growing tourism (Aboulnaga et al., 2024). These pressures not only affect the physical fabric of the landscape but also its cultural meaning and perceptual quality, dimensions often insufficiently integrated into planning processes.

Practitioners often face challenges such as mismatches between available data and heritage values, overly technical or inaccessible methods, and weak connections between research outcomes and planning needs. These issues result in fragmented visual assessments and limited public engagement.

By offering a structured and adaptable framework for combining methods, data, and thematic content, this research provides practical guidance for making informed and flexible decisions. It can support various planning tasks, including visual impact assessments, buffer zone planning, skyline management, and interpretive design. Moreover, by clarifying the relationships among data collection, visual analysis, and stakeholder engagement, it helps bridge expert knowledge and public communication, improving transparency, accountability, and cultural sensitivity in heritage management.

1.6 Research outlines

This thesis is organized into three main parts, each corresponding to a distinct phase of the research process: understanding the existing research landscape, constructing and testing new and emerging pathways, and synthesizing insights to develop a structured framework for navigating the construction of new pathways or the selection of existing ones. The structure reflects a logical progression from conceptual grounding, through empirical implementation, to integrative synthesis and strategic navigation **(FIG. 1.6)**.

The **first part (literature-grounded mapping, Chapters 2 and 3)** lays the foundation of the study. **Chapter 2** presents a structured review of existing visual research on heritage landscapes, mapping the interrelations among methods, data sources, thematic orientations, and case typologies. This chapter identifies prevailing patterns and limitations in the field. Building on this, **Chapter 3** proposes a set of potential data-method-content pathways and outlines the criteria for selecting representative case studies. It also introduces the overall research framework that informs the empirical implementation of the thesis.

The **second part (Case-based pathway exploration, Chapters 4 to 7)** presents four case studies, each testing an emerging or underexplored research pathway under distinct landscape conditions. The cases cover a diverse range of landscape types (urban, rural, cultural sites, and historic gardens), spatial scales, data availability, methodological approaches, and thematic concerns. By applying the proposed framework in varied contexts, these chapters demonstrate how integrating data and methods can serve different research and design objectives in visual heritage landscape studies. Together, the case studies offer comparative insights for evaluating and refining new pathway configurations.

The **third part (Synthesis and navigation of research pathways, Chapters 8 and 9)** integrates the findings from the case studies and reflects on their broader implications. **Chapter 8** offers a cross-case synthesis, identifying key patterns, divergences, and recurring structures among the different pathway types. Beyond summarizing practical strengths and limitations, it proposes potential new research pathways and offers a strategic framework for navigating choices across data, methods, and research contents. This includes supporting researchers and practitioners in designing context-sensitive, goal-oriented visual research strategies. **Chapter 9** concludes the thesis by consolidating its core contributions, providing integrated responses to the research questions, and outlining future directions for theory, method, and application in heritage landscape research.

TOC

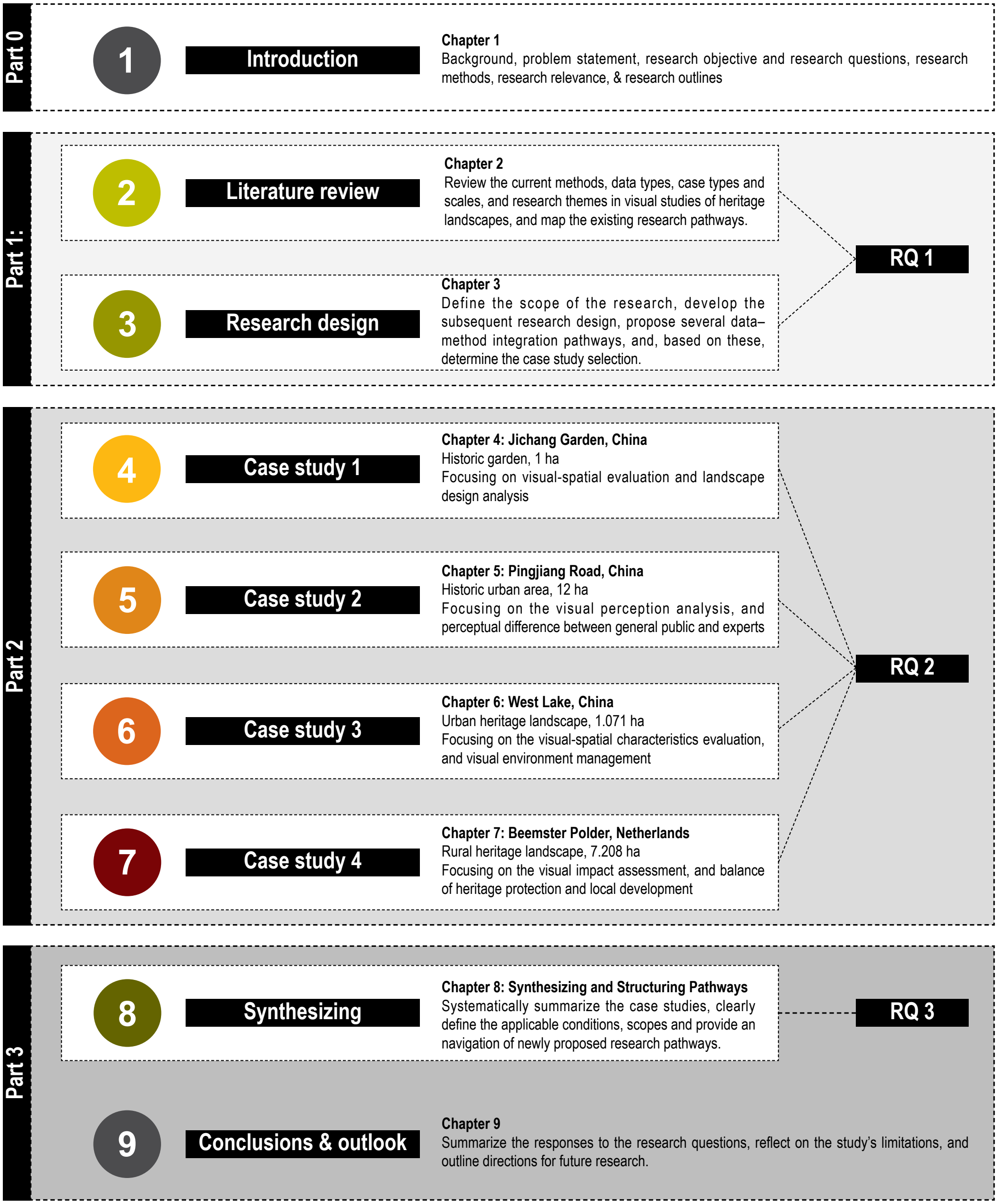

FIG. 1.6 Overall structure of the thesis: Showing its division into three main parts: literature-grounded mapping (Part 1), case-based pathway exploration (Part 2), and synthesis and navigation of research pathways (Part 3).

TOC

PART I

Literature-grounded mapping, and framework construction

This part focuses on building the conceptual and methodological foundation of the thesis by mapping the current research landscape of visual heritage landscape studies and translating it into a pathway-oriented design logic. Specifically, Chapter 2 conducts a systematic review to synthesize research themes, heritage landscape typologies, data sources, and visual methods, and to reveal how these dimensions are currently connected and where fragmentation persists. Chapter 3 then operationalizes the review insights into a data-method-content pathway framework, proposes expanded pathway types (EP-1-EP-4), and defines case-selection criteria and workflows that guide the empirical studies in the following part.

TOC

2 Literature review

Visual landscape research on heritage landscapes: A systematic review of research themes, methodological approaches, and landscape typologies across spatial scales

This chapter is based on a submitted paper in revision.
Peng, Y., Nijhuis, S., Wu, Z.* & Yu, Y. (2026). “Visual landscape research on heritage landscapes: A systematic review of research themes, methodological approaches, and landscape typologies across spatial scales”. *Landscape and Urban Planning.* (In revision)

This chapter aims to map the current research landscape of visual heritage landscape studies and to reveal how research themes, heritage objects, methods, and data sources are interconnected. Using a systematic review protocol and a multi-layer analytical workflow, it synthesizes the field’s dominant thematic directions, methodological categories, heritage landscape types, and spatial scales, while also identifying persistent biases and blind spots. Beyond describing trends, the chapter provides a structural knowledge map that exposes how certain methods cluster around particular content themes and site types, and where integration is missing between spatial modeling, perception-oriented inquiry, digital documentation, evaluation, and participatory practices. These findings establish the empirical and conceptual foundation for the pathway framework developed in the next chapter, and they clarify why navigable configurations are needed to support more coherent and transferable visual heritage landscape research design.

TOC

2.1 Introduction

Heritage landscapes are the outcome of long-term interactions between natural processes and human activities, and carry both heritage and landscape attributes (López-Sánchez et al., 2020; Tengberg et al., 2012). As heritages, they preserve collective memory and embody how societies have shaped and adapted to their environments (McDowell, 2016). As landscapes, according to the definition from the European Landscape Convention (ELC), they are "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors" (ELC, 2000), emphasizing the "perceived features" of landscapes. Among perceptual dimensions, visual perception plays a predominant role. Visual attributes, such as spatial patterns, aesthetics, and visibility, are critical for how heritage landscapes are understood and appreciated and for how they are interpreted, conserved, and planned (Garden, 2006; Liu et al., 2022). Consequently, visual landscape research constitutes a fundamental component of heritage landscape studies (Nijhuis et al., 2011).

Despite its importance, visual landscape research on heritage landscapes remains fragmented. This fragmentation arises from several interrelated factors. First, the wide variety of landscape types and scales, from large rural cultural landscapes (Arriaza et al., 2004; López-Santiago et al., 2014) to small historic parks/gardens (Liu & Nijhuis, 2020; Peng et al., 2024), leads to differences in analytical priorities and complexities in representation. Second, there is considerable methodological diversity **(FIG. 2.1)**. Scholars use a broad range of approaches, such as GIS-based visual-spatial analysis (Perotto-Baldiviezo et al., 2004), geo-visualization (Nöllenburg, 2007; Patel et al., 2012), participatory mapping (Brown & Kyttä, 2018; Chambers, 2006), and perception studies that rely on tools like street-view imagery or remote sensing (Dupont et al., 2015; Ito et al., 2024). The use of diverse data sources, including survey responses, archival materials, point cloud datasets, and satellite images, further complicates comparisons across studies (Dupont et al., 2015; Ito et al., 2024). Third, different disciplinary backgrounds and cultural contexts lead to diverse conceptual frameworks and research agendas (Krause, 2001).

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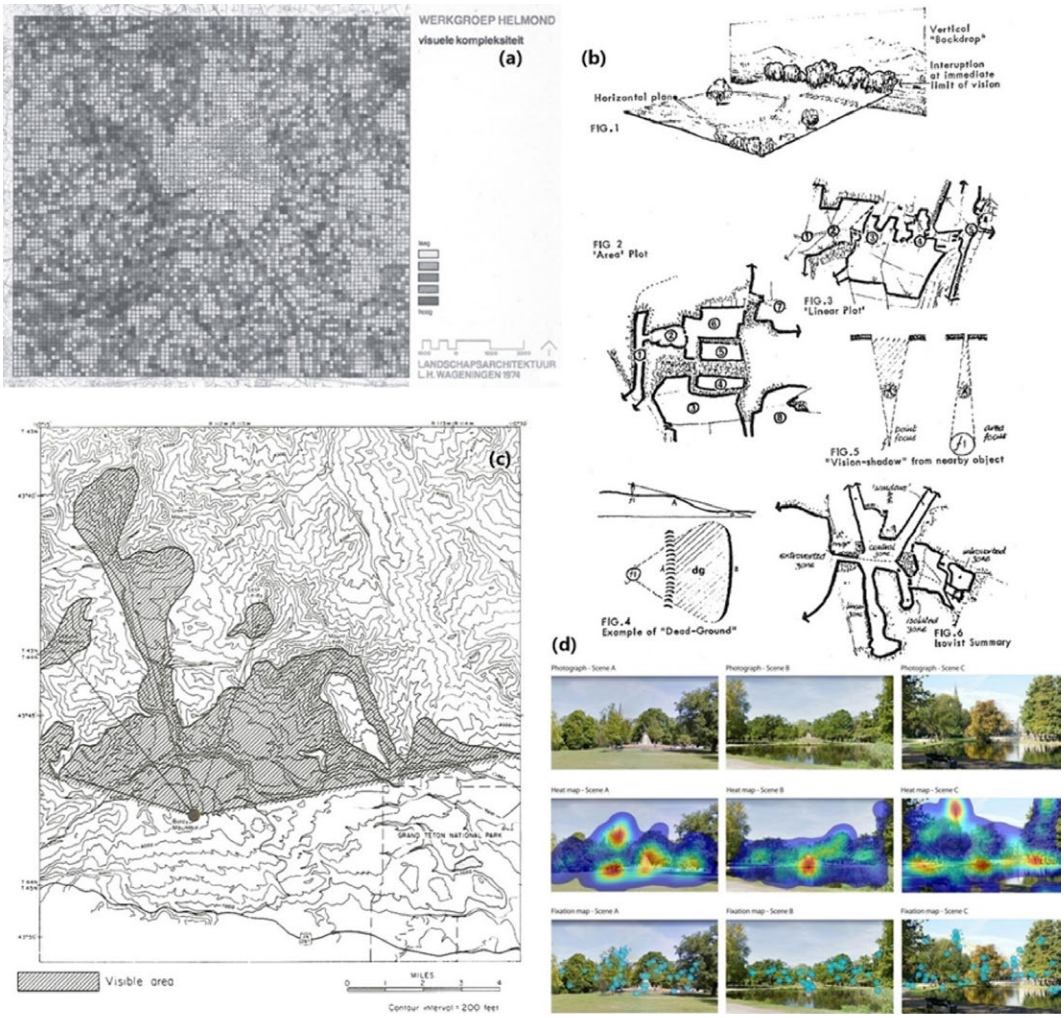


FIG. 2.1 The long-standing tradition and methodological diversity in visual landscape research: (a) an early example of GIS-based raster analysis in landscape characterization (Kerkstra, 1974); (b) a schematic example of spatial-visual analysis (Lynch, 1976); (c) an early isovist application for landscape visibility assessment (Tandy, 1967); (d) an example of eye-tracking technology used to capture visual perception behaviors in landscape contexts (Liu & Nijhuis, 2020).

Given these challenges, a systematic review is necessary to synthesize existing studies and clarify methodological trajectories within the domain of visual heritage landscape research. Although several reviews have addressed aspects of this research field, they generally fall into three categories:

a) **Reviews on visual landscape research**: A substantial number of works have examined visual landscape research, including studies on research methodologies for visual landscapes (Nijhuis et al., 2011; Wolsink & Wardt, 1989), urban landscape visual quality assessment (Daniel, 2001; Mundher et al., 2022), spatial characteristics of contemporary urban forms (Clifton et al., 2008), and GIS-based mapping and analysis techniques (Malczewski, 2004; Quan & Bansal, 2021). However, these studies often address landscapes in general terms and seldom focus on heritage contexts. Compared to "ordinary" landscapes, heritage landscapes are more vulnerable to environmental and anthropogenic changes (Hall et al., 2016; Harvey, 2015). While such reviews provide useful methodological insights, they often overlook the specific challenges of heritage landscape conservation and interpretation.

b) **Reviews on heritage landscapes**: These studies tend to focus on broader planning or heritage frameworks, where visual analysis is treated as a secondary concern. Examples include reviews on integrated management guidelines (Ginzarly et al., 2019; López Sánchez et al., 2020), cultural heritage indicators (Sowińska-Świerkosz, 2017; Spencer & and Sargeant, 2024), and the relationship between heritage landscapes and ecosystem services (Hølleland et al., 2017). However, visual landscape research within these reviews is often a subsidiary theme, lacking a detailed exploration of the methodological dimensions of visual analysis.

c) **Reviews on specific types of heritage landscapes**: This category includes studies focusing on particular types of heritage landscapes, such as historic gardens (Hosseini et al., 2024; Lian et al., 2024), cultural rural landscapes (Agnoletti, 2014), or natural heritage sites (Barrientos et al., 2021; Zhang et al., 2023). However, their scope is typically confined to specific types or regions, and few explicitly engage with visual analysis methods or perceptual dimensions—key aspects for understanding how heritage landscapes are experienced and interpreted (Ginzarly & Teller, 2018; Waterton & Watson, 2010).

These reviews demonstrate growing interest in heritage landscape research but also reveal a key gap: the lack of a systematic synthesis on visual analysis methodologies. Addressing this gap is crucial for advancing both theoretical understanding and practical approaches to heritage landscape interpretation, planning, and conservation. To answer RQ1, this chapter seeks to fill that gap by systematically reviewing the literature on visual landscape research in heritage landscape contexts, guided by the following sub-questions: (RQ2.1) What are the main research themes, emphases, and directions? (RQ2.2) What types and spatial scales characterize the heritage landscapes studied as research objects? (RQ2.3) What methods, tools, and data have been employed? (RQ2.4) How are research themes, study objects, and methodological approaches interrelated? (RQ2.5) What challenges does the field face, how has it evolved, and what future directions are emerging?

This chapter is structured as follows: The “methods” section outlines literature selection criteria and the analytical framework used in this review. The “results” section addresses RQ2.1–RQ2.4 by presenting findings on research themes, objects, methods, and their interconnections. The “discussions” section responds to RQ2.5, analyzing current challenges and suggesting future directions. This chapter makes two primary contributions: (a) It synthesizes fragmented knowledge on visual landscape research in heritage contexts, clarifying current themes, approaches, and gaps; (b) It develops a structured analytical framework that supports future research and practice in heritage landscape conservation, assessment, and intervention.

2.2 Methods

We conducted a systematic review following PRISMA 2020[10] guidelines to identify and analyze visual landscape research within heritage landscape contexts. The protocol was not pre-registered. Searches were performed in Web of Science (WoS)[11] and Scopus[12] for records published between 1990 and 10 April 2025. This review followed a three-stage analytical process **(FIG. 2.2)**: (a) literature retrieval using keyword combinations to capture the relevant corpus across disciplines; (b) screening via the PRISMA framework to enforce consistent inclusion/exclusion rules; and (c) multi-layer analysis involving coding, bibliometric mapping, and cross-dimensional synthesis to construct a structured knowledge map, expose deep regularities and trajectories, and integrate insights across perspectives and scales.

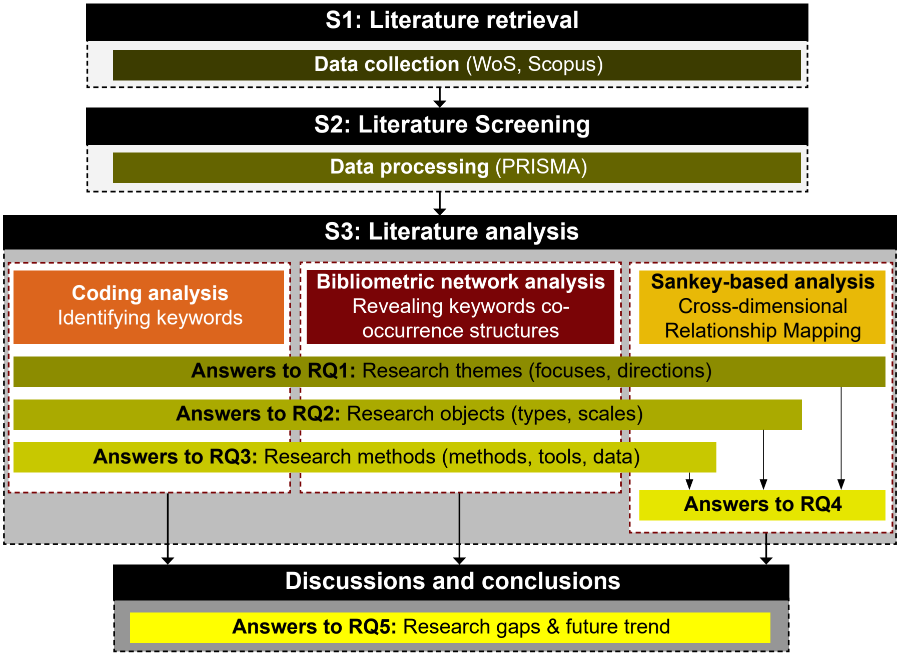


FIG. 2.2 Multimethod analytical framework: Reviewing visual landscape research in heritage landscape contexts.

10 **PRISMA Executive. 2020.** PRISMA 2020 documents. https://www.prisma-statement.org/
11 **Web of Science.** https://www-webofscience-com.tudelft.idm.oclc.org/
12 **Scopus.** https://www-elsevier-com.tudelft.idm.oclc.org/products/scopus

2.2.1 Literature retrieval

We searched WoS Core Collection (SCI-EXPANDED, SSCI, A&HCI, ESCI) and Scopus for records published between 1990 and 10 April 2025, with the last search conducted on 9 October 2025. These databases together provide comprehensive coverage across the natural sciences, social sciences, and humanities The search strategy targeted two core themes: "heritage landscapes" and "visual landscape research." The latter was divided into (a) visual analysis and evaluation (including GIS-based and perception-based methods) and (b) visual management, planning, and design (Nijhuis et al., 2011). Based on these dimensions, three keyword groups were constructed and combined as follow:

a) **Heritage landscape:** *TS (TITLE-ABS-KEY) 1 = ("heritage NEAR/1 landscape*" OR "cultural landscape*" OR "historic* NEAR/1 landscape*" OR "traditional landscape*" OR "heritage site*" OR "historic site*" OR "historic environment*" OR "historic* NEAR/1 garden*" OR "historic* NEAR/1 park" OR "heritage* NEAR/1 garden*");*

b) **Visual analysis:** *TS (TITLE-ABS-KEY) 2 = ("visual analysis" OR "Visual NEAR/1 spatial analysis*" OR "visual attribute*" OR "spatial attribute*" OR "Visual NEAR/1 spatial characteristic*" OR "visual characteristic*" OR "perceptual analysis" OR "visibility analysis" OR "landscape perception" OR "aesthetic value" OR "visual NEAR/1 evaluation*" OR "visual NEAR/1 assessment*");*

c) **Visual management:** *TS (TITLE-ABS-KEY) 3 = ("landscape NEAR/1 design" OR "landscape" NEAR/1 "plan" OR "manag* AND visual");*

d) **The combination:** *(TS1) AND ((TS2) OR (TS3)).*

Before finalizing the query, we conducted a brief search calibration step using eight widely recognized works as validation anchors. We iteratively adjusted Boolean/ proximity operators until the finalized strings automatically retrieved all eligible anchors, thereby checking sensitivity without using them as seeds. We did not systematically search grey literature (e.g., theses, technical reports, design briefs, management plans), and we excluded practice-based case files not published in peer-reviewed venues (e.g., Visual Impact Assessment, Visual Resource Management, Environmental Impact Assessment case documentation) to ensure indexing consistency and methodological comparability. In addition, this review does not cover general environmental planning and includes studies only when heritage is the central research object. In line with **Section 2.1.1**, we applied a strict heritage × method criterion (including scenic beauty evaluating methods) to ensure replicability, acknowledging that this may omit studies addressing heritage values without explicit heritage terminology; visual landscape studies outside heritage contexts were excluded.

TOC

2.2.2 Literature screening

Following PRISMA 2020 guidelines (Page et al., 2021), the screening involved two stages: title/abstract review and full-text assessment **(FIG. 2.3)**. Two reviewers independently screened records at both stages (titles/abstracts and full texts) after a brief calibration to align criteria; disagreements were resolved by discussion. After removing 285 duplicates from the 630 records retrieved from WoS and Scopus (by EndNote[13]), a total of 345 unique records were retained. In the first stage, titles and abstracts were reviewed to determine basic relevance. Records were excluded if they (a) were not published in English or (b) did not address either heritage landscapes or visual landscape research as a primary focus. In the second stage, full texts of the remaining records were assessed against more detailed inclusion criteria. Exclusions at this stage included documents that: (a) lacked full-text access (e.g., abstract-only); (b) mentioned heritage or cultural landscapes only peripherally (without treating them as a central research object); (c) did not engage with visual characteristics through methodological discussion, evaluation, or planning and design strategies.

After applying these criteria, 203 documents were selected for further analysis. The final dataset includes peer-reviewed journal articles, conference proceedings, and academic book chapters that met both thematic and methodological relevance requirements.

13 **EndNote.** https://endnote-com.tudelft.idm.oclc.org/

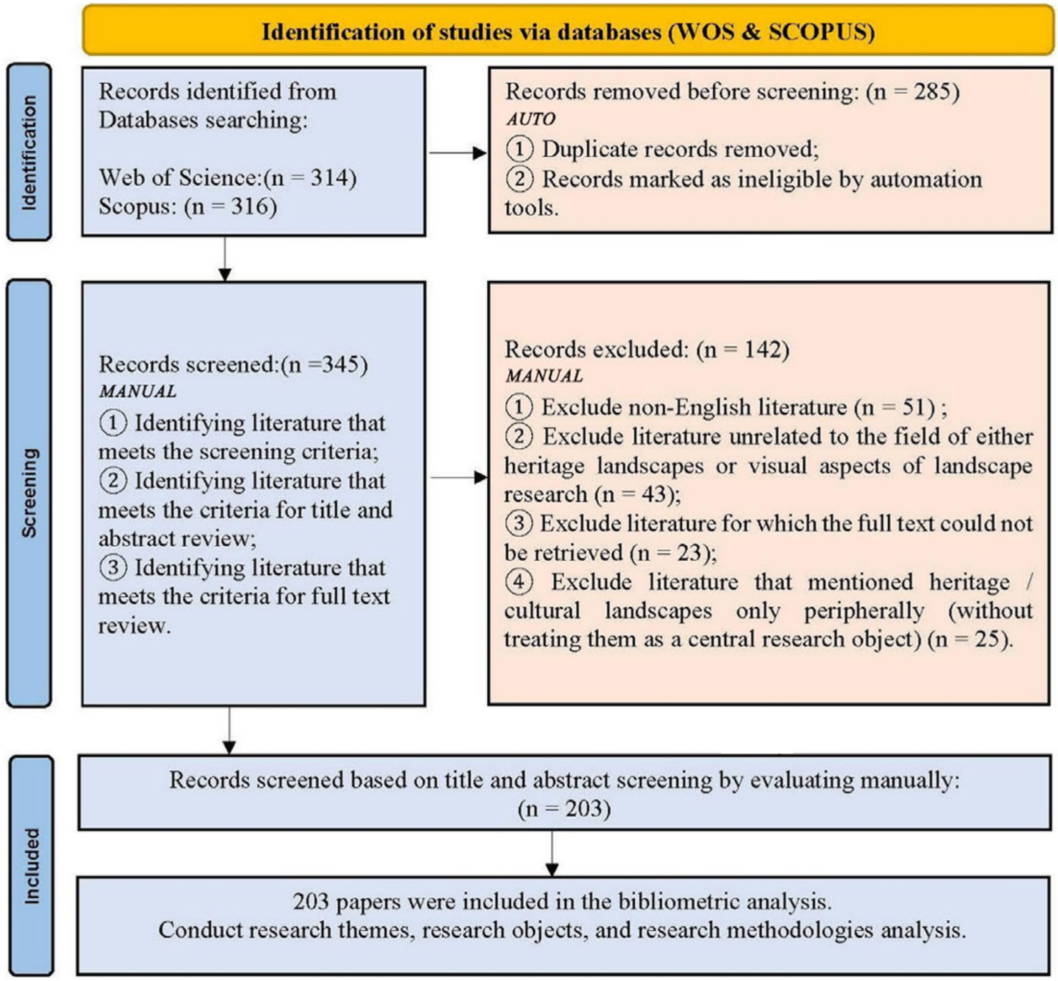


FIG. 2.3 The workflow of PRISMA: Selecting 203 literature from the 630 records.

2.2.3 Coding and reliability

We analyzed the 203 studies using a hierarchical codebook aligned with three analytical dimensions (hierarchical structures are reported in the Results): (a) research themes, (b) research objects (heritage landscape types and spatial scales), and (c) methodological approaches (methods, tools, and data). The initial codebook was drafted from a scoping review and piloted on a small subset. Two coders then independently applied it to all studies. To balance stability and openness, coders could add sub-codes under existing higher-level categories when novel terms appeared; when a potential new top-level category emerged, coding was temporarily paused for a joint decision on creation vs. merger. After independent coding, item-level discrepancies were reconciled by discussion; where both interpretations were defensible, we retained combined codes (e.g., "A+B") to preserve nuance. Inter-coder reliability was assessed using Cohen's κ, which ranged from 0.64 to 0.85 across dimensions; detailed values for each dimension and subcategory are provided in Appendix A **(Table A1-3)**.

2.2.4 Literature analysis

To understand the evolution and structure of visual landscape research for heritage landscapes, this chapter employed a three-layered analytical framework **(FIG. 2.3)**:

a) **Thematic coding layer with systematic content analysis:** Using the hierarchical codebook described in **Section 2.3**, we extracted three dimensions for each study. This enabled a fine-grained thematic classification (Onwuegbuzie et al., 2012), offering insight into dominant topics, typological distributions, and methodological diversity. This layer directly responds to RQ1–RQ3.

b) **Conceptual network layer with bibliometric mapping:** We mapped term co-occurrences with VOSviewer[14] (van Eck & Waltman, 2010) using default parameters (association-strength normalization, resolution = 1.0, minimum cluster size = 5) and binary counting. Terms appearing fewer than three times across the corpus were excluded. Before analysis, keywords were standardized and merged to remove lexical variation (plural/singular, British–American spelling, abbreviations vs. full terms). Clusters were generated algorithmically; layouts were exported to Pajek[15] for clearer spatial separation and label readability. This post-processing affected only visualization, not cluster membership.

14 **VOSviewer.** https://www.vosviewer.com/
15 **Pajek.** http://mrvar.fdv.uni-lj.si/pajek/

c) **Integrative mapping layer with cross-dimensional synthesis:** The relationships were analyzed through Sankey diagrams, which traced the flow between research themes, research objects, and research methods. This approach emphasizes directional and functional linkages, moving beyond frequency-based or cluster-based summaries. It provides a synthesized view of how different dimensions interact within the research 'landscape'.

This multi-tiered approach enhances the validity and depth of the review. By aligning with the layered logic of visual heritage landscape research, this methodology supports a more organized understanding of how the field has developed and where it is heading.

2.3 Results

2.3.1 Preliminary analysis results

The preliminary bibliometric analysis serves to contextualize the more detailed thematic and methodological findings that follow. **FIG. 2.4a** shows the annual publication trend from 1995 to 2025. Publications remained sparse before 2010, followed by steady growth after 2011 and a sharp rise from 2019 onward, with cumulative outputs surpassing 200 by 2025. This trajectory reflects increasing scholarly attention to visual approaches in heritage contexts. **FIG. 2.4b** identifies journals with three or more relevant publications. *Sustainability*, *Land*, and *Landscape and Urban Planning* are the most active, indicating strong interdisciplinary links across sustainability, spatial planning, and heritage studies. Other frequent contributors—such as *Journal of Cultural Heritage*, *Heritage Science*, and *ISPRS International Journal of Geo-Information*—highlight the integration of geospatial technologies and cultural theory. The diversity of journals suggests growing visibility across environmental sciences, conservation, and digital humanities, particularly within open-access platforms. **FIG. 2.4c** maps the geographic distribution and collaboration network. China, Italy, the UK, and the US lead in publication volume and international linkage. European countries like Germany, Spain, and France form a dense collaborative cluster, while the UK, US, and Australia constitute a second, English-speaking group. Emerging contributors such as Malaysia, Poland, and Lithuania also appear, indicating expanding global relevance.

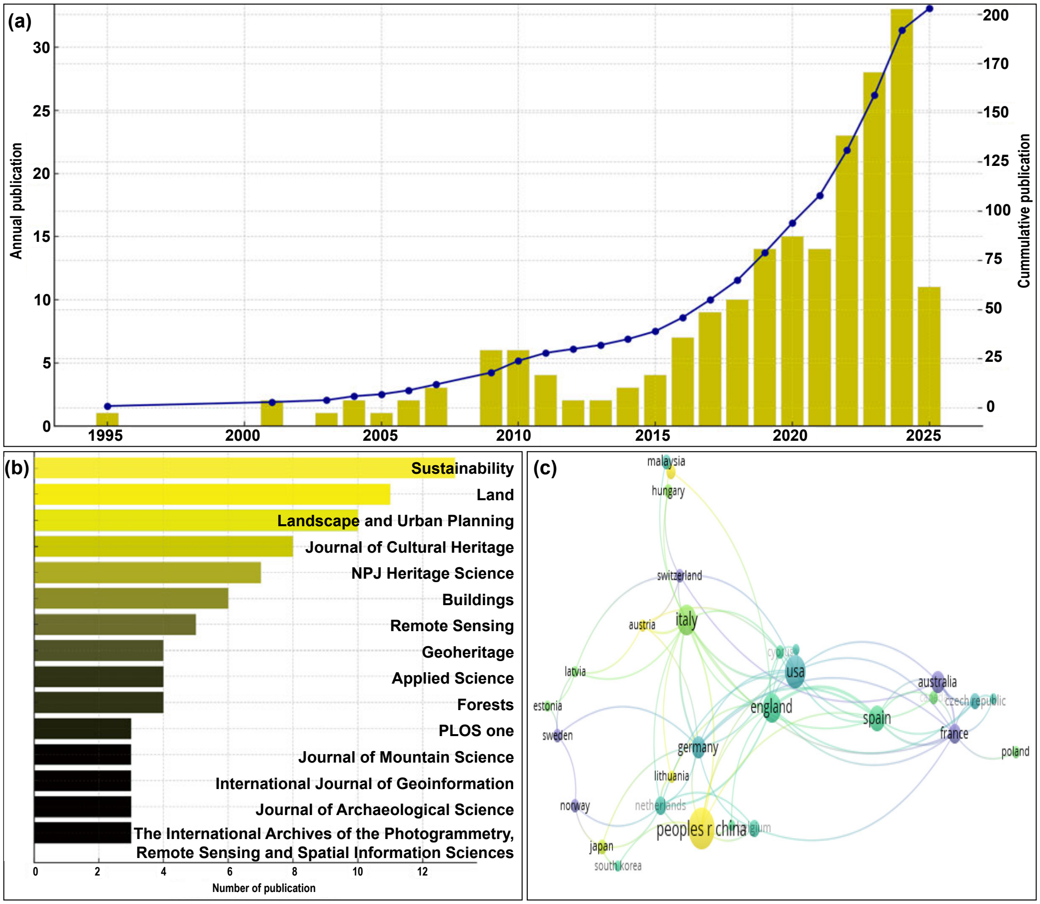


FIG. 2.4 Preliminary results of bibliometric analysis: (a) Temporal distribution of publications; (b) Journals with more than three relevant articles; (c) Geographic distribution and collaboration network of contributing countries and regions.

TOC

2.3.2 Systematic coding of research dimensions

This section presents the results of systematic manual coding, directly addressing RQ2-1, RQ2-2, and RQ2-3. Five major research themes are identified. Methodologically, 15 distinct categories of core research methods are recognized. For research objects, 13 landscape types are distinguished, examined across 7 spatial scales **(FIG. 2.5)**.

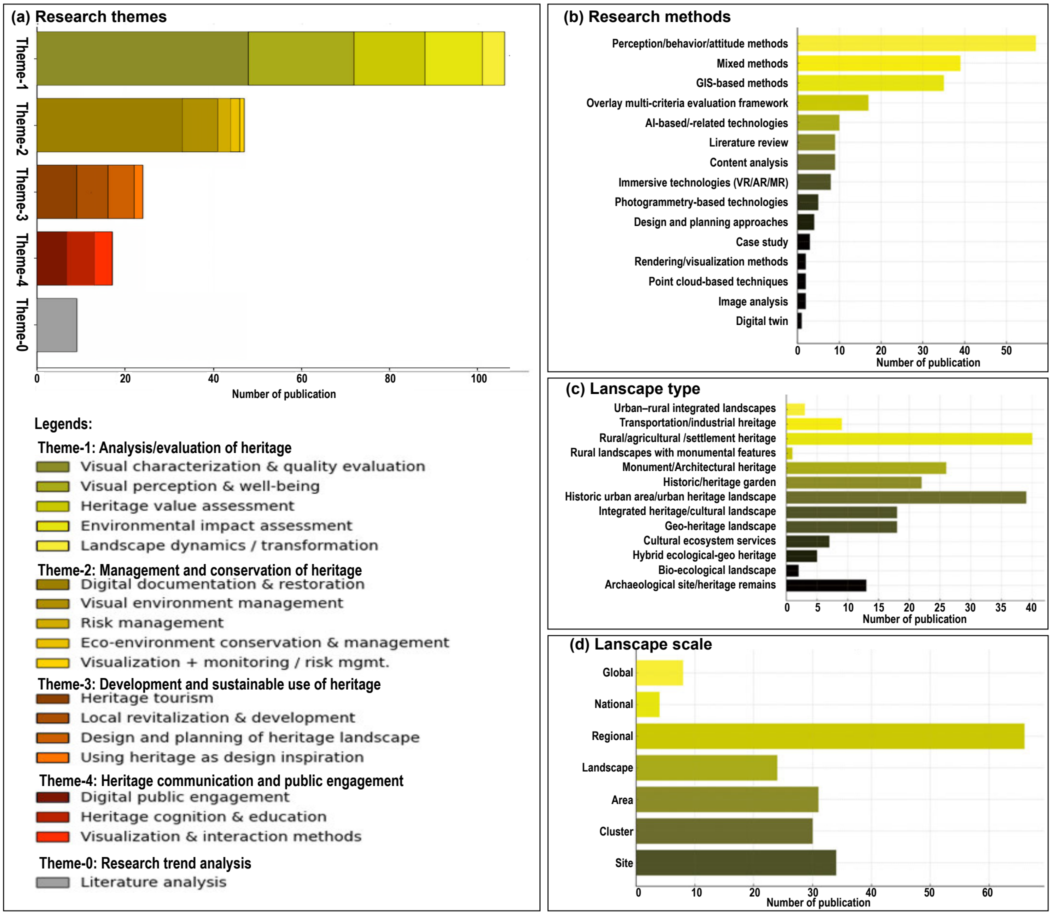


FIG. 2.5 Summary of bibliometric coding analysis: (a) Publication counts by research themes; (b) Publication counts by research methods; (c)-(d) Publication counts by research objects.

2.3.2.1 Research themes

Through systematic coding and thematic classification of the literature, 5 categories (18 sub-categories) of research themes are identified **(TABLE 2.1)**:

TABLE 2.1 Summaries of research themes.

Categories	Examples of sub-categories	Amount	Percentage
Analysis and Evaluation of Heritage	Visual quality evaluation; public perception and well-being; heritage value assessment; environmental impact assessment; landscape transformation	106	52.22%
Management and Conservation	(Digital) documentation and restoration; visual environment management; risk management	47	25.15%
Development and Sustainable Use	Heritage tourism; regional revitalization; design and planning of heritage landscapes; design applications	24	11.82%
Communication and Public Engagement	Public participation; heritage education; visualization and interaction methods	17	8.37%
Research Trend Analysis	Literature analysis	9	4.43%

Note: A detailed table listing the literature sources associated with each subtheme is provided in Appendix A (Table A1).

a) **Analysis and evaluation of heritage (106 publications, 52.22%)** is the most prevalent theme. Within this category, *visual characterization and visual quality evaluation* (48 publications, 23.65%) constitute the dominant subtheme, emphasizing aesthetic and perceptual qualities of heritage landscapes. Other notable subthemes include *public perception and well-being* (24 publications, 11.82%), focusing on psychological and emotional responses such as place attachment and mental health, along with heritage value assessment, environmental impact assessment, and landscape transformation, which span ecological, cultural, and social dimensions.

b) **Management and conservation of heritage (47 publications, 25.15%)** centers on *digital documentation and restoration* (33 publications, 16.26%). Additional subthemes include visual environment management (e.g., buffer zones, visibility control) and risk management, which address spatial regulation and vulnerability mitigation.

c) **Development and sustainable use of heritage (24 publications, 11.82%)** explores the integration of heritage resources into contemporary societal functions, with emphases on heritage tourism, regional revitalization, and landscape planning. These studies reflect the growing interest in linking heritage with economic transition and spatial sustainability agendas.

d) **Heritage communication and public engagement (17 publications, 8.37%)** covers themes such as digital participation, heritage education, and public engagement. Notably, *Visualization and interaction methods* (4 publications, 1.97%) represent an emerging subfield emphasizing immersive technologies.

e) **Research trend analysis (9 publications, 4.43%)**, though useful for identifying gaps and frameworks, is relatively narrow, with most studies centered on karst geo-heritage.

2.3.2.2 Research objects

13 landscape types and 7 spatial scales have been identified across the reviewed literature, revealing both content preferences and spatial framing in visual heritage landscape research.

a) **Landscape types (TABLE 2.2):** The most frequently studied categories are *rural/agricultural/rural settlement landscapes* (40 publications, 19.70%) and *historic urban areas/urban heritage landscapes* (39, 19.21%), followed by *monuments/architectural heritage* (26, 12.81%). Other common types include *historic/heritage gardens* (22, 10.84%), *geo-heritage landscapes* (18, 8.87%), and *integrated cultural landscapes* (18, 8.87%). These six types account for over two-thirds of the literature, reflecting a preference for tangible, visually prominent, and human-centered landscapes. Less represented types include *transportation/industrial heritage* (9, 4.43%), *cultural ecosystem service landscapes* (7, 3.45%), *hybrid ecological-geo heritage* (5, 2.46%), and *urban–rural integrated landscapes* (3, 1.48%). Rare categories, such as rural landscapes with monumental features or ecological heritage, tend to lack clear spatial framing or fall outside dominant.

b) **Spatial scales (TABLE 2.3):** Seven spatial scales were identified in the reviewed literature. *Regional* scale is the most frequently applied (55 publications, 34.98%), commonly used in studies of rural, agricultural, and geo-heritage landscapes. *Cluster* (15.27%) and *site* scales (16.75%) are also prevalent, particularly in research focused on gardens, monuments, and architectural heritages. *Area* (14.78%) and *landscape* (12.32%) scales appear with moderate frequency, reflecting intermediate spatial extents such as historic urban area. By contrast, *national* (1.97%) and *global* (3.94%) scales are rarely employed, and these instances primarily involve literature reviews or comparative meta-analyses, rather than site-based investigations.

In summary, current research is dominated by studies of spatially discrete, anthropocentric heritage types, particularly rural, urban and garden heritages, analyzed predominantly at site and regional scales **(FIG. 2.6)**. Ecological-cultural hybrids and infrastructure-related heritage remain underexplored, suggesting potential for future diversification.

FIG. 2.6 Examples of diversity in heritage landscape types and spatial scales: (a) Jichang Garden, site scale, classical heritage garden; (b) West Lake, Hangzhou, landscape scale, urban heritage landscape; (a) Beemster Polder, regional scale, agricultural heritage landscape.

TOC

TABLE 2.2 Summaries of research objects' types

Heritage landscape type	Amount	Percentage	Dominant scale(s) of this type
Rural/agricultural/settlement landscapes	40	19.70%	Regional
Historic urban areas/urban heritage landscapes	39	19.21%	Area / Landscape
Monuments/architectural heritage	26	12.81%	Site / Cluster
Historic/heritage gardens	22	10.84%	Site / Cluster / Area
Geo-heritage landscapes	18	8.87%	Regional / Landscape
Cultural heritage landscapes (no specific type)	18	8.87%	Regional
Archaeological site/Heritage remains	13	6.40%	Regional / Site / Landscape
Transportation/industrial heritage	9	4.43%	Site / Regional / Landscape
Cultural ecosystem services	7	3.45%	Landscape / Regional
Bio-ecological and geo-heritage hybrids	5	2.46%	Cluster / Landscape / Regional
Urban-rural integrated heritage landscapes	3	1.48%	Regional
Purely ecological heritage	2	0.99%	Regional
Rural heritage landscapes with monuments	1	0.49%	Cluster

TABLE 2.3 Summaries of research objects' spatial scales

Scales	Amount	Percentage	Description
Site	34	16.75%	Single heritage elements (e.g., imperial garden, monumental building)
Cluster	31	15.27%	Grouped heritage features (e.g., architectural ensemble)
Area	30	14.78%	Urban or rural sections (e.g., historic urban core, historic community)
Landscape	25	12.32%	Visually or ecologically coherent landscape units (e.g., terraced agricultural landscape, historic town)
Regional	71	34.98%	Governance-defined zones often cover multiple landscape units (e.g., cultural heritage conservation buffer zone, large-scale traditional agricultural landscape)
National	4	1.97%	(Close to) Entire country spaces
Global	8	3.94%	Cross-country spaces

Note: Appendix A (Table A2) provides a detailed table listing the literature sources associated with each landscape type/scale. Table A2b provides detailed definitions and references for these heritage landscape types

2.3.2.3 Research methods, tools, data

The analysis of 203 publications reveals 15 methodological types (core methods applied), reflecting the interdisciplinary and increasingly digital nature of visual heritage landscape research **(TABLE 2.4)**.

- **Perception-/behavior-based methods** *(i)*: Accounting for 57 studies (28.08%), this is the most frequently applied and foundational approach to studying visual perception and behavior in heritage landscapes. Common tools include surveys, interviews, participatory workshops, and field observations. In recent years, these methods also use eye-tracking, physiological sensors, and immersive environments, which enable more nuanced measurement of attention and emotion. Some studies incorporate geospatial participatory tools such as PPGIS, reflecting a broader move toward digitally enriched perception analysis.

- **GIS-based technologies** *(ii)*: This category appears in 35 studies (17.24%). GIS supports digital spatial analysis of visibility, land use, terrain, and spatial relationships through viewshed analysis, spatial modeling, and overlay techniques. Data inputs include digital elevation models, satellite imagery, point clouds, and georeferenced historical maps. GIS functions as a standalone analytical tool and as an integrative platform that brings together expert knowledge, perceptual evaluations, and AI workflows. PPGIS that directly measures perception and behavior is treated under *(i)*.

- **Multi-criteria evaluation frameworks** *(iii)*: Reported in 17 studies (8.37%), these frameworks connect qualitative perception and quantitative spatial reasoning. Applications include visual sensitivity mapping, heritage value assessment, risk analysis, and planning. They integrate expert judgment, environmental indicators, perceptual surveys, and spatial overlays. Depending on design, they may be GIS driven based on weighted spatial indicators, or perception driven using public scoring, field surveys, or stakeholder input.

- **AI-based technologies** *(iv)*: Although still emerging (4.93%), these methods reshape analytical practice through automation and large-scale data processing. Techniques include machine learning and deep learning for image classification, semantic segmentation, and content clustering. They often operate within GIS environments or image-processing pipelines. Applications include identifying visual quality metrics, classifying heritage typologies, and extracting patterns from user-generated content and large imagery datasets.

- **Content analysis** *(v)*, **literature review** *(vi)*, and **image analysis** *(xii)*: Respectively 4.43%, 4.43%, and 0.99% of the corpus, these methods illuminate discursive patterns, cultural narratives, and thematic evolution. Drawing on archival sources, user-generated content, and field documentation, they use both manual and computational tools such as coding frameworks and natural language processing. While rooted in qualitative traditions, they increasingly integrate big data and spatial technologies, which enables spatially anchored discourse analysis and interpretive mapping.

- **Immersive technologies** *(vii)*, **rendering/visualization/modeling** *(xiii),* and **digital twin** *(xiv)*: Respectively 3.94% (8 studies), 0.99% (2 studies), and 0.49% (1 study) of the corpus, these methods extend the field's digital toolkit. Immersive technologies employ virtual, augmented, and mixed reality (VR/AR/MR) to create 3D environments for experiential evaluation, participatory design, and interactive interpretation, often drawing on point clouds, multi-view imagery, and 3D meshes. Rendering, visualization, and modeling focus on 3D mesh rendering, modeling platforms, and visualization pipelines that communicate spatial qualities and support digital interpretation. Digital twin links high-fidelity 3D models with real-time building or environmental data to enable dynamic simulation, monitoring, and management of heritage landscapes.

- **Photogrammetry-based techniques** *(viii)* and **point cloud-based techniques** *(xi)*: Respectively 2.46% (5 studies) and 0.99% (2 studies) of the corpus, these are central to digital reconstruction, modeling, and documentation of heritage landscapes. Photogrammetry, often implemented with UAV imagery and Structure from Motion (SfM) algorithms, supports 3D modeling and orthophoto generation. Point cloud data, typically derived from terrestrial or airborne laser scanning, enables detailed spatial analysis, semantic segmentation, and structural documentation. These techniques increasingly converge in hybrid workflows for virtual preservation, building diagnostics, and interaction design, and their high-resolution outputs underpin rendering, simulation, and immersive visualization. They are always used in combination with other methods.

- **Design and planning approaches** *(ix)* **and case studies** *(x)*: Respectively 1.97% (4 studies) and 1.48% (3 studies) of the corpus, they provide grounded insights into site-specific interventions and local dynamics. Case studies emphasize field-based exploration and interview-driven analysis, whereas design and planning approaches focus on scenario building, co-design, and spatial prototyping. Although typically qualitative and context specific, both increasingly integrate digital modeling and visualization to support stakeholder engagement and real-world implementation.

- **Mixed methods *(xv)*:** These studies account for 39 publications (19.21%), reflecting a growing trend toward methodological integration. Combinations include **traditional + traditional** (e.g., literature review and case study), **digital + digital** (e.g., GIS and AI), and, most commonly, **traditional + digital** (e.g., surveys with GIS or photogrammetry). Representative studies include perception-led workflows that link public surveys or interviews with GIS viewshed or land-use overlays, documentation-to-experience pipelines that use photogrammetry or point clouds to produce 3D models followed by VR or AR evaluation, and computation-to-interpretation loops that connect AI-based image or text analysis with GIS overlays and multi-criteria decision analysis. This evidence suggests that integration yields richer and more actionable insights; accordingly, we highlight mixed designs as a particularly promising direction for visual heritage landscape research and elaborate on this in the Discussion.

In summary, methods like point cloud-based, immersive technologies, and AI-based, though not new, have only recently gained traction in heritage landscape research. Their uptake signals a shift from fragmented approaches to integrated, digital frameworks. As spatial, perceptual, and computational methods converge, traditional and emerging methods (including tools and data) increasingly function as components of a unified, multi-layered system **(FIG. 2.7)**.

TABLE 2.4 Summaries of core methods, tools, and data

Categories	Amount	Percentage	Example of tools	Representative data types
(i) Empirical research methods	57	28.08%	Surveys, interviews, eye-tracking, PPGIS	Behavioral, perceptual, physiological, 3D spatial data
(ii) GIS-based technologies	35	17.24%	Viewshed analysis, spatial modeling, GIS-overlay	Remote sensing, terrain, spatial layers, participatory data
(iii) Multi-criteria evaluation frameworks	17	8.37%	Risk analysis, visual sensitivity, MCDA	Expert-based, environmental, spatial, historical data
(iv) AI-based technologies	10	4.93%	Machine learning, deep learning, GIS-integrated AI	Satellite imagery, UGC, point clouds, archival data
(v) Content analysis	9	4.43%	Thematic/content coding, NLP tools, spatial text analysis	User-generated content, field observations, spatial text
(vi) Literature review	9	4.43%	CiteSpace, VOSviewer, coding analysis	Bibliographic data, textual records
(vii) Immersive technologies	8	3.94%	VR, AR, MR, 3D immersive environments	Immersive media, 3D visualization, perception data
(viii) Photogrammetry-based techniques	5	2.46%	Structure-from-Motion, aerial triangulation	UAV imagery, Ground-based DSLR imagery
(ix) Design and planning approaches	4	1.97%	Scenario design, spatial layout planning	Design schemes, spatial planning drawings
(x) Case study	3	1.48%	Field studies, interview-based case analysis	Qualitative data, interview records
(xi) Point cloud-based techniques	2	0.99%	3D modeling with point clouds, segmentation	Point clouds, 3D model files
(xii) Image analysis	2	0.99%	Color measurement, image segmentation	Images, visual metrics
(xiii)Rendering/visualization/modeling	2	0.99%	3D mesh rendering, Blender, visualization pipelines	3D scenes, rendering files, mesh data
(xiv) Digital twin	1	0.49%	Digital twin modeling, reality capture	Real-time building data, 3D scans
(xv) Mixed methods	39	19.21%	e.g., Surveys/interviews + GIS (PPGIS, viewshed, spatial overlay); photogrammetry/point clouds + VR/AR evaluation; AI image segmentation or NLP + GIS overlays;	Multi-source datasets: survey responses, DEMs and satellite imagery, point clouds, 3D models/meshes, UGC and textual records, georeferenced historical maps, etc.

Note: Appendix A (Table A3) provides a detailed table listing the literature sources associated with each method/tool/data type.

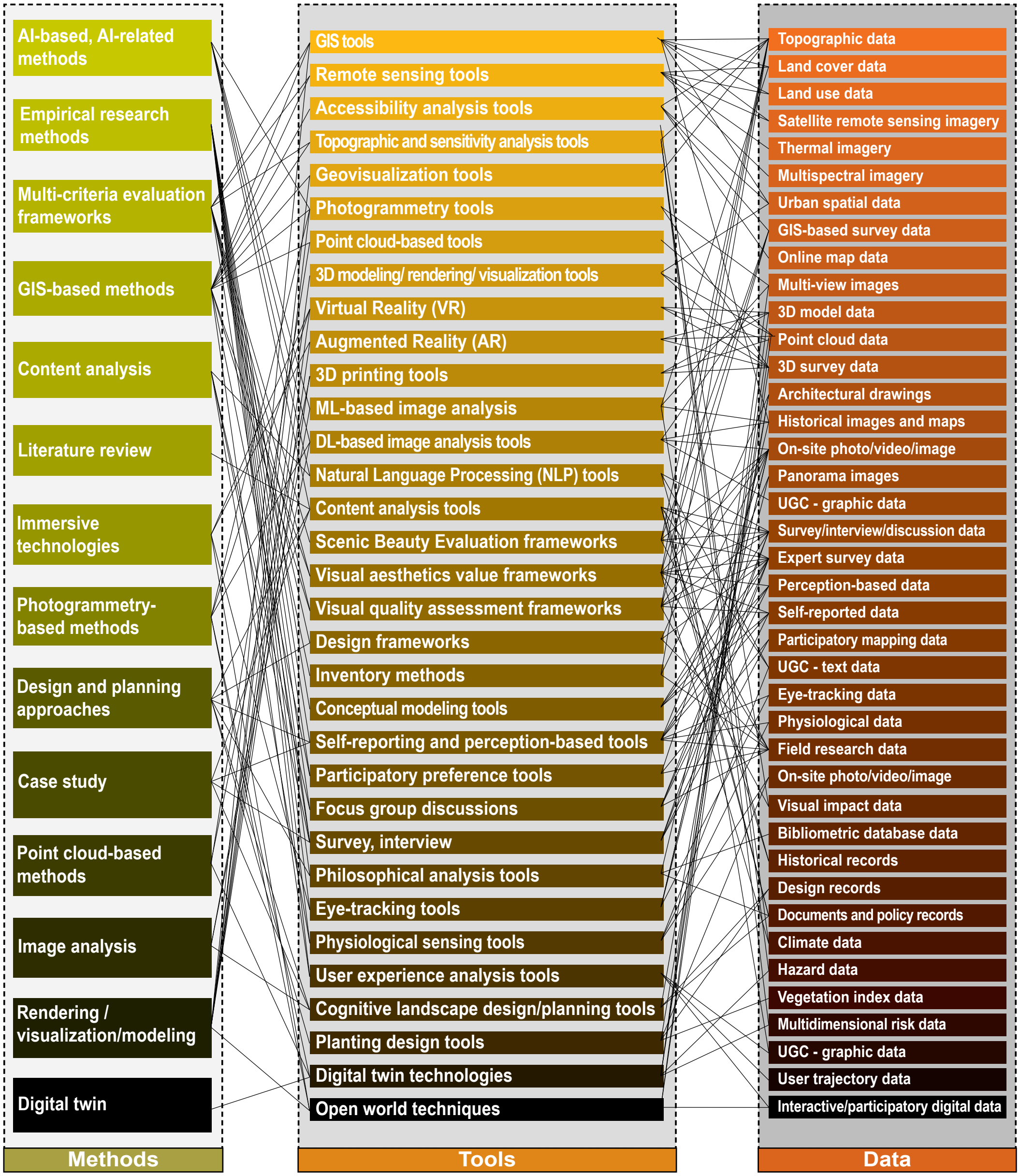


FIG. 2.7 Three levels of methodology: core methods - tools – data (details can be found in Appendix A Table A3).

2.3.3 Network visualization of conceptual structures

This section presents a bibliometric network analysis to complement the manual coding results by offering a macro-level view of conceptual linkages across the reviewed literature. Based on keyword co-occurrence extracted from titles, abstracts, and author-supplied terms, a network map was generated using VOSviewer **(FIG. 2.8)**. Nodes represent keywords (scaled by frequency), and edges indicate co-occurrence strength. The analysis reveals how research themes, methods, and landscape types cluster, interrelate, and evolve. This section includes: **(a) cluster analysis, (b) interrelationships analysis**, and **(c) temporal analysis.**

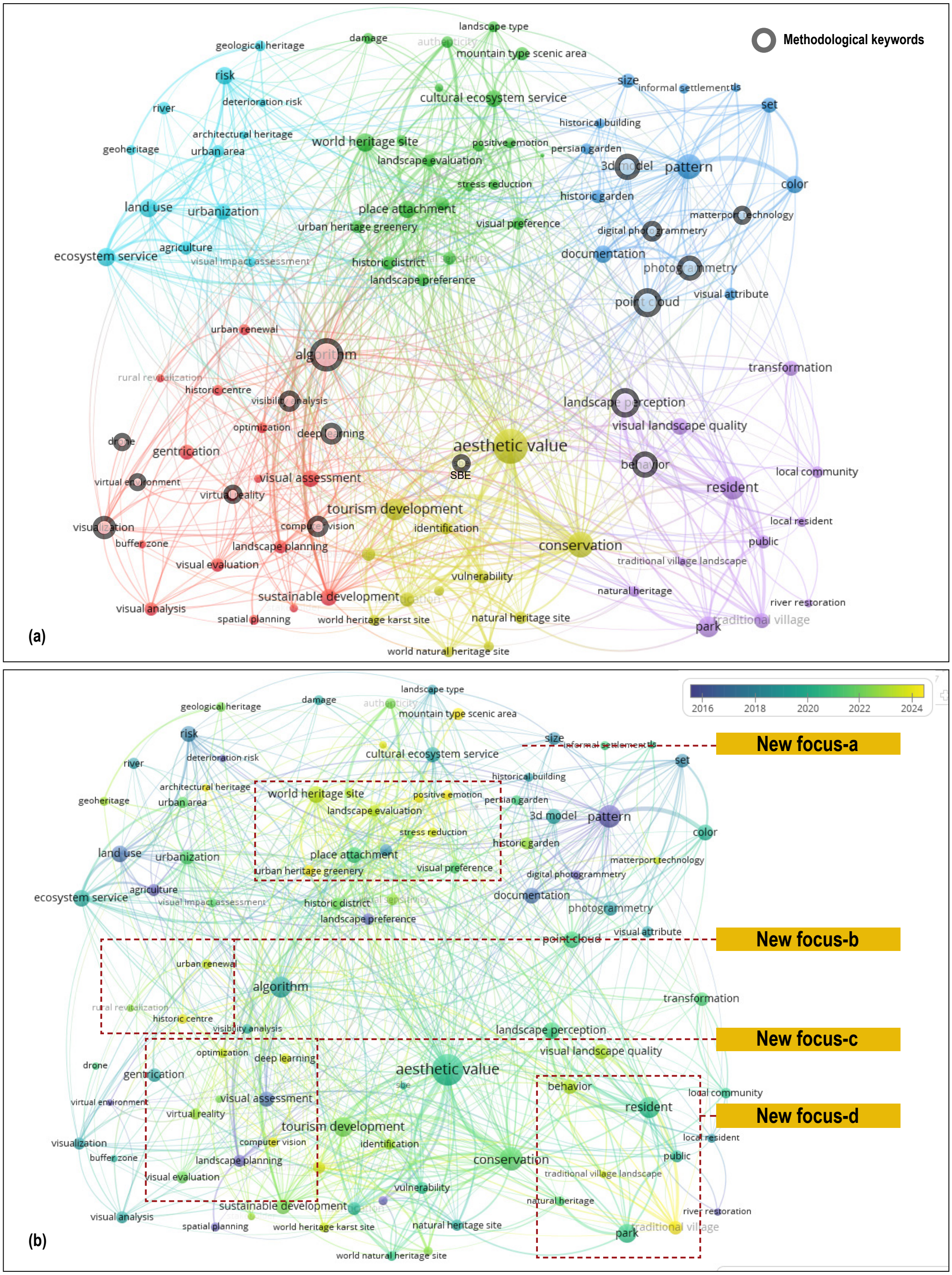


FIG. 2.8 Results of network analysis-1: (a) Keyword clustering; (b) Temporal trends in keyword emergence.

TOC

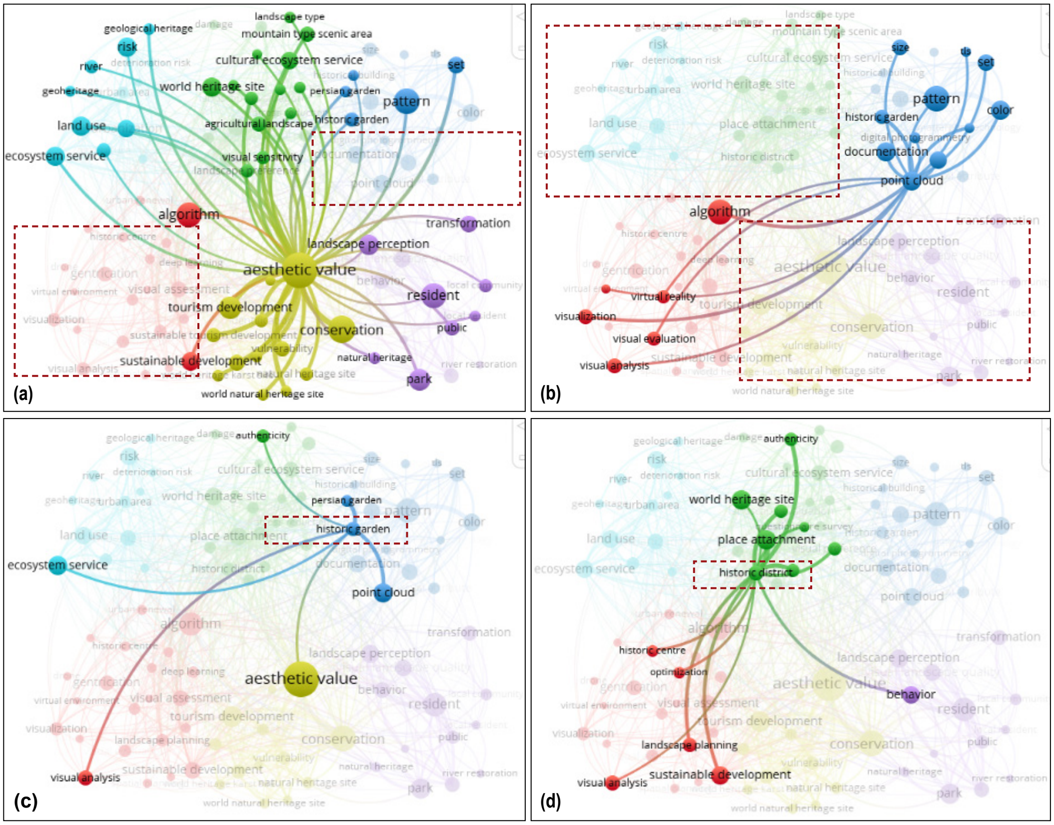


FIG. 2.9 Results of network analysis-2: (a)–(b) examples of theme–method under-coupling; The aesthetic value theme co-occurs far less often with point-cloud workflows than with perception-based or multi-criteria methods; (c)–(d) Methodological and thematic differences across landscape types, illustrated by “historic gardens” and “historic districts”.

2.3.3.1 Clustering analysis

While **Section 2.3.2** summarized five concept-driven research themes derived from manual coding, this section presents data-driven clusters generated by keyword co-occurrence analysis. The two approaches operate at different analytical levels, reflecting semantic abstraction in the coded themes and lexical structure in the co-word network. They are not expected to fully coincide but rather to provide complementary perspectives: the co-word network reveals how research vocabulary is organized, whereas the coded themes capture how scholars conceptually frame their studies. The co-word network analysis identified 6 distinct keyword groups, each combining themes, methods, and landscape types, indicating thematic-methodological alignments and disciplinary boundaries **(FIG. 2.8a)**.

a) **The yellow cluster** is predominantly oriented toward the aesthetic and conservation dimensions of natural heritage. Core keywords such as *"aesthetic value," "conservation,"* and *"tourism development"* indicate a research focus on evaluating the visual and ecological qualities of scenic landscapes. Frequently studied types include *karst mountain, geo-heritage*, *natural heritage*, and *world natural heritage* sites. The primary methodological approach identified is *Scenic Beauty Evaluation (SBE)*, which enables structured visual assessments based on expert-based evaluation.

b) **The purple cluster** emphasizes local communities and perceptual engagement with heritage landscapes. Central terms include *"resident," "local community," "public," "landscape perception,"* and *"behavior,"* highlighting socio-cultural concerns in visual heritage landscape research. Empirical methods, like surveys, interviews, and participatory tools are frequently used to examine experiential and behavioral responses, particularly in *traditional rural landscapes* and historic urban green spaces (*park*).

c) **The green cluster** foregrounds the psychological and health-related benefits of heritage landscapes. Key terms include *"place attachment," "landscape preference," "stress reduction," "positive emotion,"* and *"attention restoration,"* indicating a research orientation toward restorative function of heritage landscapes. Questionnaire-based empirical methods dominate, with an emphasis on *urban heritage greenery* and *cultural eco-system service* that enhance well-being.

d) **The cyan cluster** focuses on land use dynamics and ecosystem-related functions. Frequent keywords such as *"land use," "urbanization,"* and *"ecosystem service"* reflect concerns about environmental change and its visual-spatial impacts. Typical methods include *visual impact assessment* and *risk assessment*, often applied to *agricultural landscapes* and *geo-heritage sites* facing development pressures.

e) **The blue cluster** is associated with spatial pattern analysis and digital documentation. Prominent terms such as *"pattern," "documentation," "point cloud," "3D modeling,"* and *"photogrammetry"* suggest a focus on high-resolution spatial data acquisition and visual structure mapping. This cluster typically addresses *historic gardens* and *architectural heritage*, where precision modeling aids conservation, monitoring, and analysis of visual-spatial characteristics.

f) **The red cluster** represents a technologically intensive strand of research that integrates advanced analytical tools with landscape planning and heritage transformation agendas. Core terms include *"algorithm," "deep learning," "virtual reality," "computer vision," "landscape planning," "urban renewal,"* and *"sustainable development."* This cluster reflects the growing incorporation of AI and immersive technologies into visual heritage landscape research, particularly for predictive modeling, interactive interpretation, and design support systems.

Overall, the keywords encompass a diverse range of landscape types, research methods, and thematic focuses, suggesting a seemingly balanced distribution. However, the methods employed and the types of heritage landscapes addressed vary significantly across clusters.

2.3.3.2 Interrelationships analysis

Beyond cluster patterns, the network analysis reveals structured relationships between research themes, methodological approaches, and heritage landscape types. Three key patterns are identified:

a) **Theme–method associations:** Different research themes correspond to distinct methodological tendencies. Studies on aesthetic value often use multi-criteria analysis, perceptual evaluation, and behavioral methods involving expert judgment and public input **(FIG. 2.9a)**, but rarely employ advanced digital tools. In contrast, point cloud-related studies focus on documentation, 3D modeling, and virtual reality, with limited attention to perception or behavior **(FIG. 2.9b)**. This indicates thematic divergence in methodological preferences.

b) **Landscape types and method combinations:** Specific heritage types are linked to characteristic method-theme pairings. For instance, research on "*historic gardens*" often combines point cloud technologies with visual and behavioral analysis **(FIG. 2.9c)**. In contrast, "*historic district*" studies adopt broader, integrated frameworks—addressing perception, well-being, and place attachment, alongside practical approaches such as planning and sustainable development **(FIG. 2.9d)**.

c) **Bridging nodes across clusters:** Several keywords serve as conceptual bridges between otherwise distinct clusters. "*Transformation*" links perception studies with spatial documentation, while "*visual assessment*" connects psychological, ecological, and technological approaches. "*Point cloud*" spans traditional documentation and immersive visualization; "*landscape planning*" connects participatory and spatial-analytical research. Terms like "*public perception*" and "*place attachment*" cut across domains, reflecting shared concerns with emotion, identity, and renewal **(FIG. 2.8a)**.

These patterns suggest that visual heritage landscape research, while showing signs of integration, remains partially fragmented. Thematic and methodological silos limit cross-domain understanding, yet bridging terms offer opportunities for hybridization. Such nodes could inform more cohesive, multidimensional frameworks linking perception, evaluation, documentation, and design.

2.3.3.3 Temporal analysis

The temporal keyword co-occurrence network **(FIG. 2.8b)**, visualized via a color gradient from blue (earlier) to yellow (recent), reveals four emerging research focuses: **Focus-a** links *world heritage site*, *place attachment*, *urban heritage greenery*, *attention restoration*, and *positive emotion*, indicating interest in how green settings in heritage landscapes relate to well-being and attachment. **Focus-b** connects *urban renewal*, *historic center*, and *rural revitalization*, reflecting work on regeneration agendas in heritage contexts anchored in historic centers and their surrounding settlements. **Focus-c** centers on *deep learning*, *optimization*, *virtual reality*, and *computer vision*, signaling a technology-driven turn toward automated and immersive analysis pipelines for heritage landscape studies. **Focus** groups on *traditional village (landscape)*, *public (community)*, and *behavior*, foregrounding community-involved inquiry in traditional village settings and how public behavior intersects with conservation aims.

In contrast, keywords like *pattern*, *documentation*, *land use*, agriculture, *visual assessment*, and *landscape planning* have maintained a stable presence, continuing to structure the core of the field. Interestingly, terms such as *digital photogrammetry* and *virtual environment* appeared relatively early but have yet to be widely adopted, despite their precision and immersive potential, indicating a gap between technological innovation and mainstream research uptake.

2.3.4 Mapping interconnections across analytical dimensions

To complement the thematic **(Section 2.3.2)** and conceptual **(Section 2.3.3)** analyses, this section visualizes cross-dimensional relationships among four core categories: heritage landscape types, spatial scales, research themes, and core methods. Based on the coded dataset, a Sankey diagram was constructed to reveal both dominant trajectories and underexplored intersections **(FIG. 2.10)**. Rather than reflecting frequency alone, this visualization highlights the intensity and directionality of linkages across dimensions, offering a structural perspective on how the field is composed and where integration is still lacking.

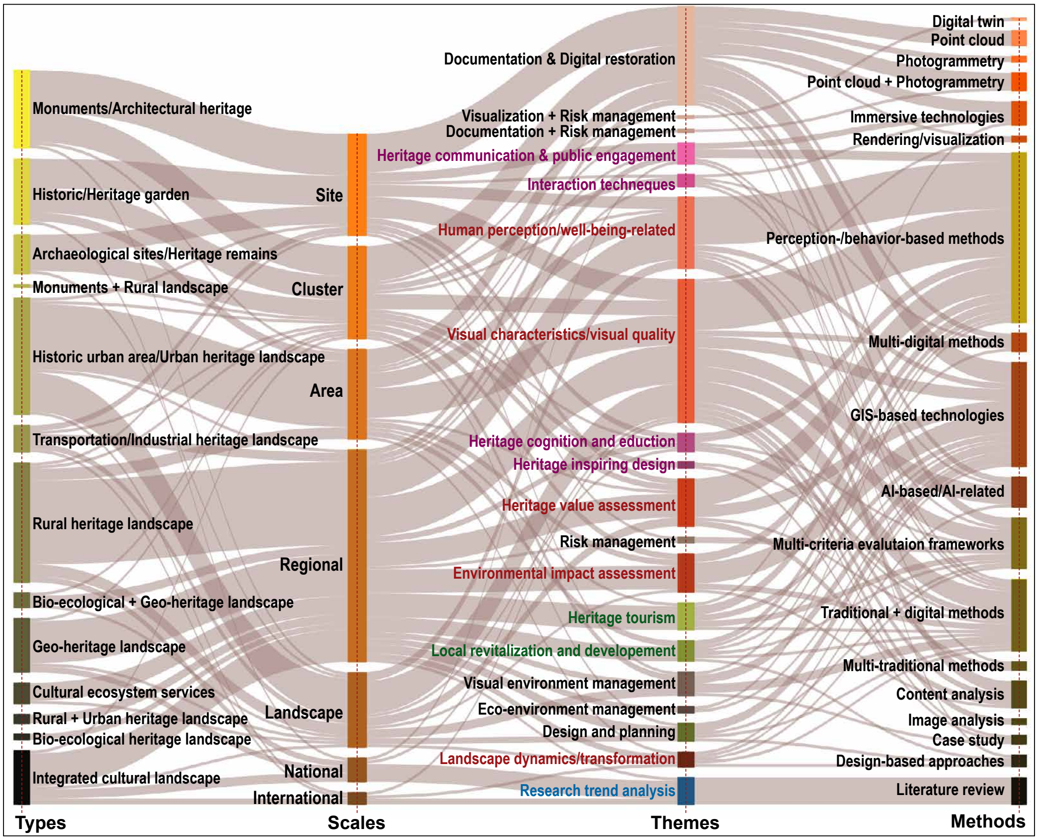


FIG. 2.10 Interconnections across analytical dimensions based on Sankey diagram analysis-1: Overall pathways from research objects to research themes and core methods.

TOC

a) **Landscape types and research themes:** The flow between landscape types and research themes reveals clear preferences and structural differences **(FIG. 2.11c)**. Three frequently landscape types, which broadly represent *regional*, *area*, and *site* scales, are analyzed in detail: *Rural/agricultural/rural settlement landscapes* display the most diverse thematic profile. Dominant themes include *visual characterization and quality evaluation*, *public perception and well-being*, and *heritage value assessment* (cultural, historic, ecological, and economic). Other recurrent topics such as *local revitalization*, *(digital) documentation and restoration*, *environmental impact assessment*, and *landscape transformation* reflect a strong planning and perceptual orientation. *Historic urban areas/urban heritage landscapes* show a more concentrated focus on *visual characterization*, with frequent attention to *public perception*, *(digital) documentation*, and *environmental impact assessment*. Themes such as *public engagement* and *revitalization* appear less often, indicating a research emphasis on visual quality, user experience, and conservation in urban built environments. *Historic/heritage gardens* are primarily associated with *visual characterization and quality evaluation* and *(digital) documentation and restoration*. Other notable themes include *visual environment management*, *heritage value assessment* (especially cultural and historic), and *design and planning of heritage landscapes*. A distinct feature of this category is the recurring theme of *using heritage as design inspiration*, rarely observed in other landscape types.

b) **Relationship between research themes and methods:** Each theme is supported by a distinct methodological foundation **(FIG. 2.11d)**. *Analysis/evaluation* draws on a broad and balanced mix of empirical research, GIS-based analysis, and multi-criteria evaluation frameworks. Together, these three categories form the methodological core of this theme, combining perceptual inquiry, spatial modeling, and decision-support structures. *Management/Conservation* is characterized by a clear technological orientation. It predominantly relies on point cloud processing, photogrammetry, and risk assessment tools, underscoring the central role of high-resolution digital data and modeling in contemporary conservation practice. *Sustainable development and use* tend to adopt planning and design approaches, often in combination with other methods, to explore the integration of heritage in evolving territorial agendas. *Communication/engagement*, meanwhile, is rooted in participatory and perception-based empirical methods, with emerging use of immersive tools such as VR/AR for enhancing interaction and interpretation.

c) **Relationship between spatial scales and methods:** Certain case scales are strongly associated with specific analytical methods **(FIG. 2.11b)**. The regional scale is typically paired with GIS-based analysis, multi-criteria evaluation and design and planning tools, particularly in studies addressing land-use dynamics, landscape transformation, or policy-making. Site-scale and cluster-scale research is often linked to point cloud technologies, photogrammetry, and perceptual assessments, reflecting a focus on detailed documentation, spatial experience, and architectural morphology. Area-scale studies commonly adopt empirical and participatory approaches, especially in neighborhood-level urban heritage research. National and global scales are primarily addressed through literature reviews and comparative content analysis. These associations suggest that spatial scale not only shapes the scope of research questions but also constrains or enables the selection of methodological tools.

d) **Relationship between landscape types and methods:** Heritage landscape types show distinct methodological preferences **(FIG. 2.11a)**. *Rural/agricultural/rural settlement landscapes* apply a wide mix of empirical, GIS-based, and planning methods, serving as testing grounds for perceptual and spatial analysis. *Historic urban areas/urban heritage landscapes* also show methodological diversity, combining perception studies, design strategies, and mixed methods. In contrast, *monuments/architectural heritage* and *historic/heritage gardens* rely more heavily on point clouds, photogrammetry, and risk models, emphasizing accuracy and preservation. *Geo-heritage landscapes* are commonly examined through GIS-based visibility and accessibility tools, often within conservation or aesthetic frameworks. Less-studied types, like *cultural ecosystem service* and *urban-rural hybrids*, show fragmented patterns, indicating methodological gaps and opportunities.

The Sankey diagram highlights both structural specialization and latent integration across the field. Clear flows exist—e.g., rural landscapes link to evaluation themes via empirical both and GIS-based; architectural heritages connect to conservation through digital documentation tools. Yet many cross-connections remain underexplored. For example, immersive technologies, and high-resolution digital tools (e.g., point cloud) are rarely applied in perception or participatory studies, while empirical data and social indicators are seldom integrated into advanced visualization. These findings collectively confirm both the scarcity and potential of integrated research: across themes, landscape types, spatial scales, and methodological domains (e.g., data, tools).

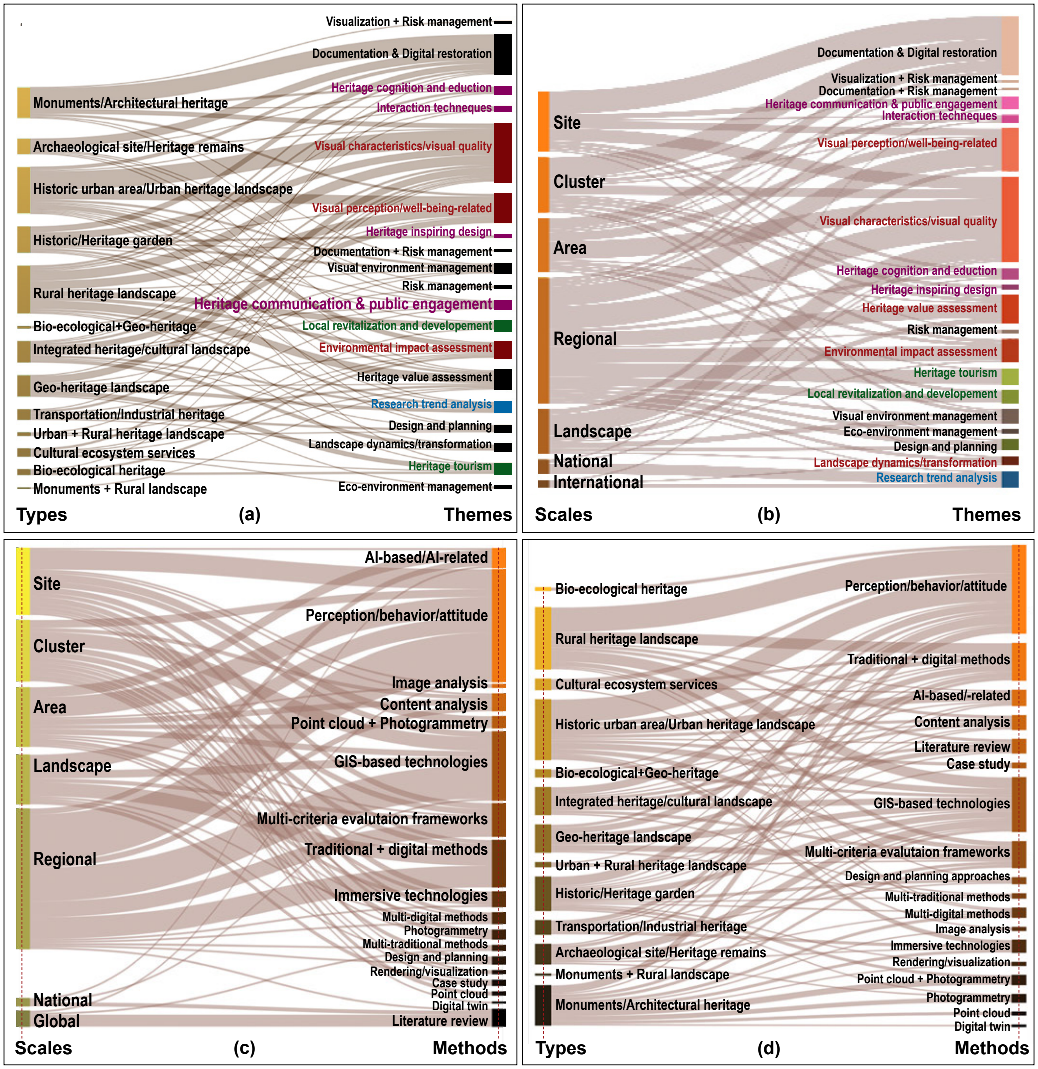


FIG. 2.11 Interconnections across analytical dimensions based on Sankey diagram analysis-2: (a) Focused linkages between landscape types and research themes; (b) Focused linkages between spatial scales and research themes; (c) Focused linkages between spatial scales and research methods; (d) Focused linkages between landscape types and research methods.

2.4 Discussions

Building on the coding and mapping results, this section moves beyond structural description to interpretive reflection. While the previous analyses identified key research themes, objects (in terms of landscape types and spatial scales), methods (including tools and data), and their interconnections, the focus now shifts to synthesizing these findings and exploring critical gaps and future directions.

2.4.1 Methodological evolution and integration trends

This section offers a synthesis of technological evolution in heritage landscape visual studies, reveals the existing research gaps, and outlines potential future directions grounded in observable trends **(FIG. 2.12a)**.

2.4.1.1 The research evolution in the past 30 years

The development of heritage landscape visual research over the past three decades can be divided into three phases **(FIG. 2.12b)**, reflecting a dual-track trajectory: one based on perception and empirical assessment, the other on spatial and computational tools.

- **Period 1 (1995–2005):** This phase marked the emergence of heritage landscape studies as a defined research field. Traditional approaches centered on visual perception, including preference studies (Chandler & Costello, 2002; Frey, 1997), place attachment (Kaltenborn & and Bjerke, 2002; Uzzell, 1996), and stress reduction (Schouten, 1995), while GIS became the primary digital tool for basic spatial visualization (Summerby-Murray, 2001) and land-use analysis (Stewart, 2001; Taillefumier & Piégay, 2003). Data use was polarized: traditional studies relied on qualitative sources like interviews and archives, while digital research used coarse-resolution satellite data and early DEMs (Nijhuis et al., 2011). Although VR technologies appeared (Gaitatzes et al., 2001), technical limitations restricted their application. This period laid the groundwork for the later divergence of empirical and computational approaches.

TOC

- **Period 2 (2005–2015):** This decade saw the diversification of both digital and traditional methods. High-resolution techniques such as photogrammetry (McCarthy, 2014; Remondino, 2011) and point cloud scanning (White, 2013) and photogrammetry enhanced spatial modeling. Empirical studies evolved through the use of physiological sensing such as eye-tracking (Sang et al., 2014), while literature-based (Brown et al., 2015) and design-oriented research gained prominence (Deghati-Najd et al., 2015; Ignatieva et al., 2011). GIS began to integrate perceptual data, enabling behavioral-spatial modeling (Nijhuis et al., 2011). Although UGC was not yet central, multi-data frameworks began to emerge, combining field surveys, historical documents, and high-resolution spatial data.

- **Period 3 (2015–2025):** The recent phase marks a shift toward AI-supported, data-rich, and integrative research. Point clouds (Grilli et al., 2019; Pierdicca et al., 2020; Sánchez-Aparicio et al., 2023) and photogrammetry (Aicardi et al., 2018; Kingsland, 2020; Rahaman & Champion, 2019) became standard tools for small- to mid-scale spatial modeling. AI and deep learning support large-scale pattern recognition, semantic segmentation, and content extraction (Liu et al., 2022; Matrone et al., 2020). Digital twins emerged as a conceptual framework for simulation and monitoring (Lucchi, 2023; Shabani et al., 2022). VR and AR re-entered the field, supported by improved 3D data quality and computational power (Debailleux et al., 2018; Gonizzi Barsanti et al., 2015). Meanwhile, rich data layers like UGC (Choo, 2023; Xu et al., 2023), panoramic imagery (Bassier et al., 2018; Koeva et al., 2017), and web-based spatial content (Nishanbaev et al., 2021) supplement traditional sources, enabling complex analyses of visual quality, transformation, and heritage perception.

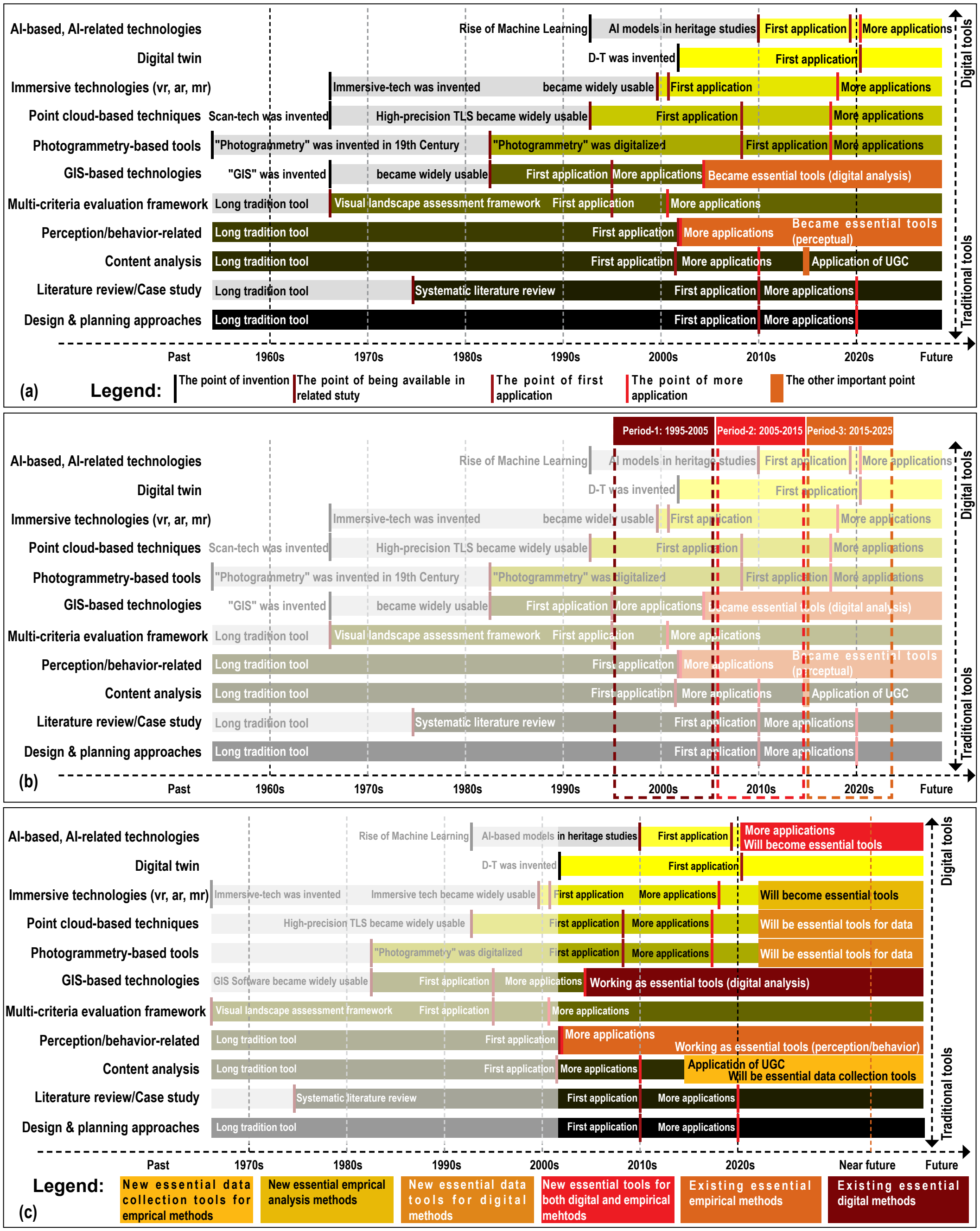


FIG. 2.12 Evolution and trends of research methods: (a) Key milestones in methodological development; (b) Distinct periods of evolution; (c) Emerging trajectories for future research.

TOC

2.4.1.2 Methodological gaps

Despite growing experimentation with mixed methods and digital tools, key methodological gaps persist. **(a) Epistemic and workflow disconnection between perception-based inquiry and spatial–computational analysis:** While Perception-/behavior-based methods such as surveys and affective mapping have advanced, they are seldom integrated into spatial analysis pipelines (Bekele et al., 2018; Jones, 2016). Conversely, GIS and 3D modeling often exclude user evidence, which limits the social grounding of spatial analyses (Zhang & Zou, 2022). A related issue concerns ecological validity: responses elicited by VR- or rendering-based visual stimuli may diverge from in situ experience and therefore require explicit testing and calibration (Harris et al., 2020). **(b) Limited modularity and transferability:** Many toolsets remain project-specific and lack standardized protocols that combine methods across data collection, modeling, and evaluation stages (Hakala et al., 2011; Su et al., 2019), which hampers the accumulation of comparable and scalable knowledge (Hudson, 2011). **(c) Uneven access to advanced hardware and platforms:** Access to high-resolution point-cloud scanners (though some smartphones can be used as mid-resolution scanners), AI platforms, and immersive systems is uneven, which can limit the breadth and reproducibility of some high-fidelity pipelines (Butcher & Pecot, 2021; Vlase & Lähdesmäki, 2023). This is an equity and scalability issue rather than a prerequisite for quality: rigorous visual heritage research can be conducted with low-cost capture and on-site protocols, provided that procedures are transparent and comparable. **(d) Weak cross-scale and cross-theme integration:** Eye-level perception analytics (for example, eye-tracking in virtual or field settings) are rarely linked to bird's-eye mapping, such as visibility analysis, and tools for simulation, assessment, and participatory design remain poorly interconnected. In contrast to gap (a), which concerns coupling evidence types within a pipeline, this gap concerns the translation of results across spatial scales and thematic domains once evidence exists. These silos hinder a holistic understanding of heritage landscapes as lived and layered spaces (Harvey, 2015).

Addressing these gaps calls for not just technical improvement, but also an epistemological shift toward modular, inclusive, and transdisciplinary research frameworks (Aimar, 2024; Liu & Nijhuis, 2020). Viewed through the lens of boundary work, their root causes lie in how disciplinary communities maintain distinct problem framings, data standards, and validation norms; bridging them requires shared protocols and the creation of “trading zones” where methods, evidence, and interpretations can be negotiated across domains (Harrison, 2012).

TOC

2.4.1.3 Future outlook: From tools to integrated frameworks

In addition, three key technological trajectories are reshaping the field: **(a) Immersive media (VR/AR/MR)** are evolving into Perception-/behavior-based tools for studying spatial experience, behavior, and preference. When combined with computer vision-based rendering (e.g., Gaussian Splatting, a rising visualization technique), they enable real-time testing of how users perceive and interact with heritage environments (Gonizzi Barsanti et al., 2015). To ensure ecological validity, outcomes from immersive experiments should be compared with matched in situ observations at the same viewpoints and along the same routes, and the analysis should be stratified by audience groups, for example, residents, heritage community members, and visitors, in order to detect group-specific responses(Strandberg, 2023; Wynveen et al., 2012). **(b) UGC and big data** offer bottom-up insights into public sentiment and spatial behavior. Through machine learning and NLP, such content complements expert-led evaluation and supports participatory heritage mapping (Choo, 2023; Hølleland et al., 2017). **(c) Point clouds and photogrammetry** are transitioning from specialized tools to core data infrastructure. New techniques and LiDAR/UAV advances allow rapid, high-resolution 3D modeling. When scaled via national repositories (e.g., AHN, Netherlands), these datasets support monitoring, planning, and multi-stakeholder engagement (Grilli et al., 2019; Khan et al., 2022). Additionally, AI-based approaches can fuse perceptual data (e.g., street-view imagery or attention traces) with GIS layers to learn perception-aware spatial indicators. Such integration helps close the gap between human experience and spatial modeling in heritage landscape analysis.

These developments suggest that future progress depends not on the accumulation of individual tools but on their orchestration into interoperable and multimodal systems **(FIG. 2.12c)**. Achieving methodological integration, linking digital technologies, perception-based inquiry, and heritage development practices, is essential for constructing comprehensive, adaptive frameworks for visual heritage research (Pintossi et al., 2021).

TOC

2.4.2 Research objects: Gaps and emerging directions

In the past decades, the scope of visual heritage landscape research has broadened in both types and spatial scales. While rural and urban heritage landscapes continue to dominate, newer categories, such as infrastructural, post-industrial, and hybrid ecological-cultural landscapes, are gradually emerging. Parallel to this, a shift from binary micro–macro analyses toward multi-scalar frameworks is taking shape.

2.4.2.1 Object-based gaps

Despite increased diversity, the current field remains typologically and spatially imbalanced. Research remains concentrated on well-bounded, visually legible types, such as traditional built environments, which align with established tools (e.g., GIS, photogrammetry) (Page et al., 2021). Complex or ambiguous heritage types, such as infrastructure corridors, ecological-cultural hybrids, or contested sites, remain underexplored, as their lack of formal recognition and clear spatial boundaries poses challenges for conventional analytical frameworks (Cortesão et al., 2020). Moreover, most studies are temporally static, focusing on fixed moments rather than dynamic visual change, thus limiting engagement with processes of transformation, memory, and visual continuity. Equally important is the social dimension of temporality: changes in population composition and cultural diversity continuously reshape how heritage landscapes are perceived and valued. Few studies address how different groups or successive communities privilege particular heritage narratives over others, leaving the socio-cultural dynamics of “whose heritage” largely unexplored(Fouseki, 2022). Spatially, the dominance of micro- and regional-scale studies results in a neglect of intermediate scales and cross-scalar integration. This constrains the capacity to inform multi-level heritage governance or to link perceptual data with broader territorial strategies (Butcher & Pecot, 2021).

2.4.2.2 Future trends

In response to these gaps, recent studies signal a shift toward broader, more complex understandings of heritage landscape objects (Vlase & Lähdesmäki, 2023). This transformation is unfolding along two main trajectories: **(a) Typological diversification**: There is growing scholarly attention to unconventional or previously excluded types, e.g., infrastructure corridors, peri-urban margins, and post-conflict landscapes (Gonçalves et al., 2021). These challenge conventional typologies and require multi-method, cross-scalar approaches to address their fragmentation, relationality, and evolving significance. Concurrently, new concepts like “everyday heritage” and “vernacular memory” reflect a growing focus on how local communities understand and value heritage in their own ways (Li et al., 2021), highlighting the need for visual research methods that can engage with informal, diverse, and sometimes unofficial heritage landscapes (Zhang et al., 2023). While the focus here is on object types and spatial scales, we note that shifts in population composition and cultural diversity can influence how those objects are perceived and valued. These socio-temporal aspects are addressed in the thematic discussion (**Section 2.4.3**). **(b) Spatial re-scaling**: Visual heritage research is advancing along two key spatial directions. At the micro-scale, it is becoming more detailed and experiential, aided by sensor-based tracking, eye movement analysis, and immersive technologies such as VR and AR (Khan et al., 2022). At the macro-scale, research increasingly draws on global visualization platforms, remote sensing technologies, and national point cloud repositories (e.g., AHN in the Netherlands), enabling large-scale comparisons and monitoring (Deghati Najd et al., 2015). Crucially, recent integrative frameworks, such as the *Historic Urban Landscape*[16] approach and *Guidance on Heritage Impact Assessments for Cultural World Heritage Properties*[17], emphasize the need for cross-scalar analysis. These approaches recognize that the visual character of heritage is not fixed, but dynamically shaped through multi-layered spatial contexts and lived human experience.

2.4.3 Thematic shifts: Gaps and emerging agendas

Visual heritage landscape research has traditionally focused on documentation, evaluation, and management, prioritizing visual recording, aesthetic assessment, and spatial regulation. However, shifts in technology, governance, and public values are prompting a turn toward applied, experiential, and inclusive agendas. These thematic changes also shape how heritage landscapes are defined and bounded, since inclusion or exclusion of particular visual and social attributes depends on whose perceptions and values are considered.

16 **UNESCO. 2011.** Recommendation on the Historic Urban Landscape.
17 **ICOMOS. 2011.** Guidance on Heritage Impact Assessments for Cultural World Heritage Properties. https://www.iccrom.org/

TOC

2.4.3.1 Conceptual and operational gaps

While research themes have diversified beyond documentation and visual assessment, several conceptual gaps continue to limit the scope and relevance of visual heritage studies. A major concern is the continued dominance of expert-driven evaluation, with limited integration of lay perspectives, emotional engagement, or community experience. While visual perception and well-being have gained visibility, they often remain peripheral to technical assessments (Gonçalves et al., 2021). In many studies, the audience question is under-specified: samples are not stratified across residents, heritage community members, visitors, or cultural cohorts, and divergences among these groups are seldom reported. Bridging expert and public perspectives requires transparent procedures that translate qualitative perceptions into comparable indicators and that document how disagreements are reconciled before informing decisions. Moreover, there is insufficient dialogue between thematic research and practice-oriented application. Implementation frameworks like HUL are frequently referenced but seldom applied in depth, with limited reporting of protocols, indicators, and feedback loops that would enable replication. Finally, ecological validity is often assumed rather than tested. Outcomes from immersive or rendering-based experiments are not consistently compared with matched in situ responses, and validations tend to focus on scenic judgements rather than meanings, memory, attachment, or short-form well-being.

2.4.3.2 Emerging thematic directions

Future trends in visual heritage landscape research reflect a gradual shift away from expert-centered paradigms toward more applied, practical, and socially grounded agendas. These new directions respond directly to the conceptual and operational limitations outlined above, offering a more inclusive and practice-oriented future for the field (Cortesão et al., 2020). This trend points to three major shifts:

a) **Technology-enabled participation and interpretation:** Technologies are increasingly mobilized to support public participation, education, and heritage-related decision-making. Tools such as AI, computer vision, and immersive media are moving from experimentation to integrated, goal-oriented workflows that translate public inputs into map layers, indicators, and scenarios (Ginzarly & Teller, 2018; Khan et al., 2022). Credibility improves when sampling is stratified by audience groups, uncertainty is reported, and clear rules are provided for reconciling divergent needs or preferences before indicators guide actions.

b) **Visuality as emotional and experiential engagement:** There is a growing emphasis on well-being, mental health, and emotional connection, particularly in relation to urban heritage green spaces (Harisanty et al., 2024). In this shift, visuality is increasingly understood not merely as a measurable attribute but as a lived and affective experience embedded in everyday interaction with the landscape. To ensure ecological validity, immersive or rendering-based results should be checked against matched in situ observations across both scenic and non-scenic outcomes, including meanings, memory, and attachment.

c) **Practice-oriented integration with policy and design:** Research is aligning more closely with policy and design practice. Visual-based approaches, such as scenario modeling, co-design, and visual impact regulation, are increasingly used to guide practices like urban renewal and rural revitalization in heritage contexts (Chong & Balasingam, 2018; Liu & Nijhuis, 2020). Effective applications make the path from indicators to controls and design choices explicit and report how validation and audience stratification modify thresholds, weights, and uncertainty carried into decisions.

2.4.4 Towards a synthesized visual heritage research framework

Visual heritage landscape research is undergoing a shift from fragmented developments across methods, themes, and heritage object types/scales toward a more integrated and multidimensional framework **(FIG. 2.13)**. In response, the field is converging around three key axes of integration: methods, research objects, and thematic priorities.

Methodologically, research is shifting from isolated tools to integrated, AI-assisted workflows that combine geospatial analysis, semantic modeling, and behavioral or perceptual data (Jordan-Palomar et al., 2018). In practice, AI contributes by structuring complex spatial information: segmenting and classifying elements in imagery or point clouds, detecting change, and generating descriptors of enclosure, skyline integrity, and corridor continuity (Biljecki et al., 2016; Wang et al., 2020). It also fuses perceptual and spatial evidence, for example, by linking eye-level imagery or attention traces with GIS layers to predict patterns of visibility and meaning (Gonizzi Barsanti et al., 2015; Hakala et al., 2011). These capabilities enable more dynamic and multi-perspective evaluations of heritage experience while keeping human expertise central. As data sources diversify, there remains a need for technical interoperability and flexible mixed-method protocols that allow replication and comparison across cases.

In terms of research objects, typologies are expanding to include hybrid, under-represented, and temporally dynamic landscapes, and analytical scales are moving from mono-scalar designs to multi- and cross-scalar approaches (Ashrafi et al., 2021; Zhang & Zou, 2022). This evolution stresses the need to navigate between micro-level perception and macro-level structure, and to make explicit how indicators are translated across scales.

Thematically, agendas are turning from expert-centered assessment toward more inclusive and value-sensitive work that addresses participation, well-being, memory, and identity, while remaining compatible with policy requirements. Our stance is balanced. The framework neither replaces expert analysis nor equates public preference with heritage value. Expert criteria that cover integrity, authenticity, and technical accuracy provide baselines and thresholds. Public and user evidence then refine sensitivity ranges and contextual weights so that cultural relevance is increased without compromising rigor.

Validation follows two complementary tracks. First, audience stratification distinguishes residents, heritage-community members, visitors, and experts, and tests whether results generalize across groups or require group-specific handling. Second, ecological validity is assessed through matched comparisons of in situ observations and immersive or rendering-based experiments at identical viewpoints and along the same routes. Outcomes include not only scenic judgments but also meanings, memory, attachment, and short-form well-being. Where discrepancies appear, simulation parameters and visual indicators are recalibrated, and the residual differences are carried forward as explicit uncertainty in scenarios and regulatory thresholds.

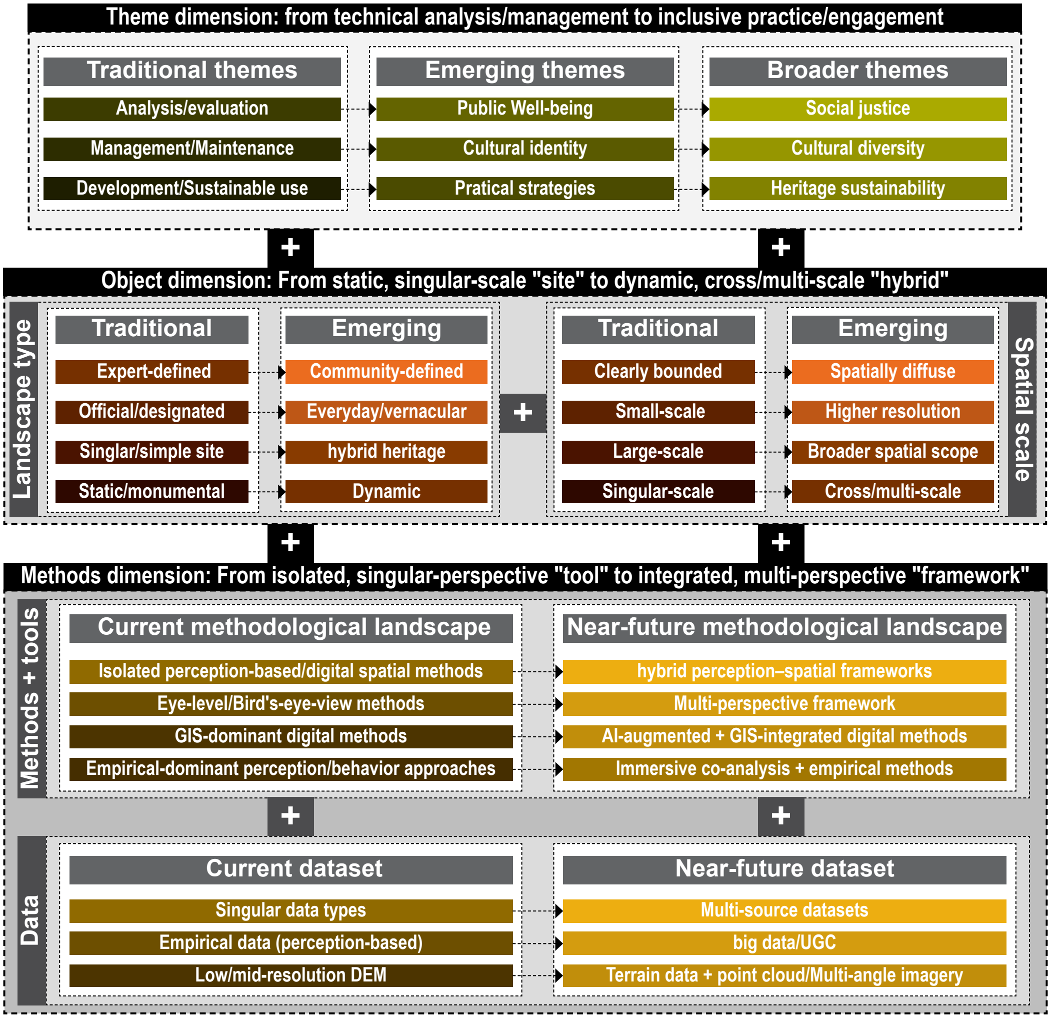


FIG. 2.13 Synthesized visual heritage research framework: A new data–method configuration characterized by greater diversity, cross-scalar integration, and dynamic, composite research objects, with a stronger practice-oriented focus and an emphasis on well-being and sociocultural benefits.

TOC

2.4.5 Limitations

This review has limitations that follow from its scope and design. The review focuses exclusively on English-language publications, potentially excluding significant research published in other languages, particularly from regions with strong local research ecosystems and rich heritage traditions (e.g., China, Japan, Latin America, and parts of Europe) (Ignatieva et al., 2011; Yasumoto et al., 2011). The search strategy also focused on peer-reviewed sources, which means that grey literature, practice reports, and policy documents were largely excluded. In addition, some studies that address visual, spatial, or cultural aspects of heritage environments may not appear in our corpus because they do not explicitly use the term “heritage/cultural landscape,” creating a degree of terminological under-coverage. Given the breadth of the field, the synthesis prioritizes coverage and integration over fine-grained critique of individual methods. We aim to reveal cross-field patterns, interfaces, and research gaps rather than to deliver an exhaustive technical evaluation of each technique. As a result, some discussions are necessarily high-level. Finally, the definition and boundaries of “heritage landscape” vary across cultural and institutional contexts and cannot be fixed universally. We therefore adopt a pragmatic, operational stance that balances expert criteria (e.g., integrity and authenticity) with community recognition, in order to keep comparisons feasible across cases while acknowledging the concept’s inherent variability.

2.5 Conclusions

This chapter provides a comprehensive review of visual heritage landscape research, revealing the field’s thematic concentration on evaluation, its methodological fragmentation, and its focus on a limited range of heritage landscape types. Through systematic coding and cross-dimensional analysis, it answers RQ1 and clarifies the structural relationships among research themes, object types and scales, and methodological approaches.

The review shows that five dominant themes, fifteen methodological categories, and thirteen heritage landscape types across seven spatial scales have shaped the field. However, current studies remain heavily oriented toward evaluation topics, conventional landscape types, and empirical or GIS-based methods. The integration of visual-perceptual inquiry with computational techniques is still rare, while multi-scale, multi-type, and participatory analyses are underrepresented. These tendencies reveal not only a methodological imbalance but also a limited capacity to capture the complexity of heritage landscapes as physical, cultural, and experiential systems. Three persistent challenges emerge from this analysis: the disconnection between perception-based and spatial-analytical approaches, the underrepresentation of hybrid or dynamic heritage types, and the gap between expert-led assessments and socially embedded practices. To address these issues, this chapter proposes a three-dimensional integrative framework that connects research objectives, landscape types and scales as the content dimension, incorporates data types as the evidentiary foundation, and links multi-source methodological pathways as the procedural dimension. This framework provides a coherent structure for aligning technical accuracy with cultural relevance and for supporting research agendas that advance well-being, inclusion, and sustainability.

Building upon these insights, the next chapter develops this conceptual foundation into a practical methodology. It systematizes existing methodological pathways, maps them to different data types, and explores how new integrative pathways—combining spatial modeling with perceptual and participatory evidence—can enhance comparative analysis and guide decision-making in heritage landscape interpretation, conservation, and planning.

– **Author’s contribution in the literature review**:

The literature review was carried out by the author under the supervision of promotor Steffen Nijhuis. The author was responsible for the writing of the literature review and part of its revision, the development of the literature analysis methodology, the reasoning and synthesis of the findings, and the production of related visualizations. Together with the co-author, the author conducted the screening and coding of the literature. The co-author contributed by performing literature screening and coding, producing additional visualizations, and carrying out part of the revision of this section.

3 Research design

A Data-Method-Content Pathway Framework and Case Selection for Visual Heritage Landscape Studies

This chapter aims to translate the literature-derived knowledge map into an operational research design that can guide integrative visual heritage landscape studies. It formalizes the data-method-content triangle as a pathway logic and proposes four expanded pathway types (EP1-EP4) that respond to different research intents, from perception-spatial explanation to practice-oriented visual management. Building on this logic, the chapter defines how emerging data sources, such as point clouds, user-generated content, street view imagery, and immersive VR evidence, can be combined with hybrid analytical methods in a structured workflow. It then outlines the criteria and rationale for selecting four representative case studies, ensuring diversity in heritage landscape type, spatial scale, visual complexity, and decision context. By the end, the chapter provides a clear blueprint for implementation, positioning the empirical chapters as testbeds for validating pathway feasibility, adaptability, and comparative value.

3.1 Introduction

Chapter 2 mapped existing visual research on heritage landscapes and showed a clear pattern: the field is rich in methods and case settings, but many studies remain difficult to compare or combine across contexts. Two persistent gaps stand out. First, several data formats and analytical techniques that could support broader heritage types and more demanding visual tasks are still underused, including newer AI-supported approaches such as machine learning and deep learning (Deng, 2025; Prados-Peña et al., 2023; Wang, 2022). Second, many studies rely on stable method–data pairings and narrowly bounded scales or themes, which limits cross-method complementarity and makes it difficult to connect results across evidence types (Dabaut & Carrer, 2020; Fairclough, 2006; Goodarzi et al., 2023).

These gaps point to the need for a clearer understanding of how data types, analytical workflows, and research aims can be aligned and combined to address different visual questions in heritage landscapes (Anna et al., 2020; Martin, 2011). In particular, the field needs research designs that can connect cross-scale spatial evidence with eye-level scene information and, where relevant, perception evidence, while keeping choices explicit and defensible (Deming & Swaffield, 2011). To respond to this need, this chapter introduces a pathway-oriented research design that treats each pathway as a repeatable combination of evidence sources and analysis steps, matched to a specific visual task and landscape context. Framing the subsequent case studies as pathway implementations allows the thesis to compare what different pathway choices can deliver, and under what evidence conditions they remain feasible.

The chapter is organized into three sections. **Section 3.2** identifies six dominant data–method–content pathway types in the literature and summarizes their typical evidence bases, outputs, and limitations. **Section 3.3** proposes four emerging pathway variants that address common crossover gaps, including multi-source spatial evidence, multi-view scene interpretation, and, where appropriate, perception-oriented evidence. **Section 3.4** explains the selection of four case studies, chosen to represent different landscape types, spatial scales, data conditions, and visual tasks, and to serve as testbeds for demonstrating pathway feasibility in practice.

TOC

3.2 Typologies of dominant data-method-content pathways

Building on the review of visual research on heritage landscapes, this section identifies six dominant pathway types by examining recurring co-occurrences among evidence sources (data), analysis workflows (methods), and research aims (content). The aim is not to label studies by discipline, but to summarize how research designs are typically assembled in practice. To keep the typology comparable across pathways, each type is described using the same four aspects: typical evidence base, typical analysis focus, common outputs, and recurring limitations. The six types summarize the main “default recipes” in the literature and clarify where crossovers between evidence types remain rare.

a) **P1, GIS-based visual-spatial analysis pathway (FIG. 3.1):** This pathway relies primarily on terrain and land-surface representations, such as DEM/DSM and land-use or land-cover layers, combined with GIS-based visibility and landscape-structure analysis. Typical methods include viewshed and cumulative viewshed modeling, isovist-related measures, landscape metrics, and grid-based summaries (Chiesa & La Riccia, 2016; Peng et al., 2025). The main outputs are map-based visibility indicators, skyline or horizon-related diagnostics, and spatial exposure zones that support cross-scale interpretation and screening (Sarihan, 2021; Wu et al., 2023; Zhang et al., 2024). Its main strength is scalable spatial diagnosis with clear computational rules. Its main limitation is that outputs are often interpreted without eye-level evidence and without direct checks against what people attend to or report in real scenes.

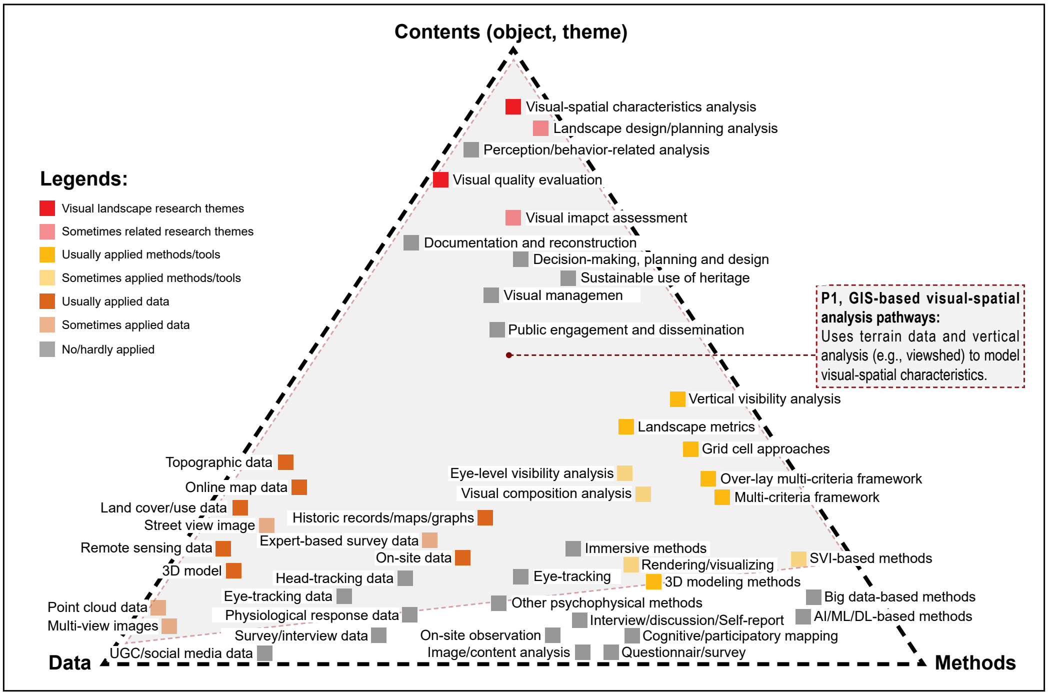


FIG. 3.1 GIS-based visual-spatial analysis pathway pattern: These pathways form a tightly bounded triangle extending from commonly used terrain data and GIS modeling methods to spatial planning-related contents.

b) **P2, perception-/behavior-oriented pathway (FIG. 3.2):** This pathway centers on empirical evidence of how people see, feel, and evaluate heritage scenes, drawing on environmental psychology and behavioral research (Giuliani & Scopelliti, 2009; Kuliga et al., 2015). Typical evidence includes eye-tracking or head-tracking records, surveys, interviews, and on-site or lab-based protocols (Cloves, 2025; Lin et al., 2020). Common methods include preference ranking, semantic differential analysis, attention mapping, and movement or route observation (Fu et al., 2023; Ren, 2024). Outputs are distributions of attention, preference, and meaning themes, sometimes compared across groups. Its strength is direct access to experiential evidence. Its recurring limitations are small or uneven samples, controlled settings that simplify real conditions, and weak anchoring of perception results in spatial structure when spatial evidence is minimal.

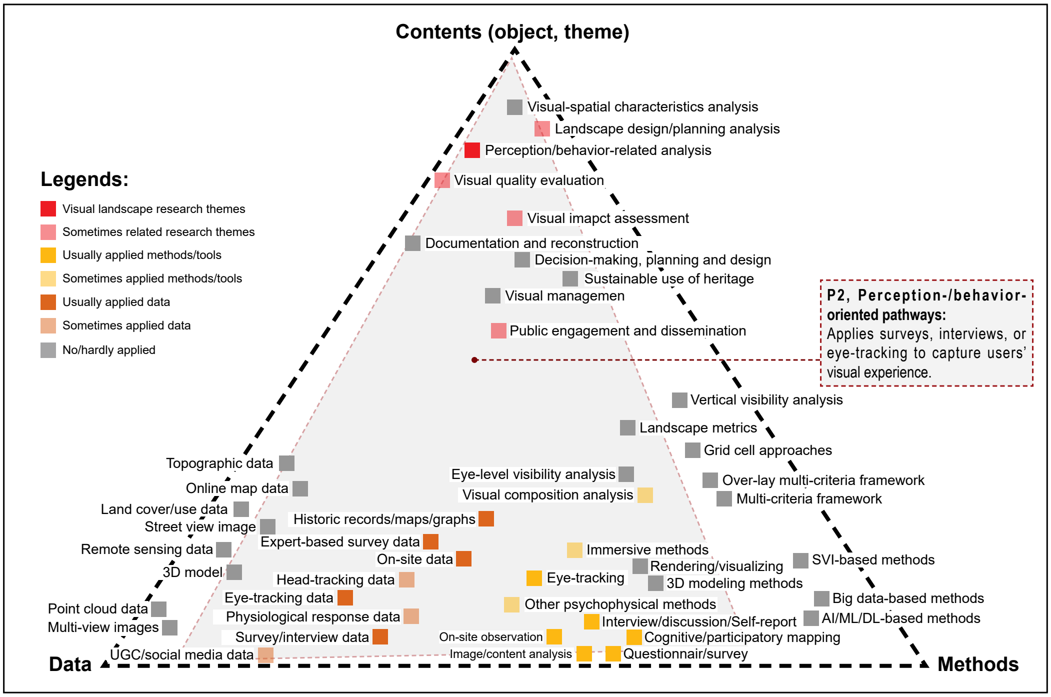


FIG. 3.2 Perception- and behavior-oriented pathway pattern: This pathway links participant-based evidence (e.g., eye tracking, surveys, interviews) with perception and behavior analysis to produce attention and evaluation outputs, often with limited connection to spatial structure at scale.

c) **P3, digital documentation and reconstruction pathway (FIG. 3.3):** This pathway prioritizes high-fidelity recording of heritage sites for preservation, visualization, and reuse in digital environments. Typical evidence includes point clouds, multi-view images, photogrammetric products, meshes, and model-based representations (e.g., BIM) (Liu et al., 2019; Walliss & Rahmann, 2016; Zhang & Zhang, 2022; Zhou et al., 2024). Methods focus on capture, reconstruction, registration, model optimization, and rendering, with outputs such as detailed 3D models, textured scenes, and digital archives used for documentation, restoration support, monitoring, and visual communication (Han et al., 2020). Its strength is geometric and visual precision and high reuse value. Its limitation is that the workflow often stops at producing the record and does not, by default, include analyses of visibility structure, user attention, or interpretation (Vitale, 2017).

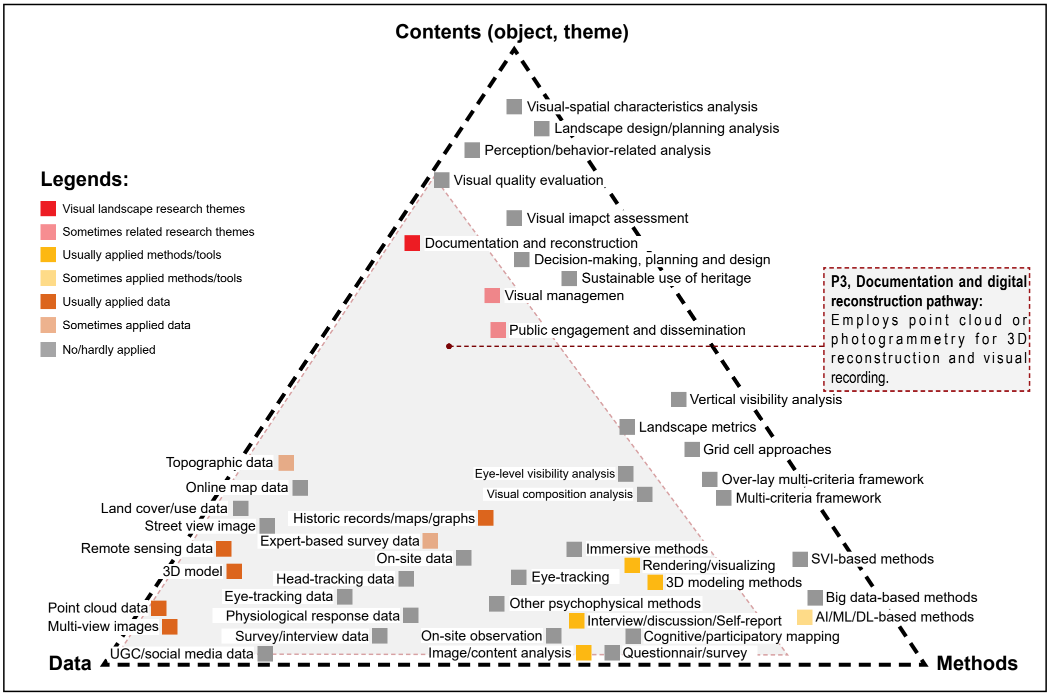


FIG. 3.3 Documentation and digital reconstruction pathway pattern: This pathway is structured around high-precision data such as point clouds, 3D models, and multi-view images, aligning closely with digital modeling and rendering methods.

TOC

d) **P4, expert evaluation pathway (FIG. 3.4):** This pathway is driven by structured expert judgment, often framed through criteria-based evaluation and multi-criteria decision analysis (Allain et al., 2017). Evidence typically includes expert-annotated maps, indicator lists, assessment forms, and supporting spatial layers, sometimes organized within GIS environments (Mrak, 2013). Methods commonly involve weighted overlays, scoring matrices, criteria-based classification, and composite indices for prioritization and zoning (Cerreta & Poli, 2017; Salehipour et al., 2025). Outputs include evaluation maps, composite scores, and policy-facing classifications that can be used in visual impact assessment and management discussions. Its strengths are clarity, consistency, and direct policy relevance. Its limitations are heavy dependence on normative criteria, limited public input, and frequent separation from direct perception evidence.

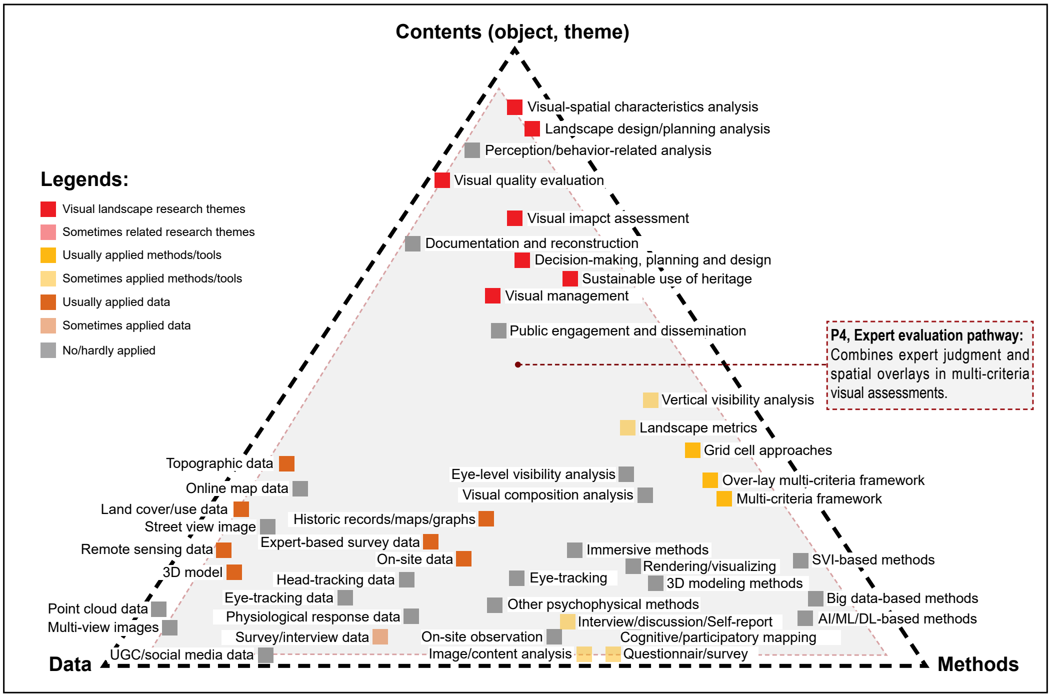


FIG. 3.4 Expert evaluation pathway pattern: This pathway integrates expert-derived data with structured evaluation frameworks such as multi-criteria overlays and visual impact matrices. It forms a methodologically dense cluster around spatial scoring tools and decision-making content, relying heavily on expert-based survey data and composite assessment methods.

TOC

e) **P5, practice-oriented pathway (FIG. 3.5):** This pathway applies visibility and spatial diagnosis in planning and management contexts where the deliverable is a control instrument rather than a research explanation. Evidence and tools may resemble P1 (terrain, built-form layers, road networks, viewshed outputs), but the content aim shifts toward delineating view corridors, defining buffer zones, setting visual control areas, and supporting guideline-making (Eslamian & Eslamian, 2024; Mudalige & Carver, 2024; Robson, 2025). Outputs are typically plan-ready zones, corridor definitions, and management recommendations. Its strength is direct usability in governance settings. Its recurring limitations are that evidence packages are often simplified for feasibility, eye-level scene evidence remains peripheral, and decision criteria may not be transparent enough to support comparison across alternatives.

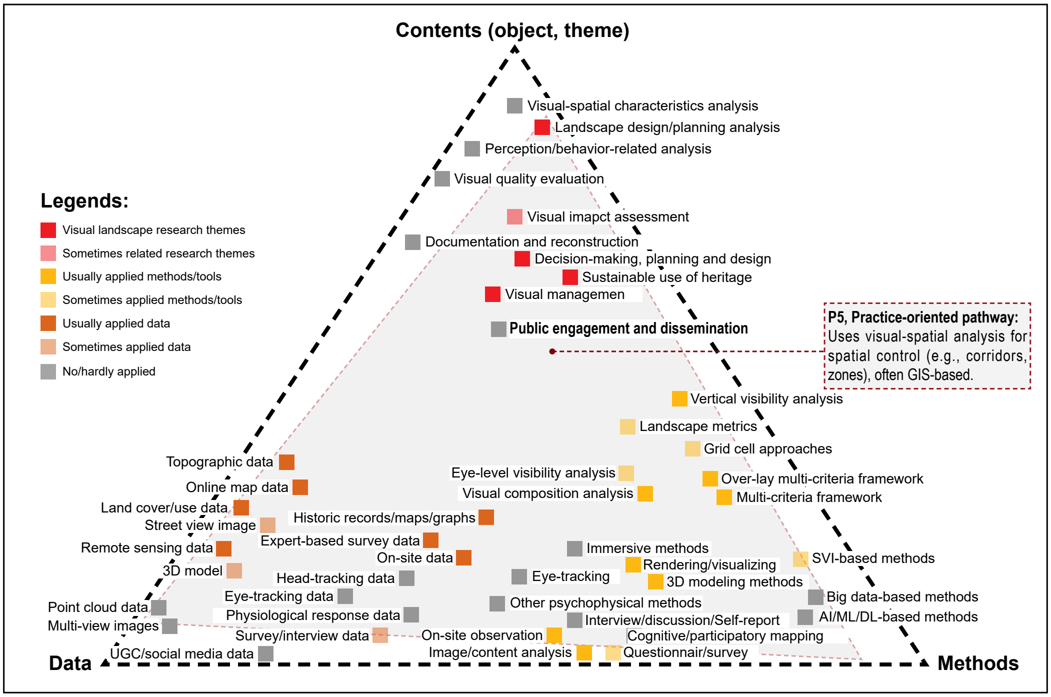


FIG. 3.5 Practice-oriented pathway pattern: This pathway employs GIS-based spatial visibility analysis to support planning and management practices, such as defining view corridors or visual buffer zones. It shares data and tool choices with P1 but shifts toward applied content like visual management and spatial control.

f) **P6, public engagement and dissemination pathway (FIG. 3.6):** This pathway focuses on participation, communication, and the social uptake of heritage meanings, often emphasizing narrative, interpretation, and contested viewpoints. Evidence sources commonly include interviews, narrative mapping, participatory workshops, social media or user-generated content, and collaborative annotation (Giaccardi, 2012; Lähdesmäki et al., 2025; Perry et al., 2024). Methods include participatory mapping, co-design sessions, visual annotation, and interpretive frameworks for storytelling and shared understanding (Fredheim, 2019). Outputs include mapped narratives, participation records, communication materials, and negotiated interpretations. Its strength is the ability to surface local knowledge and value conflicts. Its limitations are inconsistent spatial precision and uneven methodological repeatability, which can make it difficult to connect participation outputs to spatial diagnosis or to compare results across projects.

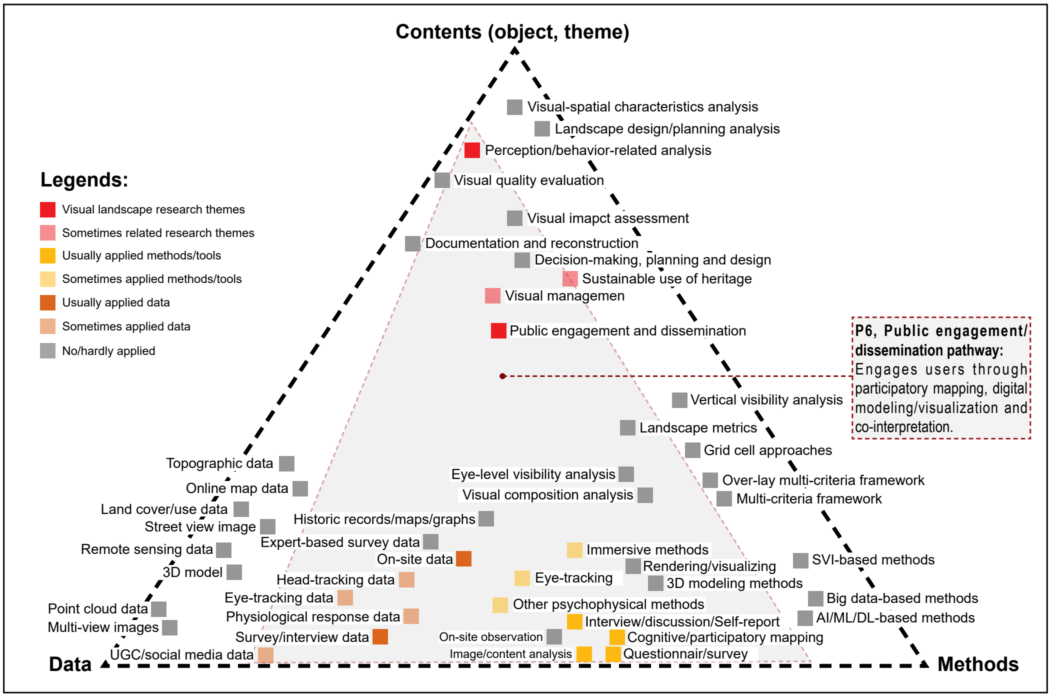


FIG. 3.6 Public engagement/dissemination pathway pattern: This pathway links participatory data sources—such as interviews, mapping, and social media—with co-interpretive and communicative methods. It forms a unique triangle anchored in public engagement themes, immersive or narrative-based tools, and qualitative datasets.

These six pathway types summarize the dominant modes of aligning evidence, methods, and aims in the literature **(FIG. 3.7)**. Their overall pattern is rich but compartmentalized: spatial diagnosis (P1) is rarely paired with perception evidence (P2), documentation outputs (P3) are often not carried into analysis workflows, expert scoring (P4) often proceeds without broader stakeholder evidence, and participatory outputs (P6) are difficult to translate into spatially comparable indicators. FIG. 3.7 is therefore used as a “gap map” that highlights where crossovers remain uncommon and where new pathway designs are most needed.

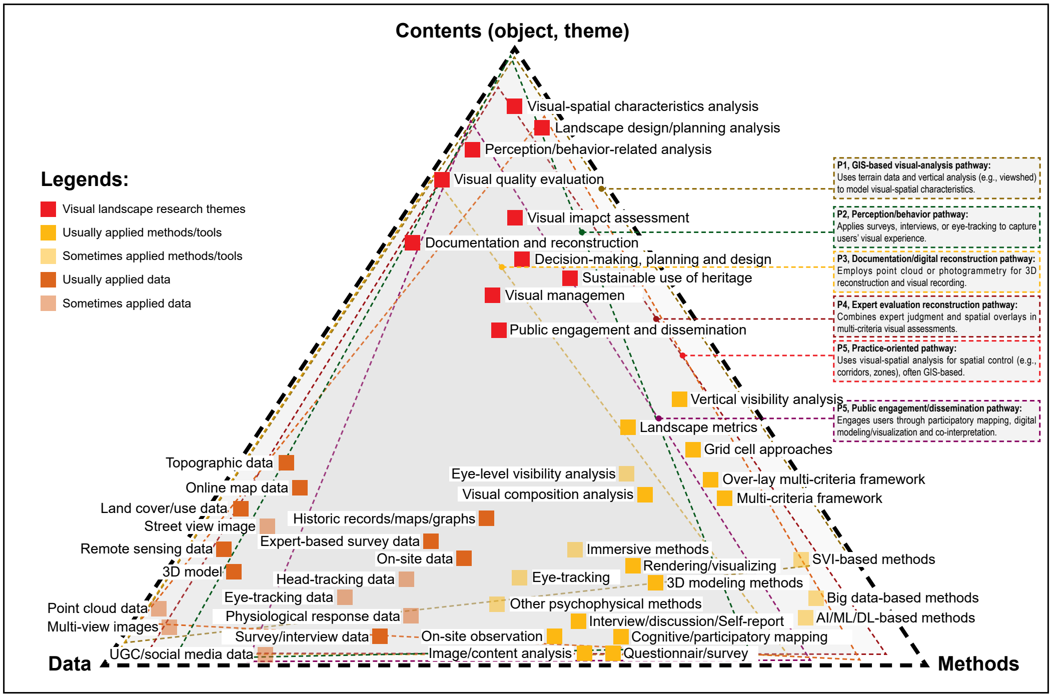


FIG. 3.7 Overview of six pathway types and crossover gaps: This figure summarizes the six dominant data–method–content pathways and highlights the main clusters and missing crossovers.

TOC

3.3 Expanded pathways

— **Section 3.2** shows that dominant pathway types often run on stable evidence–method routines, with limited crossover: spatial diagnosis is frequently separated from eye-level scene evidence and perception checks, while perception studies are often weakly anchored in spatial structure. As a result, results are hard to compare across cases, and research designs are slow to adjust when scale, data access, or decision needs change. To address these gaps, this section proposes four **extended pathways** (EP1–EP4) derived from the dominant types but reassembled to connect evidence components that are rarely combined in the literature **(FIG. 3.8)**. The aim is to clarify repeatable pathway designs that can be selected according to the task at hand.

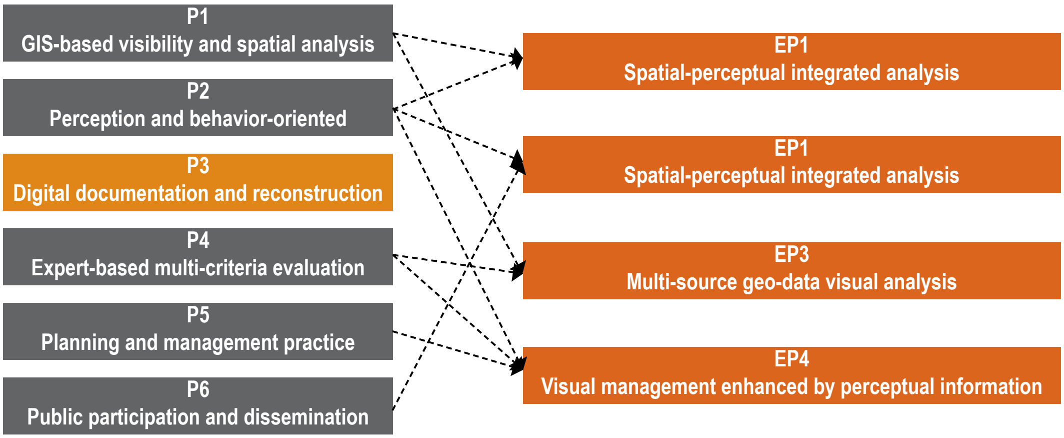


FIG. 3.8 The establishing of emerging pathways from the traditional ones (the documentation pathway is still an essential and basic pathway)

a) **EP-1, integrated visual-spatial and visual-perceptual landscape analysis (FIG. 3.9):** EP-1 is selected when the research goal is to relate measurable visual–spatial features to observed attention or reported experience. It combines spatial visibility and configuration analysis (e.g., viewsheds, isovists, line-of-sight reasoning) with perception evidence such as eye-tracking, structured ratings (e.g., semantic differential), or guided walkthrough protocols. EP-1 typically benefits from higher-resolution spatial representations (e.g., point clouds or dense reconstructions) when occlusion, vegetation layering, or narrow view corridors are central to the visual task. Where appropriate, classification or segmentation tools (including ML-based techniques) may be used to summarize complex scene evidence or distinguish key elements for analysis (Sharma, 2025; Xing et al., 2025). Typical outputs include (i) spatial indicators of exposure, enclosure, or sequence structure, (ii) attention or evaluation distributions across viewpoints or route segments, and (iii) relationship tests that show where spatial structure aligns—or fails to align—with what observers attend to or report. EP-1 is therefore most suitable when both spatial structure and perception evidence can be collected at compatible resolution and the intended claim is about structure–experience linkage.

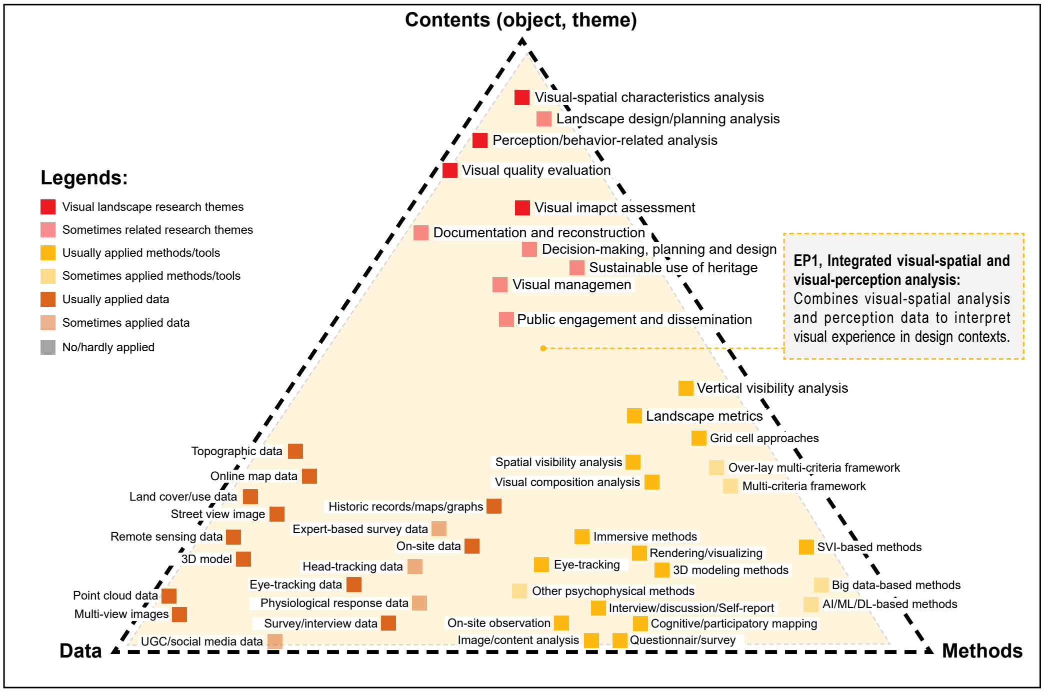


FIG. 3.9 EP-1, integrated visual-spatial and visual-perceptual landscape analysis: This emerging pathway bridges GIS-based spatial modeling and perception-driven analysis by combining spatial visibility metrics with empirical perception data.

TOC

b) **EP2, digital-supported perceptual evaluation for multi-audience (FIG. 3.10):** EP-2 is selected when the main goal is to compare experience, preference, or interpretation across audience groups and to anchor these differences in scene or place conditions. It centers on perception evidence—surveys, interviews, eye tracking, and, where feasible, physiological measures—organized to distinguish attention, affect, and meaning. Digital tools are used to strengthen stimulus consistency, sampling structure, and interpretability. Spatial and visual analysis plays a supporting role: it helps define representative viewpoints or segments, extract eye-level scene descriptors (e.g., composition shares, element presence), and map group results back onto specific settings. Typical outputs include (i) group-difference profiles and perception distributions across scene types, (ii) mapped layers that connect audience evidence to spatial conditions, and (iii) interpretation summaries that clarify what different groups value and why. EP-2 is therefore most suitable when perception evidence is feasible and the research deliverable requires multi-audience comparison rather than mechanism-level coupling between spatial structure and perception.

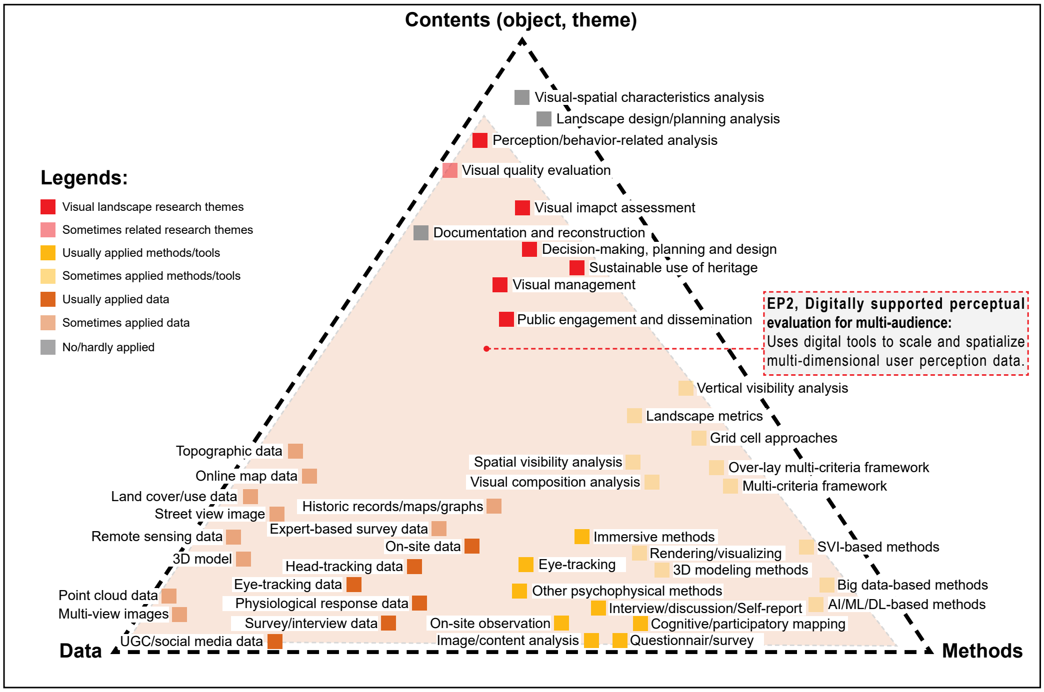


FIG. 3.10 EP2, digital-supported perceptual evaluation for multi-audience: This pathway integrates heterogeneous geo-data sources and multiple spatial perspectives, such as UGC, SVI, aerial views, and eye-level imagery, to support multidimensional visual-spatial interpretation.

TOC

c) **EP-3, multi-source geo-data visual analysis pathway (FIG. 3.11)**: EP-3 is selected when the main need is to diagnose visual–spatial structure across a site, corridor, or larger landscape using multiple geo-data sources and viewpoints, without requiring dedicated perception studies. It strengthens conventional GIS-based visual–spatial analysis by combining heterogeneous datasets and perspectives (for example, terrain and built-form layers with street-level imagery, panoramic datasets, user-generated images, or geotagged photographs) so that corridor structure, skyline relations, exposure patterns, and obstruction risks can be interpreted from complementary angles (Peng et al., 2025). The pathway supports cross-checking between top-down visibility measures and eye-level scene evidence, which is particularly valuable in complex settings where single-perspective analysis is insufficient. Typical outputs include (i) corridor and node diagnostics, (ii) exposure and obstruction patterns across zones, (iii) typologies of view conditions, and (iv) rapid screening accounts that can inform management discussions or guide where deeper perception work is needed. EP-3 is therefore most suitable when spatial evidence is available at scale, multi-view scene evidence can be assembled from platforms or archives, and the deliverable is a defensible structural diagnosis rather than perception-based evaluation.

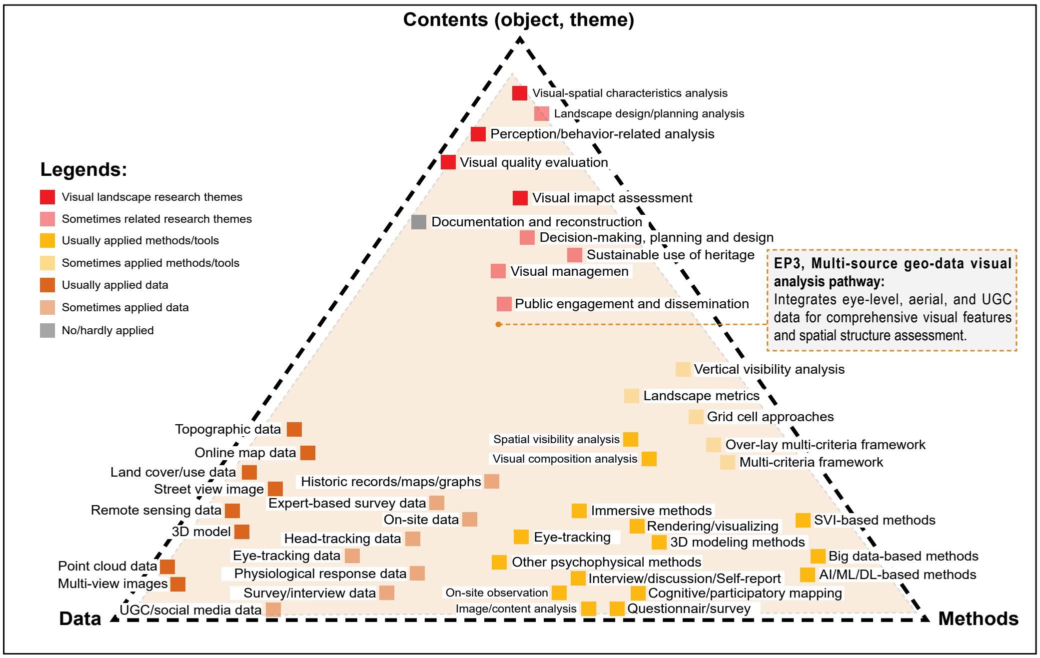


FIG. 3.11 EP-3, multi-source geo-data visual analysis pathway: This extended pathway type integrates eye-level, aerial, and UGC data to support perceptual evaluation across spatial and experiential dimensions. It combines conventional empirical methods, such as surveys, interviews, and eye-tracking—with immersive technologies and digital mapping tools.

TOC

d) **EP-4, visual management enhanced by perceptual information pathway (FIG. 3.12):** EP-4 is selected when the task is to evaluate change, compare options, and support decision-facing outputs such as thresholds, rankings, or mitigation priorities. It combines scenario-based spatial evidence (e.g., visibility change under alternative massing or layout options) with perception evidence when feasibility allows, so that visual impact assessment is not based on expert reading alone (Moreno-Arjonilla et al., 2024; Sundstedt & Garro, 2022). High-resolution spatial data and advanced visualization can improve the realism and comparability of scenarios, while perception protocols (e.g., preference surveys, structured judgments, or eye tracking in controlled or immersive settings) can reveal acceptability bands and trade-offs in contested contexts. Typical outputs include (i) scenario comparisons and risk concentration at key observation points, (ii) evidence-supported priorities for mitigation, and (iii) decision-ready summaries that translate evidence into control cues or planning guidance. EP-4 is therefore most suitable when change management is central, scenarios can be defined, and the project needs outputs that support negotiation and implementation.

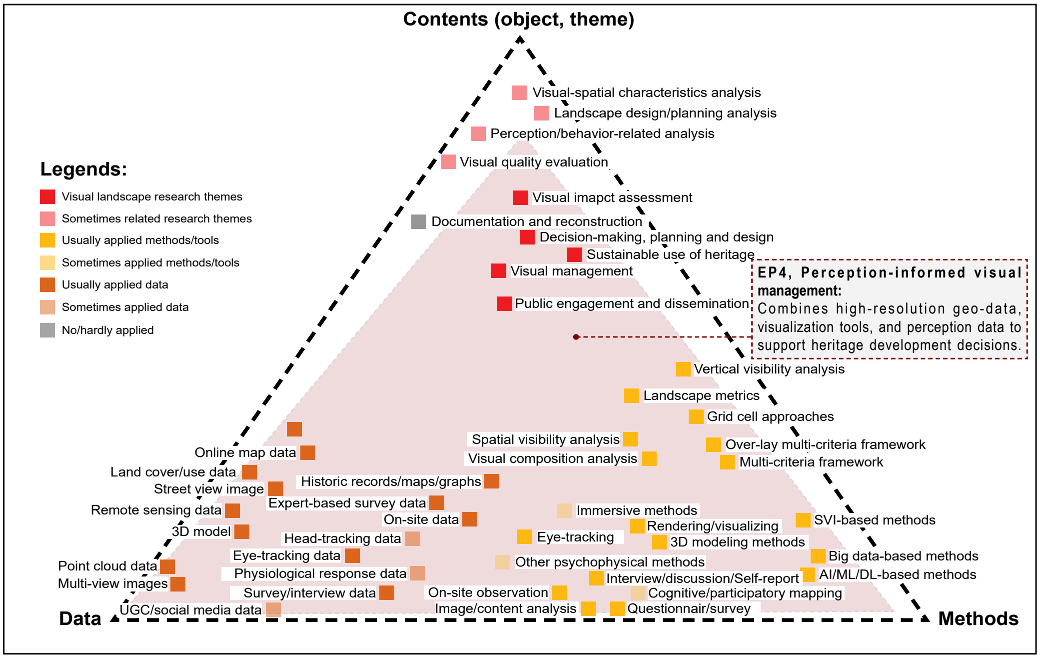


FIG. 3.12 EP-4, visual management enhanced by perceptual information pathway: This pathway integrates high-resolution spatial data, digital visualization, and perception-based evaluation to inform heritage development decisions. It connects visual impact assessment tools with empirical perception data, such as eye-tracking and preference surveys.

TOC

EP-1 to EP-4 describe four extended pathways that address different crossover needs in the field: EP-1 couples spatial structure with perception evidence to examine structure–experience relationships; EP-2 organizes multi-audience perception evidence and anchors it in scene and place conditions; EP-3 strengthens spatial diagnosis by combining multi-source geo-data with multi-view scene evidence; and EP-4 evaluates change under scenarios and translates evidence into decision-facing outputs, strengthened by perception evidence where feasible **(FIG. 3.13)**.

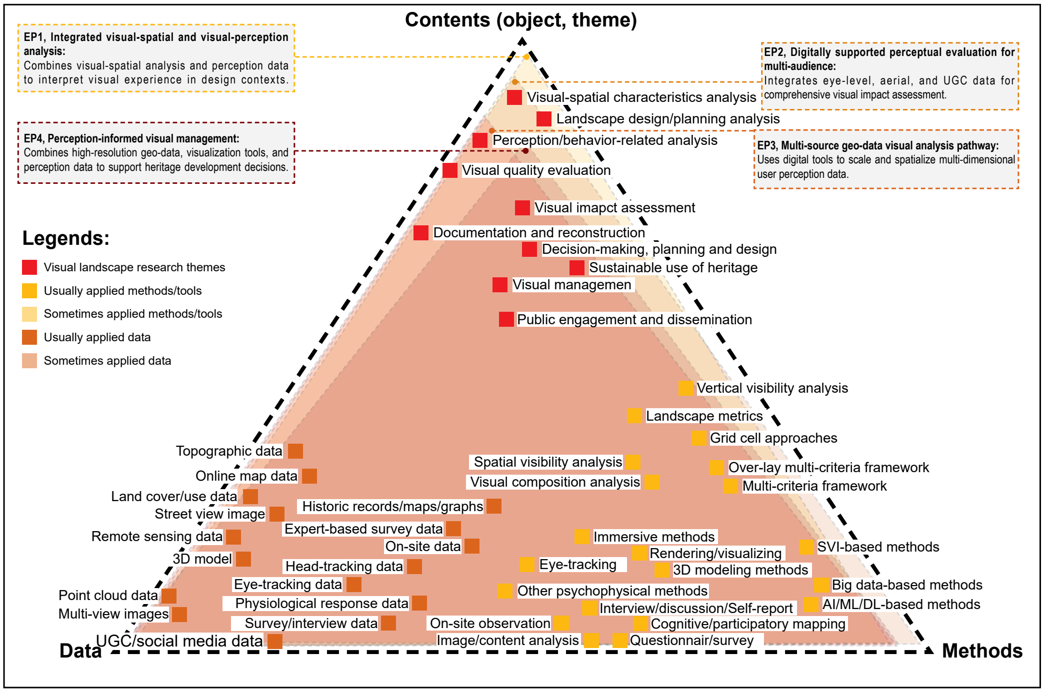


FIG. 3.13 Overview of EP-1 to EP-4 as extended pathways: This figure summarizes how the four pathways combine spatial evidence, eye-level scene evidence, and perception evidence in different proportions to support distinct research and application tasks.

The following case studies implement these extended pathways under contrasting landscape conditions. The case chapters also test specific representation choices when they improve stimulus consistency or scenario comparability. For example, in addition to mesh-based models, this research tests 3D Gaussian Splatting as a rendering approach for producing continuous scene representations for interactive viewing (Kerbl et al., 2023; Yu et al., 2025). Such techniques are treated as case-level implementation choices rather than requirements of the extended pathways, and their role is examined in the empirical chapters that follow.

3.4 Case selection and pathway application

Heritage landscapes span a broad spectrum from culturally constructed environments to ecologically driven systems (Head, 2017; Tengberg et al., 2012). This thesis focuses on the middle range where cultural and natural processes jointly shape landscape form and experience over time. These mixed cultural–natural settings are neither purely architectural nor entirely natural. They are characterized by coupled spatial form, ecological context, and lived visual experience. The empirical work is positioned at site to regional scales, where spatial modeling, scene-based analysis, and, when required, perception protocols are feasible and can be linked to management questions (Zhao & Klippel, 2019). By concentrating on this scale range, the study balances operational precision with landscape relevance, while keeping pathway choices comparable across cases **(FIG. 3.14)**.

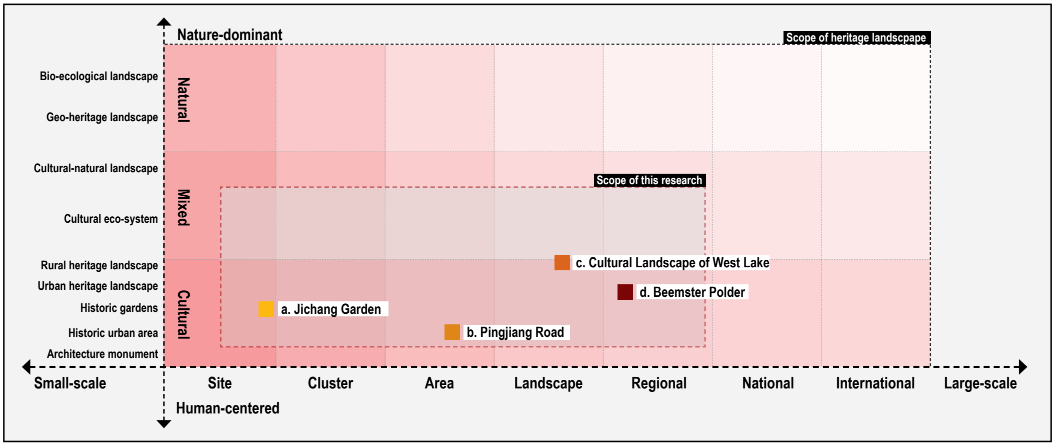


FIG. 3.14 Defining the Scope of case selection: In both typological and spatial dimensions.

TOC

Case selection was guided by the extended pathways proposed in Section 3.3. Each case was chosen to represent one pathway, from EP-1 to EP-4, under contrasting landscape conditions. The purpose is to demonstrate what each pathway can deliver and what minimum evidence package is required for defensible results. **TABLE 3.1** summarizes the selection logic, the minimum evidence package for each case, and the main outputs that are carried forward into the empirical chapters.

TABLE 3.1 Overview of case selection and pathway application (EP-1 to EP-4)

Case	Primary task focus	Minimum evidence package (what must be available)	Main outputs used in later chapters
Jichang Garden, historic garden, site scale, EP-1	Relate visual-spatial features to attention or experience	a) High-resolution 3D representation (point cloud or 3D model); b) Defined viewpoints or route nodes; c) Perception channel (eye tracking or structured ratings).	a) Human-scale structure indicators; b) Attention patterns; c) Evidence of structure-attention linkage.
Pingjiang Road, historic urban area, area scale, EP-2	Compare perception across audiences and link differences to scene conditions	a) Scene stimuli with basic spatial anchoring (geo-referenced viewpoints or segments); b) Multi-audience perception evidence (survey, interview, or eye tracking); c) Basic scene descriptors.	a) Group-difference profiles; b) Perception distributions across scene types; c) Mapped interpretation layers.
West Lake, urban heritage landscape, landscape scale, EP-3	Diagnose visual-spatial structure using multi-source, multi-view evidence	a) Geo-data baseline (DEM/DSM plus built form and roads); b) Defined viewpoints or routes; c) Eye-level scene evidence (street-level imagery or archives).	a) view diagnostics; b) Exposure and obstruction patterns; c) View-condition typologies for management screening.
Beemster Polder, rural heritage landscape, regional scale, EP-4	Evaluate change under scenarios and support decision-facing outputs	a) Scenario definition; b) Visibility and structure indicators from geo-data; c) Key observation points; where feasible, perception evidence for acceptability and trade-offs.	a) Scenario comparison; b) Risk concentration at key observation points; c) Decision-facing summaries such as priorities or control cues.

— **Case study 1, Jichang Garden (historic garden, FIG. 3.15)**: Jichang Garden was selected to implement EP-1, integrated visual-spatial and visual-perceptual landscape analysis, because classical gardens provide controlled viewpoint sequences where occlusion, framing, and depth layering are central to visual experience. The case combines a high-resolution 3D representation with viewpoint-based visibility reasoning and an immersive perception protocol to examine how spatial features relate to attention allocation. The intended contribution is to demonstrate EP-1's ability to connect human-scale structure indicators with measurable attention patterns. Detailed feature extraction, perception protocol design, and relationship testing are reported in **Chapter 4**.

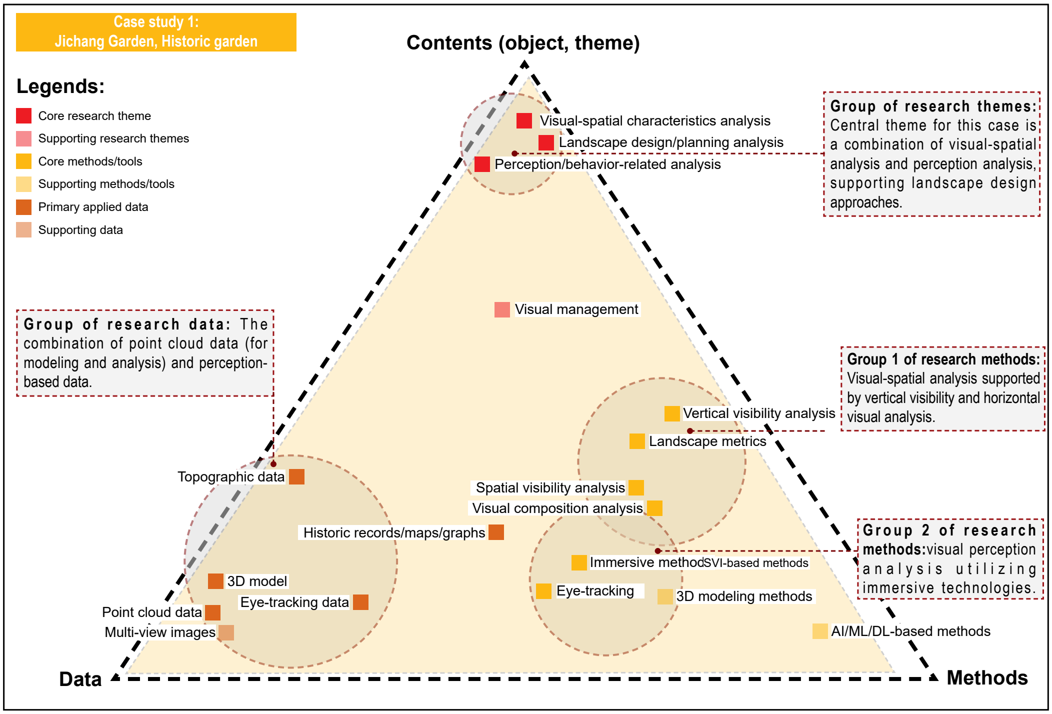


FIG. 3.15 Constructed pathway for the case study of Jichang Garden (modified from EP-1).

TOC

— **Case Study 2, Pingjiang Road (historic urban area, FIG. 3.16)**: Pingjiang Road was selected to implement EP-2, digitally supported perceptual evaluation for multi-audience, because historic streets allow comparison of perception across groups under consistent scene conditions. The case uses scene representations anchored to street segments and combines multiple perception channels to compare attention and evaluation patterns between public and expert participants. Spatial and scene descriptors are used to structure sampling and interpret group differences rather than to replace perception evidence. The case demonstrates EP-2's role in making multi-audience perception evidence comparable and spatially interpretable. Detailed methods and analyses are provided in **Chapter 5**.

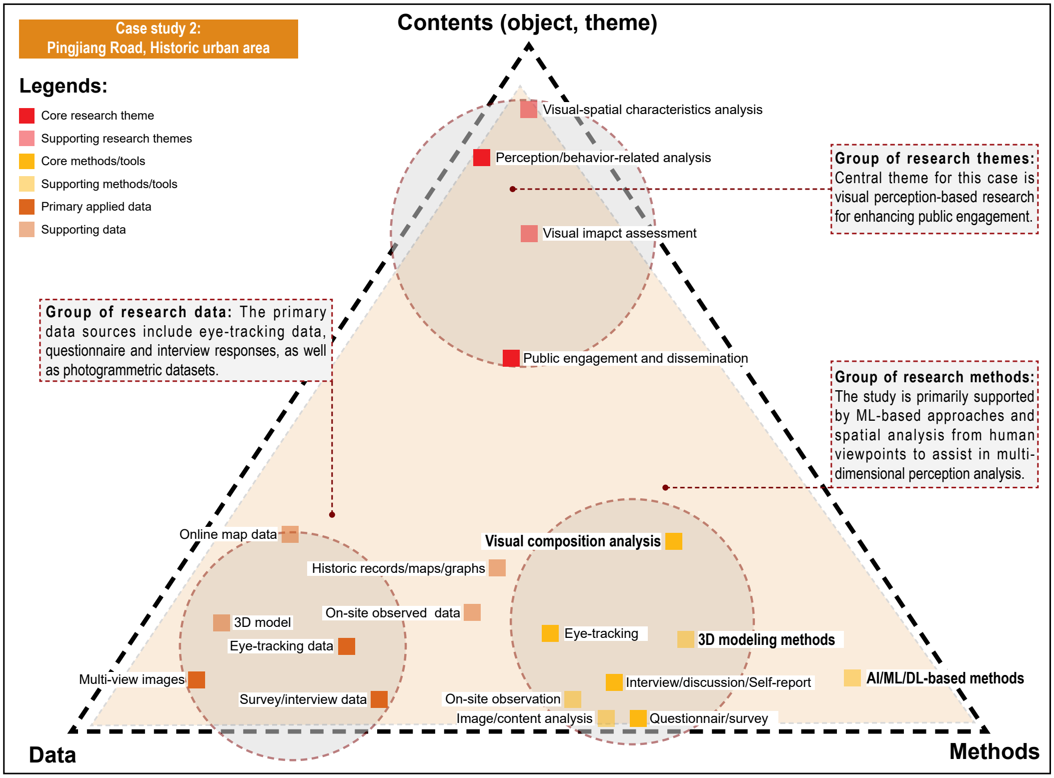


FIG. 3.16 Constructed pathway for the case study of Pingjiang Road (modified from EP-2).

TOC

— **Case Study 3, West Lake (Urban heritage landscape, FIG. 3.17)**: West Lake was selected to implement EP-3, multi-source geo-data visual analysis, because the lake–city interface requires cross-scale spatial diagnosis and multi-view interpretation. The case assembles a geo-data baseline and combines multiple GIS-based visibility measures with eye-level scene evidence to diagnose corridor continuity, skyline relations, and obstruction patterns across different lakeside zones. This case does not rely on dedicated perception experiments. It demonstrates how EP-3 strengthens structural interpretation by combining top-down and eye-level evidence sources. The detailed workflows and outputs are reported in **Chapter 6**.

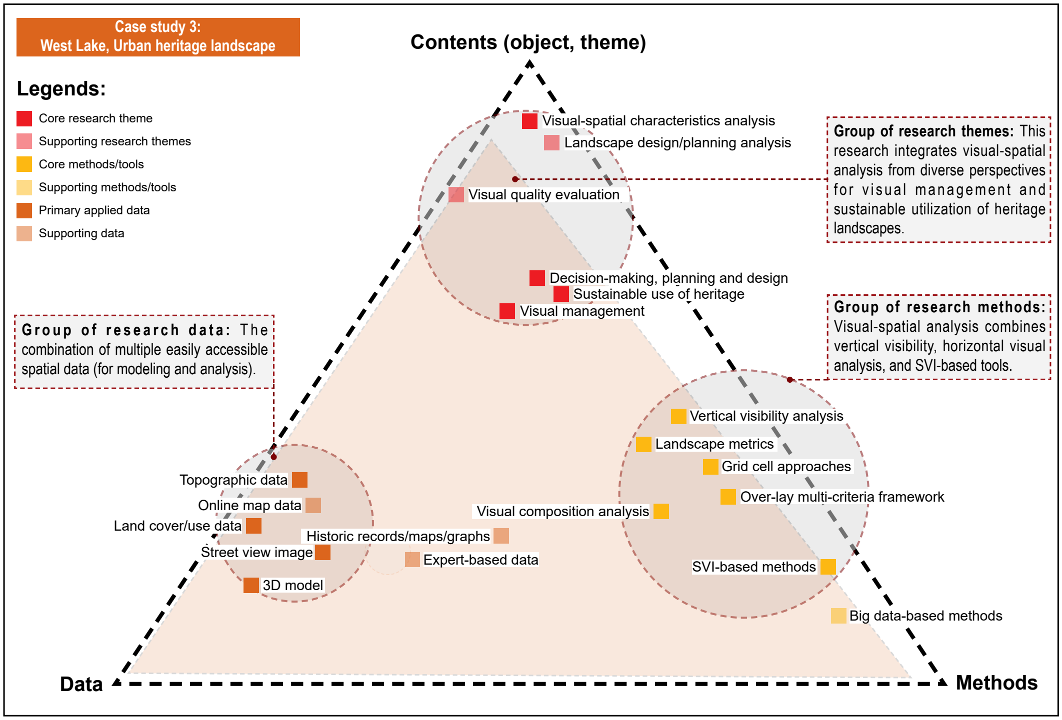


FIG. 3.17 Constructed pathway for the case study of West Lake (modified from the EP3).

TOC

— **Case Study 4, Beemster Polder (Rural heritage landscape, FIG. 3.18)**: Beemster Polder was selected to implement EP-4, visual management enhanced by perceptual information, because it is a large-scale rural landscape where incremental change creates governance pressure and scenario comparison is essential. The case uses a multi-source dataset, such as open LiDAR, UAV photogrammetry, and mobile survey material, and defines key observation points to evaluate how alternative expansion scenarios affect long-distance views and landscape legibility. Where feasible, perception-oriented evidence is used to test acceptability and viewing behavior under scenario stimuli, strengthening decision-facing interpretation beyond visibility mapping alone. The case demonstrates EP-4's ability to translate scenario-based evidence into priorities and control cues. Detailed procedures are provided in **Chapter 7**.

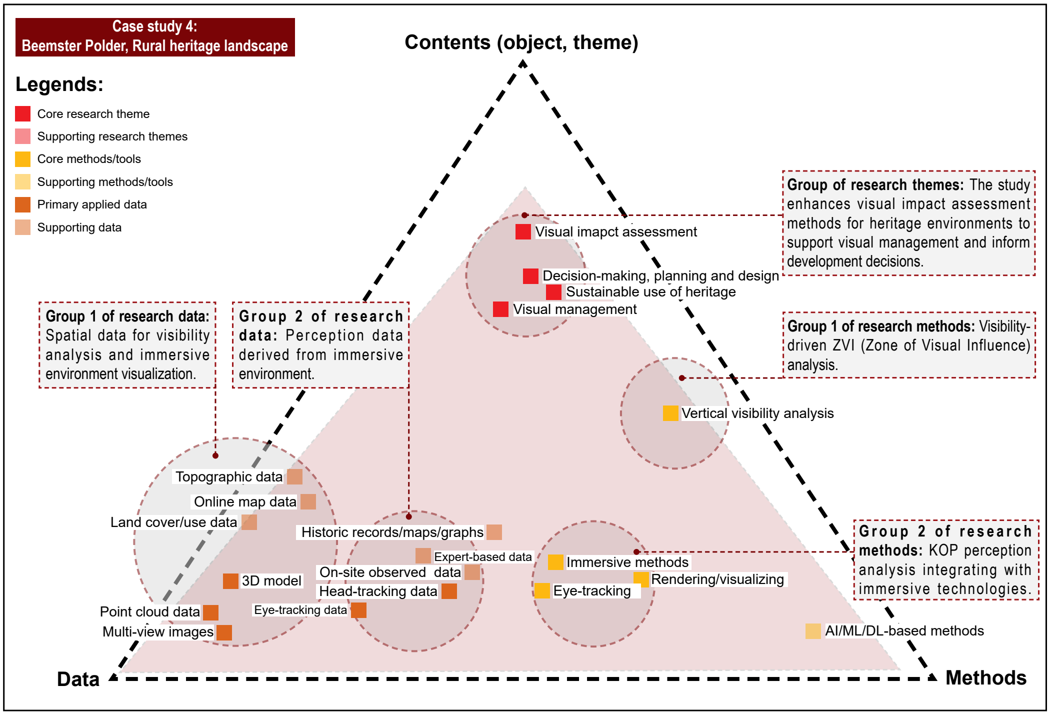


FIG. 3.18 Constructed pathway for the case study of Beemster Polder (modified from EP-4).

TOC

Together, the four cases form a deliberately varied set that ranges from an enclosed designed space to a linear historic street, then to an urban lake–city system, and finally to an open rural grid landscape. This design supports both pathway differentiation, meaning what each pathway is for, and pathway feasibility, meaning what minimum evidence is required. It establishes the basis for the empirical chapters that follow **(FIG. 3.19)**.

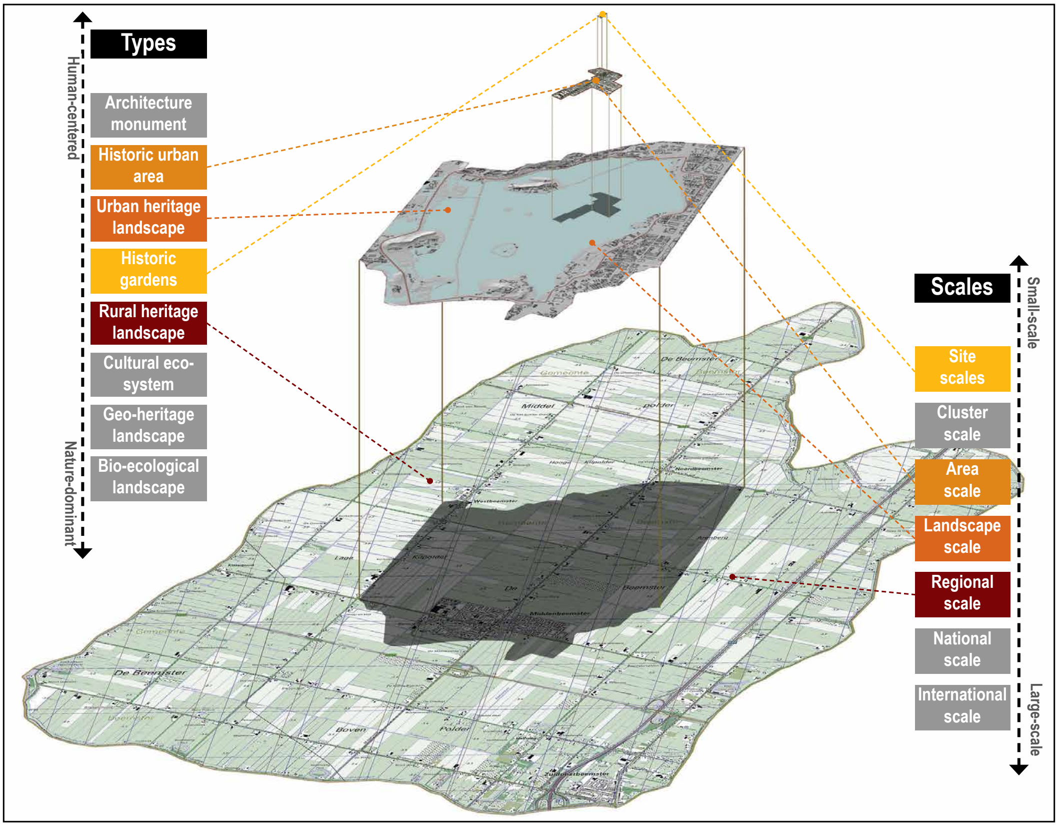


FIG. 3.19 Positioning four case studies within the heritage type-scale framework.

3.5 Conclusion

This chapter builds the design foundation for the empirical work that follows. It first maps six dominant pathways in visual heritage landscape research and clarifies where they remain separated in practice, especially between spatial diagnosis, eye-level scene evidence, and perception-based evaluation. It then formulates four extended pathways (EP-1 to EP-4) as repeatable research designs that respond to these crossover gaps. Finally, four case studies are selected to implement one pathway each under contrasting landscape types and scales, so that the thesis can demonstrate what each pathway can deliver and what minimum evidence is required to support defensible claims. **Chapters 4 to 7** report the case applications in detail, and the synthesis chapters later draw cross-case lessons to support pathway selection and adaptation.

PART II

Case-based pathway exploration, and empirical demonstration

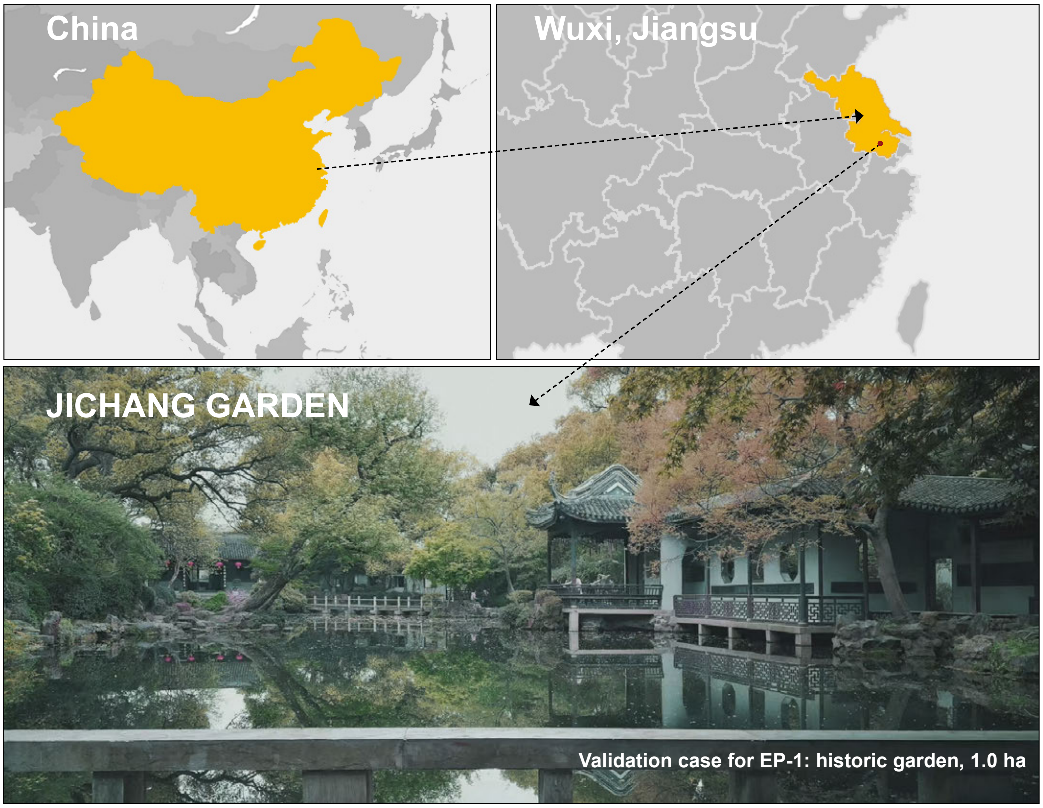
This part focuses on testing and refining the proposed pathway logic through four contrasting case studies, showing how different combinations of data and methods can be matched to diverse heritage types, scales, and research tasks. Chapter 4 (Jichang Garden) demonstrates a spatial-perceptual integrated pathway by linking quantified visual-spatial features with immersive eye-tracking behaviors and design interpretation. Chapter 5 (Pingjiang Road) examines how blue-green infrastructure shapes heritage experience in historic urban areas through visually oriented assessment strategies. Chapter 6 (West Lake) develops a multi-method GIS-based visual analysis workflow to improve the comprehension of complex urban heritage visual structures across viewpoints and routes. Chapter 7 (Beemster Polder) advances a perception-informed visual impact assessment framework that connects spatial visibility modeling with immersive evaluation to define actionable thresholds for incremental change.

4 EP-1: Case study of historic garden

Perception-Informed Design Analysis of Historic Gardens: Linking Visual-Spatial Features, Eye-Tracking Behaviors, and Design Translation

This chapter is composed of three published/in-revision papers:
Peng, Y.*, Zhang, G., Nijhuis, S., Stoter, J. E., & Agugiaro, G. (2024)."Towards a Framework for Point-cloud-based Visual Analysis of Historical Gardens: Jichang Garden as a Case Study"; *Urban Forestry & Urban Greening.*
Peng, Y., Nijhuis, S., Yu, Y.*, Agugiaro, G. & Zhang, G. (2026). "Visual-spatial predictors of attentional pathways in heritage landscapes: Evidence from VR eye tracking and LiDAR-based 3D visibility". *Journal of Environmental Psychology.* (In revision)
Peng, Y.*, Nijhuis, S., Zhang, G., Stoter, J. E., & Agugiaro, G. (2022). "Towards a practical method for voxel-based visibility analysis with point cloud data for landscape architects: Jichang garden (Wuxi, China) as an example"; *Journal of Digital Landscape Architecture.*

This chapter aims to demonstrate a proposed spatial-perceptual pathway for interpreting how historic garden design orchestrates visual experience. Using Jichang Garden as a highly enclosed and sequential heritage landscape, the chapter combines high-resolution spatial data and immersive perceptual evidence within a single workflow. It deploys point-cloud-based visibility analysis across multiple viewpoints to quantify spatial openness, enclosure, route sequence, and vegetation layering, and then validates these spatial interpretations with VR-based eye-tracking and machine-learning-supported gaze pattern classification. The results reveal measurable links between garden spatial configurations and attention dynamics, highlighting how vegetation acts as both frame and filter in shaping scene composition and perception. Finally, the chapter translates the empirical evidence into design-relevant insights that can support conservation reasoning and design interpretation for complex historic gardens.



Contents	Methods	Data
A. Object: historic garden, site scale; B. Theme: Design interpretation via spatial-perceptual analysis.	A. Horizontal FOV analysis B. Vertical visibility analysis C. VR eye-tracking D. Design diagramming	A. Dense point clouds B. Eye-tracking data C. Interview data

FIG. 4.1 Summary for the cases study: location, contents, methods and data.

TABLE for abbreviations used in Chapter 4

Abbreviation	Full term	Meaning in Ch.4
EP-1	Expanded Pathway 1	The pathway type implemented in Chapter 4 (integrated spatial–perceptual analysis).
VR	Virtual Reality	Immersive experiment environment for collecting perceptual evidence (e.g., eye-tracking in VR).
VP	Viewpoint	Viewpoint unit used in experiments and analyses (e.g., VP 20).
LoS	Line of Sight	Ray-based visibility calculation used to construct 3D viewsheds and extract visual-spatial features.
FOV	Field of View	Used for visual-composition analysis per viewpoint.
ELV	Eye-level viewing	Vertical viewing-angle bin (5° to −5°).
SDV	Slightly downward viewing	Vertical viewing-angle bin (−6° to −30°).
LDV	Downward viewing	Vertical viewing-angle bin (−31° to −70°).
SUV	Slightly upward viewing	Vertical viewing-angle bin (6° to 15°).
LUV	Upward viewing	Vertical viewing-angle bin (16° to 50°).
Top	Overhead space	Vertical viewing-angle bin (≥51°).
LDI	Layered Depth Index	Depth-related indicator.
ADI	Absolute Depth Index	Depth-related indicator.
DI	Depth Index	Combined depth indicator (used in models/results).
SEC	Shannon Entropy for visual composition	Entropy-based composition indicator.
SES	Shannon Entropy for spatial complexity	Entropy-based complexity indicator.
CI	Complexity Index	Composite complexity indicator.
ESP	Exploratory Scanning Pattern	Gaze behavior pattern (broad scanning, dispersed fixations).
HAP	Hotspot Attention Pattern	Gaze behavior pattern (localized fixations on landmarks).
ROAP	Route-oriented Attention Pattern	Gaze behavior pattern (path-oriented, vanishing-point tendency).
NFAP	Near–far Alternation Pattern	Gaze behavior pattern (alternation between foreground/background).
k-means	k-means clustering	Used to group gaze-pattern profiles into exploration strategies.
RF	Random Forest	Used for predictive modeling and variable importance/local threshold exploration.
LMM	Linear Mixed-effects Model	Cross-classified mixed models for variance partitioning and confirmatory effects.
ICC	Intraclass Correlation Coefficient	Variance partitioning metric (viewpoint/participant).
CLR	Centered Log-Ratio transformation	Outcome transformation used in confirmatory LMMs (“CLR outcomes”).
BH	Benjamini–Hochberg procedure	Multiple-testing adjustment reported as q(BH).
ρ	Spearman correlation coefficient	Symbol used in correlation analysis reporting.
R^2	Coefficient of determination	Model fit / predictive strength (e.g., cross-validated R^2).
MAE	Mean Absolute Error	Model error metric.
MSE	Mean Squared Error	Model error metric.

4.1 Introduction

Historic gardens, as defined by the International Council on Monuments and Sites (ICOMOS), are “architectural and horticultural compositions of historic or artistic interest to the public” (The Florence Charter, 1982). Such gardens embody diverse aesthetic styles and horticultural techniques across historical periods and regions, reflecting deep interactions between human civilization and the natural environment (O’Donnell, 2014; Olivadese & Dindo, 2022). Throughout history, numerous garden masterpieces have distinguished themselves through exceptional visual design and ingenious spatial composition (Peng et al., 2024; Shen & Yu, 2024). These visual-spatial features form a critical foundation for human visual perception, positioning historic gardens as vital repositories of collective memory and sources of rich visual-spatial experiences (Rössler Chief, 2006).

Despite their acknowledged importance, the precise mechanisms through which visual-spatial characteristics influence human perception and behavior in historic gardens remain inadequately understood (Carrasco, 2018). Current research in this area typically employs two broad methodological approaches: analyses focusing on objective spatial features, attempting to infer perceptual effects from spatial characteristics (Sugimoto, 2018; Wu et al., 2023), and studies emphasizing human visual perception, aiming to infer environmental characteristics from perceptual outcomes (Gao et al., 2020; Zhang et al., 2024). However, these two perspectives remain largely disconnected, limiting their practical utility in landscape design and management. This gap poses critical challenges in historic garden conservation and heritage landscape design, preventing precise guidance for designers and managers aiming to optimize visitor experiences. Therefore, the core questions driving this research are: *(a) Which specific visual-spatial features significantly influence visitors’ visual perception behaviors in historic gardens? (b) How can quantitative methods precisely elucidate the relationship between spatial layouts and visual perceptual behaviors?* Building on these, a further question emerges: *(c) How can this knowledge help us interpret the spatial–visual design of historic gardens and applying the resulting strategies to heritage management and broader landscape design?* Addressing these questions is crucial for deepening theoretical understandings of environmental perception and enhancing practical landscape design and conservation strategies.

TOC

4.1.1 Visual-spatial analysis for historic gardens

Visual-spatial analysis methods applied to historic gardens have a long research tradition (Lian et al., 2024; Nijhuis, 2015), evolving from early diagrammatic approaches (Steenbergen et al., 2003) to advanced digital technologies, such as GIS-based (Cazzani et al., 2019; Nijhuis, 2015) and point cloud-based tools (Peng et al., 2024; Qi et al., 2022). Specifically, these methods can be categorized as follows: first, viewpoint-based analyses, involving line-of-sight (LoS) and visibility simulations utilizing digital elevation models (DEM) or 3d digital models (Lu & Liu, 2023; Sun & Bao, 2025), as well as landscape element segmentation analyses based on image processing (Liu & Nijhuis, 2020; Schirpke et al., 2022); second, comprehensive analyses targeting overall visual characteristics, encompassing viewshed analyses, visibility analyses (Ogburn, 2006; Santosa et al., 2023), and spatial structure analyses informed by (Griffiths, 2012), aiming to reveal how garden layouts influence overall visual experiences; third, dynamic visual analyses centered around roads or pathways, including sequential landscape analysis and visual landscape change analysis, highlighting how the visual experience dynamically shifts during movement (Hunt, 1992; Stewart & Buggey, 1975).

However, these approaches exhibit significant limitations in practical application and theoretical integration. Firstly, existing analytical methods seldom directly interface with empirical perception research, often relying instead on visual perception theories or hypotheses (e.g., restoration theory, preference theory) to indirectly infer how specific spatial features or indicators (e.g., depth, openness) might influence visitor visual experiences. Empirical and systematic validation studies remain scarce (Ito et al., 2024; Schiewe, 2019). Secondly, integrating visual-spatial analysis with perception research faces substantial challenges due to the complexity of visual perceptual behaviors (Ito et al., 2024; Quinlan, 2003). Research methodologies thus must advance beyond coarse spatial quantifications to precisely capturing detailed spatial information, such as plant canopy structures and irregular architectural forms. Currently prevalent methods have significant limitations: image-based landscape element proportion analyses (panoramic or monocular images) completely lack spatial information (Biljecki & Ito, 2021; Peng et al., 2025), while visibility analyses based on viewpoints typically provide only 2D or 2.5D visibility ranges, failing to capture comprehensive 3D environments and often missing essential semantic information needed for nuanced perceptual analyses (Lonergan & Hedley, 2016; Wróżyński et al., 2024).

Given current technological trends, methods based on point cloud technologies (such as high-density laser scanning and photogrammetry) offer significant potential to overcome these limitations (Alsadik et al., 2014; Wróżyński et al., 2024).

These techniques efficiently and accurately capture 3D spatial details of vegetation, architecture, and structures, enriching point cloud data with semantic information. Consequently, they provide robust technological support and a foundational research basis for deeper explorations into how specific spatial forms concretely influence human visual perception.

4.1.2 Visual perceptual behaviors in historic gardens

Visual perception significantly shapes visitors' experiences, emotional responses, aesthetic appreciation, and cognitive engagement in historic gardens, guiding their attention through deliberate arrangements of landscapes, vegetation, architectural elements, and spatial sequences (Kong et al., 2022; Sheppard & Picard, 2006). Visitors' perception is substantially shaped by visual exploratory activities, including gaze shifts, fixations, prolonged attention, and physiological responses (Bajcsy & Campos, 1992), all of which are influenced by personal preferences, cultural backgrounds, higher cognitive processes, and emotional processing (de Rojas & Camarero, 2008; López-Guzmán et al., 2019). Thus, analyzing perceptual behaviors greatly contributes to comprehending visitors' emotional and aesthetic responses to historic gardens.

Traditional methods of perception research, such as questionnaires, interviews, and behavioral observations, often seek to analyze emotional shifts, perceptual outcomes, and behavioral patterns (Chamberlain & Broderick, 2007; Scherer & Tannenbaum, 1986). However, these methods typically suffer from subjective biases introduced by researchers or participants (Phellas et al., 2011). In contrast, eye movement data provides objective insights, as gaze patterns reveal both subconscious spatial cognition strategies and deliberate appreciation behaviors, encompassing wayfinding, exploration, and attentive fixation (De Lucio et al., 1996; Wiener et al., 2012). Despite these advantages, current landscape research rarely fully utilizes the potential of gaze pattern analysis, primarily relying instead on simpler metrics such as fixation durations (Peysakhovich & Hurter, 2018). This limited approach stems from the prevalent use of static images, which restrict gaze trajectory analyses to basic sequence studies within defined areas of interest (Carter & Luke, 2020). Moreover, gaze trajectories inherently exhibit considerable randomness, complicating their systematic analysis compared to fixation durations, which are more straightforwardly quantified (Dupont et al., 2014; Scott et al., 2019).

The integration of immersive technologies such as Virtual Reality (VR) with eye-tracking provides a robust solution (Adhanom et al., 2023; Pastel et al., 2023). VR compensates for the spatial limitations inherent in static imagery by enhancing spatial immersion, making trajectory analysis more meaningful. Moreover, the individual variability in gaze trajectories aligns well with contemporary deep learning methods in computer vision, such as convolutional neural networks (CNNs) (Cazzato et al., 2020).

4.1.3 Design analysis of historic gardens

Traditional analyses read historic gardens through composition and movement. Scholars interpret sequences, framed views, axes and vistas, and layered depth along designed routes. Bird's-view readings explain the placement of water, rockeries, vegetation, and focal buildings at the scale of the whole site. Eye-level readings explain how near and far elements are staged to reveal scenes and extend perceived space. These approaches guide conservation and route design by identifying key viewpoints and intended sightlines.

A digital turn has made these readings mappable and comparable. GIS based studies formalize viewsheds, visibility fields, and spatial structure. Point cloud-based models capture three-dimensional detail and support viewshed construction, element composition statistics, and indicators such as openness, depth, orientation, and complexity. These tools translate intuitive design tactics into measurable variables and scenario tests that inform low impact management, including vegetation layering, landmark salience, and corridor pruning.

Perception oriented research adds the visitor's experience. Interviews and questionnaires document affect and preference. VR with eye-tracking records fixations and trajectories in immersive scenes and recovers recurrent patterns and strategies. Yet most studies still rely on qualitative description or preference assessment, and high precision data are often used for illustration rather than for reproducible metrics that couple space and behavior. A gap remains between quantitative spatial indicators and measured perceptual pathways that can travel across sites and support design and stewardship decisions.

4.1.4 Research gaps and objectives

Therefore, it is evident that a comprehensive understanding of how visual–spatial features in historic gardens influence human perception and behavior requires an integrated analytical framework that combines point cloud–based spatial analyses with VR technologies, thereby providing new insights into the design logic of heritage landscapes. Nevertheless, several research gaps remain. However, several key research gaps remain: Firstly, current visual-spatial analysis methods rarely integrate spatial and semantic information simultaneously, making it challenging to accurately capture or abstract the detailed visual-spatial characteristics (Alsadik et al., 2014; Biasutti et al., 2019). Any effective method must balance analytic precision and computational feasibility (Peng et al., 2025). Secondly, describing visual perceptual behaviors presents difficulties, particularly in identifying and summarizing gaze trajectories into meaningful information that directly corresponds with visual-spatial features (Dupont et al., 2014; Scott et al., 2019). Third, despite technical advances, precise and empirical methods are still seldom applied to the design analysis of historic gardens or to the extraction of design inspiration; most studies continue to depend on diagrammatic interpretations or subjective preferences rather than on reproducible evidence.

To address these gaps, this study proposes an analytical framework that combines point cloud-based spatial analyses with VR eye-tracking methodologies. Specifically, three research objectives are established: (a) develop a robust visual-spatial analysis method leveraging precise point cloud data to accurately quantify visual-spatial characteristics pertinent to human visual perception; (b) establish a flexible VR-based method to systematically analyze visual perceptual behaviors, emphasizing detailed eye-movement trajectories captured through immersive virtual environments; (c) conduct a correlation analysis to quantitatively explore the relationship between objective visual-spatial characteristics and visual perceptual behaviors in historic gardens, elucidating how designed garden spaces influence visitor visual experiences; and (d) propose multi-perspective procedures grounded in perceptual pathways for design analysis and the extraction of transferable design insights for historic gardens. Jichang Garden, an exemplary historic garden in southeastern China renowned for its intricate spatial arrangements and sophisticated visual design, is selected as the case study. Its representative and prototypical characteristics make it an ideal context to demonstrate the effectiveness and broad applicability of the proposed methodological framework.

4.2 Methods

To achieve the research objectives outlined above, we employed an integrated methodological framework composed of three interconnected analytical components **(FIG. 4.2a)**: (a) point cloud-based visual-spatial analysis, (b) VR-based eye-tracking experiments, an analytical module that combined systematic correlation analysis and cultural-semantic interviews, and (d) multi-perspective analysis to interpret historic garden design.

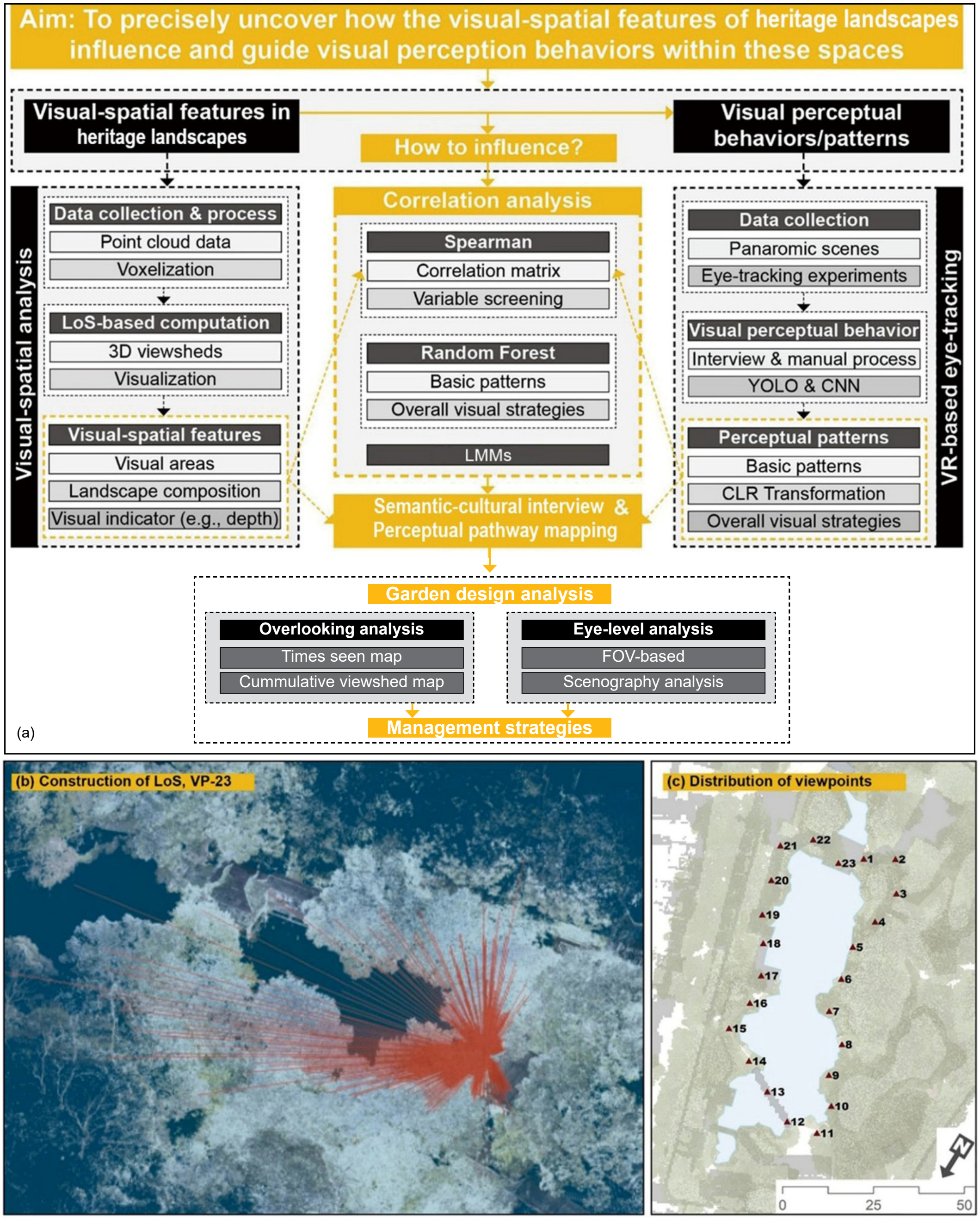


FIG. 4.2 Research methodology: (a) Technical route of the study; (b) Illustration of LoS construction in the point cloud environment, taking viewpoint No.23 as an example; (c) Study area: Jichang Garden and the 23 viewpoints used in this study.

4.2.1 Case selection and participants recruitment

Jichang Garden **(FIG. 4.1)**, located in Wuxi, China, is recognized as a quintessential example of Chinese classical garden design (Keswick, 2003). Its layout seamlessly integrates diverse elements such as mountains, water, rocks, corridors, and pavilions, creating a richly layered spatial experience (Shu et al., 2018). The complexity of Jichang Garden manifests through continuous visual rhythms shaped by pathways, bridges, rockeries, water, vegetation, and architectural elements (Yang, 2022). This complexity makes Jichang Garden an ideal context for the perceptual research, effectively showcasing the strengths of precise analytical algorithms and capturing nuanced visual perception behaviors.

Because the study materials involved explicitly Chinese cases, we restricted recruitment to Chinese participants to minimize cultural-unfamiliarity bias and targeted approximate gender balance at recruitment. Recruitment was conducted on university campuses proximate to the study site. The study protocol was approved by the institutional ethics committee, and all participants provided informed consent. Following pre-specified eligibility and quality-control procedures, the final analytic sample comprised 53 valid participants (N = 53, **TABLE 4.1**).

TABLE 4.1 Demographic characteristics of the participants

Group	Features	Count
Age	18-25	25
	26-30	25
	31-35	3
Gender	Male	28
	Female	25
Education	Bachelor’s	29
	Master’s	22
	PhD	2

4.2.2 Point cloud-based visual-spatial analysis

Compared to traditional 2D visibility methods, the proposed point cloud-based visual-spatial analysis enables accurate three-dimensional quantification of historic landscape spaces (Lonergan & Hedley, 2016; Wróżyński et al., 2024). Each visual space is characterized by two core features: the shape of the visible space and the observed landscape elements (Liu & Nijhuis, 2020). From these core features, we derive additional visual indicators to provide a robust foundation for subsequent correlation analyses.

Step-1: Data collection and preprocessing

Point cloud data were collected using two complementary scanning methods: handheld scanning and stationary scanning. Handheld scanning enabled flexible data capture in narrow or irregular spaces, such as secondary pathways, whereas stationary scanning provided higher accuracy suitable for critical areas like waterfront zones. The resulting datasets were stored in two formats: RGB-colored point clouds (PLY format), facilitating visual analysis and material differentiation; and non-RGB point clouds (LAS format), primarily for spatial measurements and structural analyses.

After acquiring the point cloud data, the next step was to perform voxelization (Alsadik et al., 2014). This process involved a series of steps, including (a) reading the point cloud data using Python and Open3D and determining the voxel size by specifying the length of the cube’s edges based on the computational requirements; (b) gridding the point cloud data utilizing Open3D; (c) extracting the coordinate data for each voxel’s central point in “pts” format; (d) importing the “pts” file into Arcscene and loading the central points’ coordinate data as well as category data; (e) modeling each voxel using the central point’s coordinate (a voxel size is 0.1 m); (f) categorizing the voxels according to the central points’ category information; (h) finalizing the voxelization process for the point cloud data, and exporting the resulting digital model as a Shapefile consisting of “multipatch” geometries, which is suitable for use in the ArcGIS platform.

Step-2: 3D viewshed computation

We strategically selected 23 viewpoints along waterfront pathways, precisely corresponding to locations utilized in VR panoramic experiments **(FIG. 4.2c)**. For each viewpoint, LoS rays were systematically generated at horizontal intervals of 5° covering azimuth angles from 0° to 355°, and vertical angles ranging from -80° to 85°, simulating typical human visual fields **(FIG. 4.2b)**. A maximum LoS length of 100 m was employed to realistically represent human visibility. Intersection coordinates and corresponding voxel attributes were recorded for rays intersecting voxels or water surfaces, while rays without intersections were categorized as "sky."

To accurately characterize the spatial visibility at each viewpoint, endpoints of LoS rays across various vertical angles were connected to construct closed 3D viewsheds (Peng et al., 2024). The resulting viewshed areas effectively indicate spatial visibility extent, while their shape and orientation provide critical insights into spatial characteristics. For instance, notably smaller viewshed areas at vertical angles between 60° and 80°, typically obstructed by building voxels, indicate viewpoints located under covered structures.

Step-3: Visual-spatial feature extraction

In this phase, two primary data categories were systematically analyzed: visual landscape composition and visual spatial morphology. For landscape elements, we statistically calculated the frequency and proportion of voxel types intersected by LoS rays, including vegetation, water surfaces, buildings, and sky. Additionally, their spatial distributions were visualized relative to the distance from each viewpoint. For spatial morphology, we first visualized the 3D viewshed shapes to intuitively assess spatial characteristics. We then quantitatively analyzed the viewshed areas across defined vertical viewing angles reflecting typical human visual perception ranges (Liu, 2020; Nijhuis, 2015): eye-level viewing (ELV, 5° to -5°), slightly downward (SDV, -6° to -30°), downward (LDV, -31° to -70°), slightly upward (SUV, 6° to 15°), upward (LUV, 16° to 50°), and overhead space ("Top", angles of 51° and above).

Step-4: Visual indicator computation

To precisely quantify spatial visual characteristics, several established visual indicators were selected and refined based on detailed LoS data from individual viewpoints. These indicators provide more accurate and nuanced representations compared to traditional methods (for detailed calculation methods, see **Appendix B1**):

a) **Depth:** Refers to perceived layering and distance variation within a visual scene, critically influencing spatial interest, legibility, and exploratory potential (Kaplan, 1987; Koseoglu & Onder, 2011). Depth was calculated using a layered computational approach, producing three indices: Layered Depth Index (LDI), Absolute Depth Index (ADI), and a composite weighted Depth Index (DI), with higher DI values indicating greater visual layering and spatial complexity.

b) **Orientation:** Indicates the directional concentration within the horizontal visual field, quantified using directional entropy. This method specifically considers both the number of visible directions and the extent of visibility along each approximate horizontal direction, providing a nuanced measure of spatial orientation. Orientation significantly influences spatial orientation, navigability, and visual clarity (Hillier & Hanson, 1989; Liu & Nijhuis, 2022). Values approaching 1 indicate fewer dominant directions, thus implying stronger spatial guidance and enhanced directional clarity.

c) **Openness:** Represents the degree of visually unobstructed space within the observer's visual field, calculated via a spherical area approximation. Openness greatly affects perceived comfort, safety, and aesthetic appeal (Kaplan et al., 1989; Nasar, 1989; Stamps, 2013). Values closer to 1 signify higher openness and greater visual expansiveness, thus enhancing overall spatial preference.

d) **Complexity:** Reflects visual richness and intricacy, arising from diverse and spatially arranged landscape elements. Moderate complexity enhances visual interest, while excessive complexity may induce visual fatigue (Kaplan et al., 1989; Liu & Nijhuis, 2022). Complexity was measured through a Weighted Shannon Entropy approach, yielding three specific metrics: traditional Shannon Entropy (composition diversity, SEC), spatial Shannon Entropy (spatial complexity, SES), and a comprehensive weighted Complexity Index (CI). Higher CI values indicate richer and more visually engaging environments.

4.2.3 Visual perceptual behavior analysis

To capture perceptual pathways, this study integrated VR and eye-tracking technology to record immersive visual behaviors beyond the limits of static-image analyses. A HTC VIVE Pro Eye with Tobii eyetracking recorded gaze in panoramic scenes aligned with selected 3D viewsheds. Data were collected and processed in Tobii Pro Lab with preset parameters and analyzed via a deeplearning pipeline; the eyetracker operates at 120 Hz with ~0.5°–1.1° accuracy.

Step-1: Eye-tracking experiment

The eye-tracking experiment included three sequential steps. **(a) Pilot phase:** Participants first experienced a panoramic environment similar to the formal test scenes, ensuring familiarity with the VR setting and experimental procedures. **(b) Formal experiment:** Participants began each trial with a standardized initial gaze directed toward the lake. They subsequently explored each VR panoramic scene freely for a standardized duration of 30 seconds per viewpoint, during which eye movements were recorded using the integrated eye-tracking system. **(c) Data collection:** Eye-tracking metrics, including fixation points and trajectory paths, were systematically recorded. The collected data were later visualized using scanpath diagrams and heatmaps, clearly illustrating gaze distributions and attentional shifts.

Step-2: Visual perceptual behavior analysis

Following the eye-tracking experiments, basic visual-perceptual behavior patterns were initially identified through participant interviews and preliminary qualitative analysis of eye-tracking data (Carter & Luke, 2020), informed by established theories on visual attention in environmental contexts (Doshi & Trivedi, 2012; Jovancevic-Misic & Hayhoe, 2009). To classify gaze trajectories into different behavior patterns, we employed a dual approach combining manual coding and exploratory machine learning.

a) **Manual coding:** All valid trajectories (N = 1,166; 22 viewpoints × 53 participants, excluding VP3 due to low-quality recordings) were independently coded by two trained raters. The classification was based on multiple complementary cues: (i) *semantic interpretation of the viewed scene* (e.g., presence of routes or depth contrasts), (ii) *visual inspection of scanpath diagrams and fixation heatmaps* (distribution and clustering of fixations), and (iii) *quantitative indicators from the raw coordinates*, including fixation counts, dispersion, and relative dwell times at different distances. Using these combined criteria, coders judged whether a trajectory represented broad exploratory scanning, sustained hotspot attention, near–far alternation, or route-oriented following. Raters were blind to spatial indicators and study hypotheses. Inter-rater reliability was high (Cohen’s $\kappa = 0.82$), and disagreements were resolved by discussion to yield a consensus label for each trajectory. This manual procedure ensured strong construct validity and close alignment with established theoretical categories.

b) **Machine learning attempt:** In parallel, we implemented an experimental pipeline (YOLO-based detection of gaze clusters followed by CNN classification of scanpath images) (Simon et al., 2024; Yin et al., 2018). Preliminary results showed broad consistency with manual labels, but classification accuracy varied by pattern. Given these limitations and the higher precision of manual labels, we adopted the manually coded results as the basis for all subsequent analyses. The automated pipeline is reported here for transparency and will be elaborated in future methods-focused research.

Step-3: Clustering to identify overall visual exploration strategies

For each participant and panoramic scene, the proportion of each visual perceptual behavior pattern was computed, ensuring all proportions summed to one. These compositional data were then transformed using the Centered Log-Ratio (CLR) transformation to handle their inherent compositional constraints, followed by K-means cluster analysis to systematically characterize overall visual exploration strategies across scenes and participants.

4.2.4 Correlation analysis

4.2.4.1 Confirmatory analysis: Linear mixed-effects models

Because observations are crossed repeated measures (participants × viewpoints), we used linear mixedeffects models (LMMs) on CLRtransformed behavioral compositions that were inductively derived from interviewassisted inspection of scanpaths. Each composition dimension was modeled as a function of depth, orientation, openness, and complexity. All predictors were zstandardized. We included random intercepts for participants and viewpoints to account for betweensubject and betweenviewpoint variability. For each model, we report fixedeffect estimates with 95% confidence intervals, variance components, intraclass correlations for participants and viewpoints, and marginal/conditional R^2 (Nakagawa). Multiple comparisons across predictors within an outcome were controlled using Benjamini-Hochberg FDR.

4.2.4.2 Exploratory correlation analysis: Spearman and Random Forest

To elucidate the relationship between visual-spatial features and visual-perceptual behaviors, Spearman and Random Forest analyses were treated as exploratory tools to complement the confirmatory mixed-effects models, providing descriptive associations, non-linearities, and potential thresholds. First, Spearman correlation analysis identified preliminary associations between visual-spatial indicators and classified visual perceptual behaviors. Second, a Random Forest (RF) regression model was employed to precisely determine key spatial features influencing visual perceptual behaviors. Multicollinearity was carefully assessed, and highly correlated variables were consolidated to ensure model robustness. RF model performance was evaluated using standard metrics including mean squared error (MSE), coefficient of determination (R^2), and mean absolute error (MAE). Additionally, local analyses were conducted to further interpret and validate the influence of specific spatial factors on visual perceptual behaviors within heritage environments.

4.2.4.3 Validation with cultural-semantic interview

In addition to quantitative correlation analysis, supplementary light-touch feedback interviews were conducted with participants to validate the cultural and semantic dimensions of observed perceptual patterns. After completing the VR eye-tracking sessions, participants were briefly shown heatmap visualizations of their gaze data, which highlighted areas of concentrated attention and typical scanpath tendencies. On this basis, participants were asked to comment on what attracted their attention, and more importantly, *why* such visual behaviors might have occurred, and how they associated specific visual-spatial features with meanings such as aesthetic enjoyment, historical symbolism, or recreational value.

4.2.5 Design analysis of Jichang Garden

With perceptual pathways and salient fixation AOIs identified, we proceed to the design analysis of Jichang Garden. We adopt two complementary lenses: an “overlooking” (vertical) perspective and an “eye-level” (horizontal) perspective, each capturing distinct but interrelated aspects of cognitive visual space.

When applied together, these methods broaden the scope of research objectives and improve the explanatory power of spatial-visual characteristics. Integrating both perspectives and cross-validating their outcomes enhances the robustness and credibility of the analysis. Due to space limitations, this chapter presents only a partial analysis focusing on the water-related garden design.

a) **"Vertical" Mapping analysis:** Water constitutes a defining component of the Jichang Garden environment (a point corroborated by our perceptual findings). For water-focused visual landscape analysis, visibility is a critical visual-spatial attribute. Among vertical-mapping techniques, visibility algorithms are widely used and effective. Accordingly, we generated: (i) a "times-seen" map and an accumulated viewsheds map to quantify the visibility of the pond surface across observation points, and (ii) interpolated surfaces with continuous color gradients to visualize spatial variation in visibility intensity. These results highlight where the pond is most persistently revealed or concealed in plan-based cognition and support hypotheses regarding designed exposure and concealment.

b) **"Horizontal" landscape composition analysis:** For the eye-level analysis, the west-shore route was selected as the study transect because of its proximity to the pond and its role in connecting the primary buildings from north to south. Along this route, we analyzed (i) the FOV composition (e.g., proportions of water, vegetation, architectural elements) at stepwise intervals, and (ii) compared these FOV profiles with previously derived perceptual metrics such as fixations, dwell times, and transition patterns. The correspondence between FOV composition and perceptual responses provides insights into design intentions.

Drawing on prior interviews and eye-tracking data, we identified several focal points and phenomena in the visual experience of Jichang Garden. Owing to space constraints, this chapter concentrates on two questions: (a) how the water surface organizes the garden's overall visual attention, and (b) how the visual-spatial experience along the west-side path is enriched by spatial and visual design techniques.

4.3 Results-1: Establishing visual-perceptual pathway in historic garden

4.3.1 Visual-spatial analysis results

The point cloud-based analyses revealed clear variations in the spatial configurations and visual compositions of the 23 selected viewpoints. These results establish the objective environmental conditions that later shape visitors' perceptual behaviors, which will be examined in the following sections. The 3D viewsheds and panoramic visualizations demonstrate marked contrasts in spatial form **(FIG. 4.3, Appendix B2)**. For example, VP 3 is notably enclosed, while VP 1 and VP 10 show more open and complex configurations. Such differences indicate distinct possibilities for how observers may explore or focus within each space.

Quantitative measurements further highlight these variations. For instance, VP 7 and VP 11 displayed exceptionally high upward and overhead visibility, emphasizing vertical openness, whereas VP 1 and VP 2 showed very limited vertical visibility, reflecting introverted, architecturally bounded spaces **(TABLE 4.2)**. Horizontal openness at VP 10 and VP 16 created extended sightlines, while VP 17 and VP 2 presented more restricted visual volumes.

The proportions of visible landscape elements also varied substantially **(TABLE 4.3)**. Viewpoints such as VP 17-21 were dominated by buildings, indicating strongly built environments, while VP 7-12 emphasized vegetation and waterscapes. Rockeries were prominent at VP 7-9, and waterscapes at VP 12-13, reflecting the environmental diversity present within the study area.

Finally, the calculated spatial indicators demonstrate nuanced differences across viewpoints **(TABLE 4.4)**. Openness values ranged from highly expansive (e.g., VP 11: 0.4122) to extremely enclosed (e.g., VP 17: 0.0131). Depth indices were particularly high at VP 1, VP 4, and VP 12, suggesting complex layering, while VP 20–22 showed much simpler depth structures. Complexity was especially pronounced at VP 12–13, reflecting visually intricate environments, whereas VP 17 and VP 21 were comparatively simple.

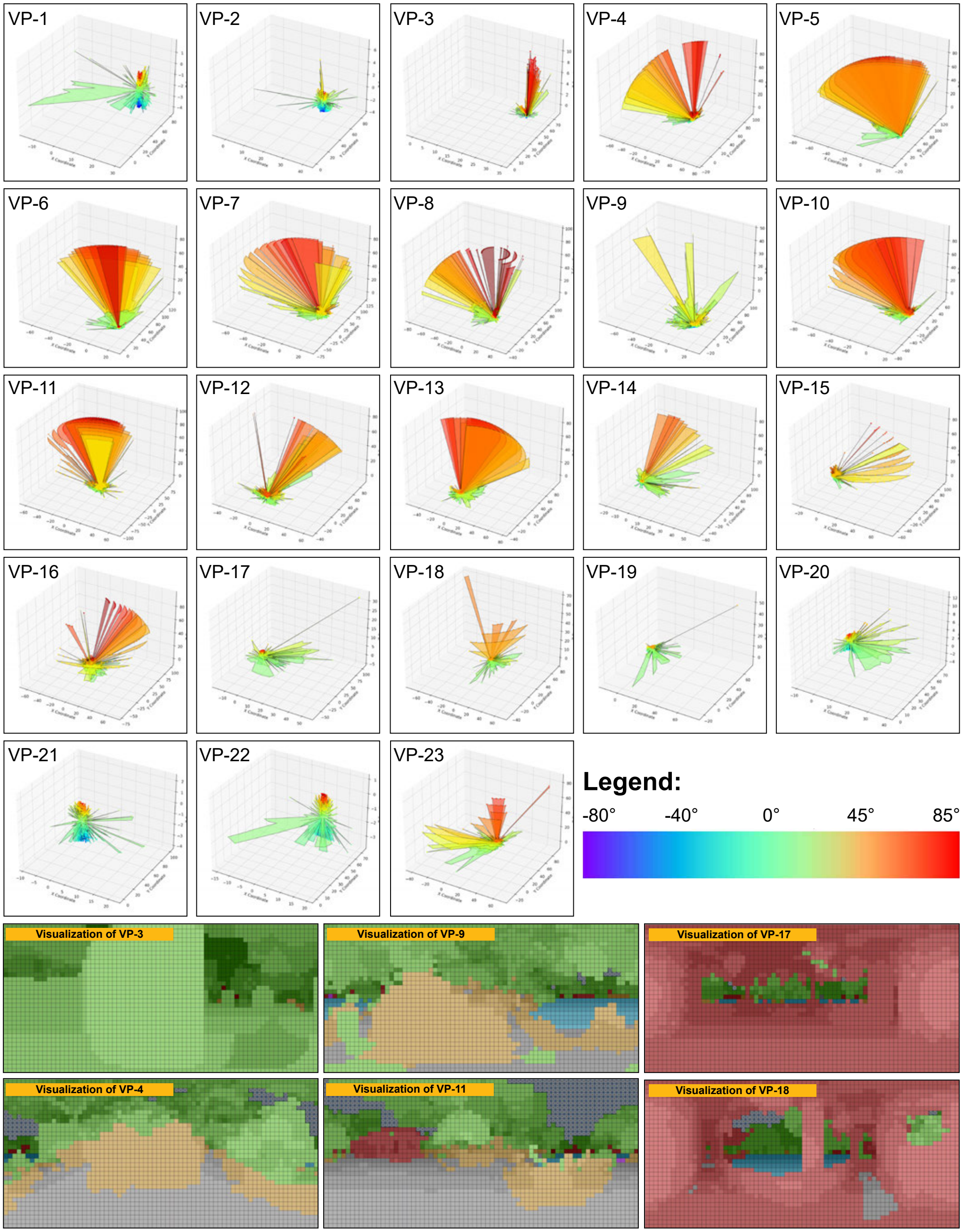


FIG. 4.3 The computation results of the visual-spatial features of the 23 viewpoints: (a) Visualization of the 3D viewsheds (upper graphs); (b) Visualization of selected panoramic environments, where hue represents element types and brightness indicates distance (red for building and structures, blue for waterscape, green for vegetation, purple for bridge, light gray for ground, yellow for rockery, and dark gray for sky)

TABLE 4.2 Results of visual area measurements

VP	LDV	SDV	ELV	SUV	LUV	Top
1	35.3	602.9	3346.8	225.0	140.6	29.0
2	60.7	412.9	804.1	268.0	349.8	17.7
4	15.7	395.6	2840.3	3627.7	50591.4	34290.1
5	32.2	237.5	2797.9	4535.9	109932.1	33939.1
6	36.5	254.7	2980.4	4104.4	59447.0	17167.0
7	57.3	402.5	6309.3	9984.2	124560.7	33631.7
8	47.1	263.8	3608.0	9048.0	63684.4	40158.9
9	35.45	294.7	6332.8	11876.0	21015.5	579.5
10	46.0	439.4	8352.4	4474.1	81440.9	56180.4
11	73.4	731.6	5309.0	7842.1	150555.1	82058.8
12	36.4	383.3	6702.7	14947	53936.8	31698.8
13	41.0	533.6	7254.9	8393.2	93722.6	50432.5
14	54.6	447.9	5455.6	8429.7	28639.6	1472.0
15	55.7	417.9	1549.4	1837.3	64166.9	9901.4
16	65.5	690.6	8853.0	6692.4	93511.1	40239.9
17	52.6	256.5	9161.7	12594.0	3106.7	115.8
18	39.5	332.8	6609.6	3083.8	39499.8	98.3
19	65.1	528.4	4387.4	593.5	1631.3	53.5
20	61.7	487.7	4028.1	3439.9	1154.4	47.3
21	67.9	551.7	3420.6	275.5	180.4	34.6
22	45.9	472.5	1471.0	115.0	132.0	25.7
23	60.4	463.9	8132.2	13571.0	35206.2	14645.3

Notes: LDV = Look-down view, SDV = Slight-down view, ELV = Eye-level view, SUV = Slight-upward view, LUV = Look-upward view, Top = Overhead space.

TABLE 4.3 Results of proportions of visual landscape elements in different scenarios

VP	Sky	Ground	Water	Vegetation	Buildings	Rockery	Bridge
1	0.0000	0.0874	0.0093	0.0459	0.8364	0.0210	0.0000
2	0.0000	0.0125	0.0004	0.0878	0.8815	0.0177	0.0000
4	0.0383	0.2655	0.0040	0.4500	0.0020	0.2401	0.0000
5	0.0826	0.2103	0.1120	0.4093	0.0117	0.1741	0.0000
6	0.0500	0.2744	0.0919	0.3936	0.0105	0.1797	0.0000
7	0.0463	0.1160	0.0375	0.4525	0.0048	0.3413	0.0016
8	0.0584	0.0322	0.0185	0.5302	0.0012	0.3594	0.0000
9	0.0040	0.1023	0.0548	0.4996	0.0048	0.3340	0.0004
10	0.0774	0.1567	0.0766	0.3791	0.0109	0.2977	0.0016
11	0.1261	0.3634	0.0044	0.3292	0.0471	0.1289	0.0008
12	0.0210	0.0375	0.2119	0.5077	0.0125	0.0334	0.1761
13	0.0830	0.0016	0.3143	0.3973	0.0153	0.0113	0.1773

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TOC

TABLE 4.3 Results of proportions of visual landscape elements in different scenarios

VP	Sky	Ground	Water	Vegetation	Buildings	Rockery	Bridge
14	0.0093	0.2023	0.0250	0.5165	0.0052	0.2361	0.0056
15	0.0278	0.2671	0.0016	0.4065	0.0669	0.2297	0.0004
16	0.0572	0.2917	0.0250	0.4311	0.0516	0.1434	0.0000
17	0.0012	0.0004	0.0073	0.0608	0.9271	0.0032	0.0000
18	0.0137	0.0262	0.0290	0.0802	0.8493	0.0016	0.0000
19	0.0004	0.0403	0.0137	0.0496	0.8618	0.0342	0.0000
20	0.0000	0.0161	0.0121	0.0705	0.8892	0.0121	0.0000
21	0.0000	0.0356	0.0006	0.0379	0.9243	0.0017	0.0000
22	0.0000	0.0266	0.0060	0.1092	0.8533	0.0048	0.0000
23	0.0193	0.2393	0.0431	0.3638	0.3243	0.0101	0.0000

TABLE 4.4 Results of visual indicator computation

VP	Openness	Depth			Orientation	Complexity		
		LDI	ADI	DI		SEC	SES	CI
1	0.1752	3.7412	1.0000	0.9829	0.0056	0.6285	1.8468	0.5952
2	0.0168	1.6892	0.3564	0.3228	0.0375	0.4542	1.3384	0.4310
4	0.2281	3.8434	1.0000	1.0177	0.2365	1.2136	1.4128	0.6315
5	0.3861	3.1010	0.595	0.6866	0.1333	1.5010	1.2498	0.6614
6	0.3626	3.2526	1.0000	0.9154	0.1478	1.4471	1.4077	0.6864
7	0.2306	2.9771	1.0000	0.8676	0.0500	1.2772	1.5549	0.6810
8	0.1040	3.5776	1.0000	0.9767	0.1045	1.0629	1.4687	0.6087
9	0.1387	2.9972	1.0000	0.8711	0.0982	1.1565	1.4370	0.6236
10	0.2745	3.4443	0.6457	0.7714	0.1088	1.4731	1.5859	0.7355
11	0.4122	2.6921	1.0000	0.8183	0.0436	1.4326	1.6305	0.7365
12	0.2247	3.6270	1.0000	0.9802	0.0696	1.3512	1.7599	0.7481
13	0.3534	3.1369	1.0000	0.8953	0.0337	1.3687	1.7322	0.7456
14	0.1701	3.0526	1.0000	0.8807	0.0973	1.1976	1.5733	0.6663
15	0.2266	3.2881	0.3302	0.5866	0.0826	1.3504	1.5290	0.6924
16	0.3062	2.9593	1.0000	0.8646	0.0553	1.4094	1.5757	0.7178
17	0.0131	1.9232	1.0000	0.6851	0.1177	0.3060	1.0612	0.3287
18	0.0819	3.4322	0.5937	0.7433	0.1423	0.6083	1.5415	0.5169
19	0.0680	1.2995	0.7129	0.4335	0.0776	0.5839	1.5197	0.5058
20	0.0366	1.1235	0.5569	0.3250	0.1262	0.4647	1.5259	0.4786
21	0.0419	0.8833	0.4791	0.2445	0.0480	0.4357	1.3331	0.4253
22	0.0206	0.8547	0.666	0.3330	0.0472	0.5303	1.2891	0.4375
23	0.2446	2.6352	1.0000	0.8084	0.0590	1.3334	1.5158	0.6851

Notes: LDI = Layered depth index, ADI = Absolute depth index, DI = Depth index, SEC = Shannon Entropy for visual composition, SES = Shannon Entropy for spatial complexity, CI = Complexity index.

4.3.2 VR eye-tracking analysis results

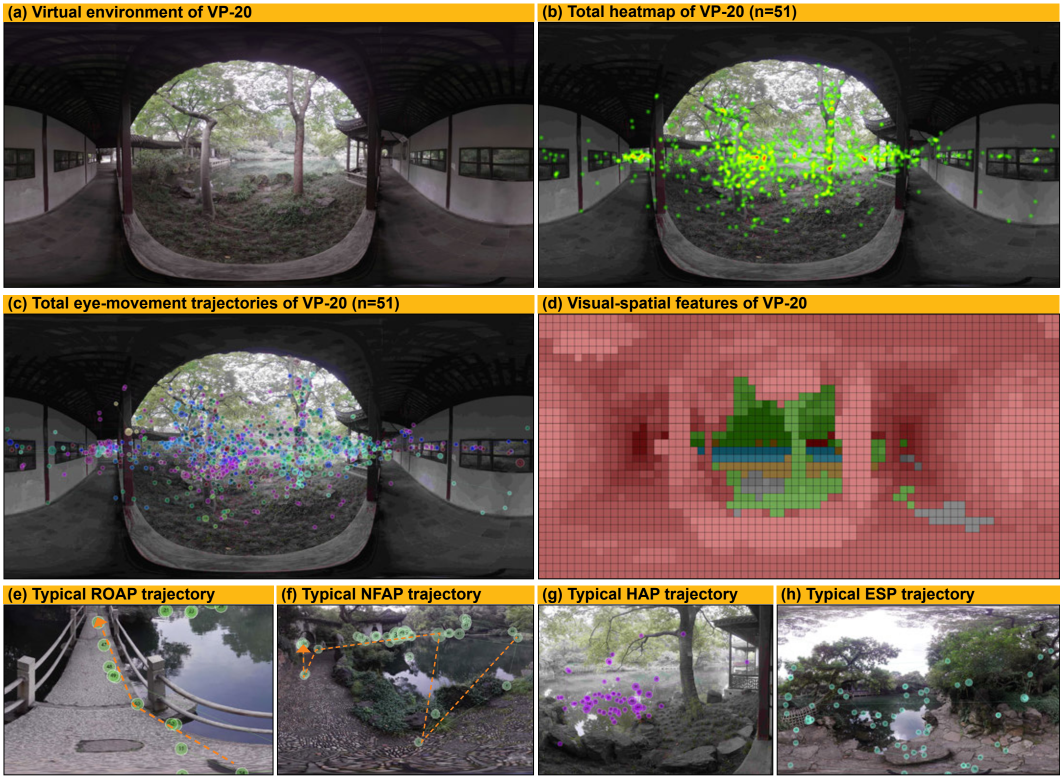


FIG. 4.4 Example of eye-tracking experiment and the theoretical movement trajectories for the gaze patterns: (a) The panoramic scene of VP 20; (b) Fixation heatmap for the VP 20; (c) Eye-movement trajectories of the VP 20; (d) Visualization of the VP 20's spatial features and landscape elements; (e) A typical example of ROAP scanpath; (f) A typical example of NFAP scanpath; (g) A typical example of HAP scanpath; (h) A typical example of ESP scanpath.

Eye-tracking experiments in immersive VR generated dynamic gaze data for 22 viewpoints (excluding VP 3 due to lowquality VR recordings that did not provide reliable gaze data). The processed results included fixation heatmaps, trajectory diagrams, and fixation duration analyses, enabling the identification of recurrent perceptual patterns and broader exploration strategies **(FIG. 4.4a-d, Appendix B3-4).**

Across participants (including interview) and viewpoints, four fundamental gaze behavior patterns were consistently observed **(FIG. 4.4e-h)**. *(a) The exploratory scanning pattern (ESP)* was characterized by broad, irregular trajectories and dispersed fixations, reflecting wide-ranging exploration without concentration on specific elements (Steil et al., 2018). *(b) The hotspot attention pattern (HAP)* was defined by short trajectories and localized clusters, indicating sustained attention to distinct landmarks such as buildings, waterscape reflections, or uniquely shaped vegetation (Henderson, 2003). *(c) The route-oriented attention pattern (ROAP)* followed the orientation of paths, concentrating gaze toward vanishing points and central perspectives (Wiener et al., 2012). Finally, *(d) the near–far alternation pattern (NFAP)* was marked by repeated shifts between foreground and background elements, demonstrating sensitivity to depth contrasts (Sitzmann et al., 2018).

The occurrence of these patterns varied notably across viewpoints **(Appendix B4)**. ROAP was more prevalent at VP 5, VP 7, and VP 13, where linear pathways structured visual engagement. NFAP was frequent at VP 5 and VP 17, corresponding to strong depth contrasts. HAP dominated at VP 1, VP 18–20, where prominent landmarks attracted concentrated fixations. ESP was more evident at VP 11, VP 13–15, suggesting environments that encouraged extensive scanning with limited focus **(FIG. 4.5a-d)**.

Based on k-means clustering analysis (with the optimal number of clusters set to 3 using the Silhouette Score or Elbow Method), three distinct visual perception strategies were identified: *(a) Environmental exploration* (Cluster 0, N = 364) was dominated by ESP, with participants scanning broadly across scenes without strong fixation. *(b) Specific element attention* (Cluster 1, N = 316) was characterized by high HAP values, reflecting targeted viewing of distinctive features with limited exploratory scanning. *(c) Holistic appreciation* (Cluster 2, N = 442) combined HAP with NFAP, indicating both concentrated attention on landmarks and alternation between near and far elements, while route-following tendencies remained weak. The distribution of these strategies also varied spatially: some viewpoints, such as VP 5 and VP 19, displayed a balanced mix of strategies, suggesting visually diverse settings, whereas others, such as VP 7, VP 9, and VP 10, were dominated by a single mode, reflecting more uniform visual structuring **(FIG. 4.5e–f)**.

In summary, the VR eye-tracking analysis reveals four basic gaze patterns and three broader exploration strategies that capture how participants interact with the spatial settings. These patterns represent the perceptual pathways through which environmental characteristics shape visual engagement, forming the basis for the correlation analysis presented in the next section.

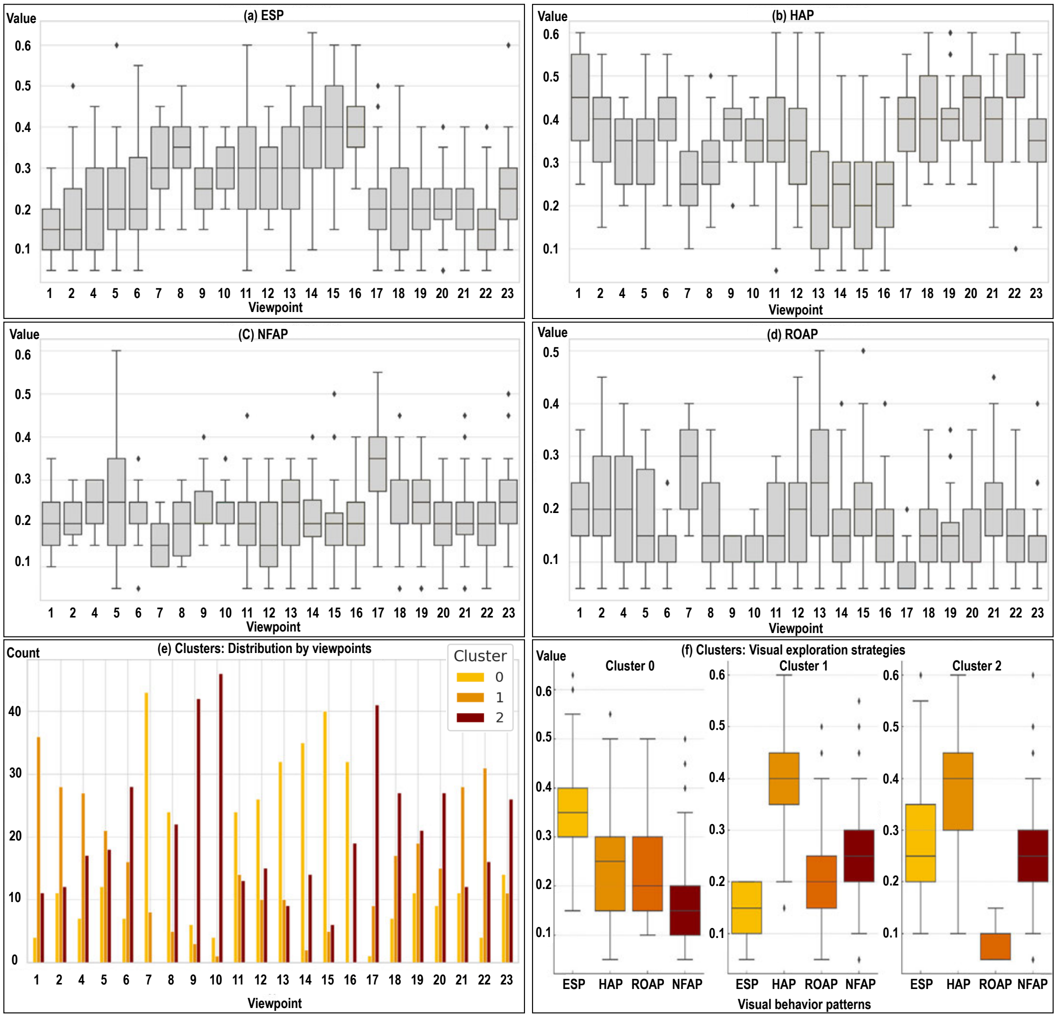


FIG. 4.5 Analysis results of visual perceptual behavior patterns and visual exploration strategies: (a)-(d) Values and viewpoint distributions of ESP, HAP, NFAP, and ROAP; (e) Clustering of visual exploration strategies and viewpoint distribution (Error bars are not applicable); (f) Value distribution of each pattern within the three clusters.

TOC

4.3.3 Linking visual-spatial features to perceptual behaviors

To clarify how the heritage landscape environment influenced perceptual responses, we correlated quantified visual-spatial features with the four gaze behavior patterns and the three overarching exploration strategies. Before these correlations, we ran cross-classified linear mixed-effects models to partition variance and determine whether scene-level or observer-level factors predominated. Scene-level differences clearly dominated, with fixed effects explaining a modest share and full models achieving substantial fit **(TABLE 4.5)**. These results justify centering the subsequent analyses on viewpoint-level spatial predictors while retaining participant as a random intercept.

Beyond variance partitioning, mixed-effects models identified *complexity* as the clearest driver (more ESP, less HAP), while *openness* related negatively to ESP and *orientation* related negatively to NFAP; ROAP showed no fixed-effect predictors. Overall fixed-effect contributions were limited (low marginal R^2) but the models retained strong conditional fit, reflecting pronounced scene-level structure **(TABLE 4.6)**.

The Spearman correlation results revealed that ESP and HAP displayed the clearest and strongest associations, while NFAP and ROAP showed only weak relationships **(FIG. 4.6)**. ESP was positively related to vegetation, complexity, rockeries, and upward views (including sky and overhead openness), but negatively to buildings or structures. This indicates that ESP was typically activated in visually rich and intricate environments with abundant natural elements. By contrast, HAP was positively associated with building structures and negatively correlated with vegetation, complexity, and vertical openness, confirming its tendency to focus on distinct landmarks under simpler spatial conditions. NFAP and ROAP exhibited weaker trends, with NFAP showing modest links to orientation and ROAP a slight negative correlation with orientation, suggesting only limited influence from directional cues.

TABLE 4.5 Mixed-effects variance partitioning and model fit (ICCs, R^2)

Outcome	Var (viewpoint)	Var (participant)	Var (residual)	ICC (viewpoint)	ICC (participant)	R^2 (marginal)	R^2 (conditional)
ESP	0.172	0.002	0.082	0.67	0.009	0.141	0.724
HAP	0.131	0.007	0.065	0.645	0.035	0.139	0.725
ROAP	0.193	0	0.092	0.677	0	0.06	0.697
NFAP	0.128	0	0.062	0.675	0	0.085	0.703

Notes: Models include z-standardized spatial predictors as fixed effects and random intercepts for participant and viewpoint. ICC (viewpoint/participant) = variance_component / total variance; R^2 values follow Nakagawa's marginal/conditional definition.

TABLE 4.6 Fixed-effect estimates from confirmatory LMMs (CLR outcomes; z-standardized predictors)

Outcome	Predictor	β	95% CI	q (BH)
ESP	Complexity	0.44	[0.34, 0.55]	< 0.001
ESP	Openness	-0.28	[-0.39, -0.17]	< 0.001
HAP	Complexity	-0.17	[-0.26, -0.07]	0.002
HAP	Depth (DI)*	0.04	[-0.00, 0.08]	0.089
NFAP	Orientation	-0.05	[-0.08, -0.02]	0.001
ROAP	—	—	—	—

*Notes: Only effects with q(FDR)<.10 are shown; *indicates trend-level (q≈.089). Outcomes are CLR-transformed; predictors z-standardized; crossed random intercepts for participant and viewpoint.*

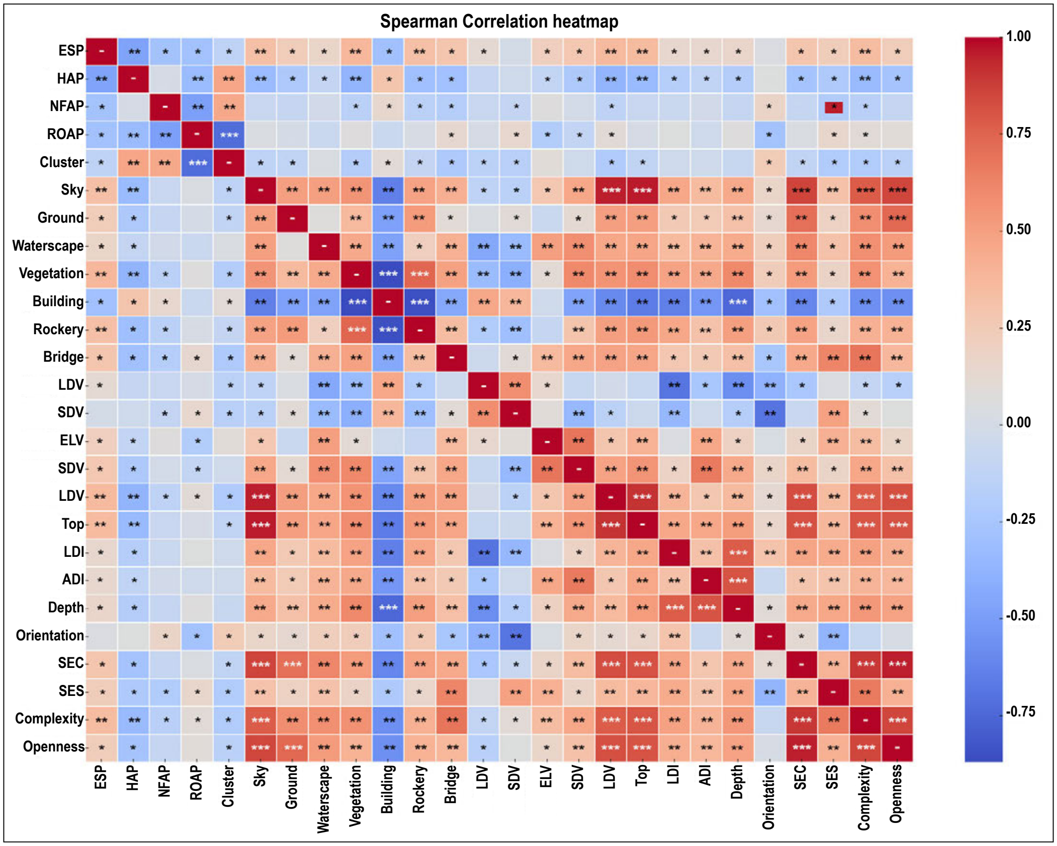


FIG. 4.6 Spearman correlation heatmap with all the variables: In general, Spearman correlation coefficients (ρ) above 0.7 (***) are considered strongly correlated, values between 0.3 and 0.7 (**) indicate moderate correlation, 0.1 to 0.3 (*) represent weak correlation, and below 0.1 are classified as very weak or negligible correlations. However, considering the exploratory nature of subsequent RF analyses and to ensure comprehensiveness as well as potential interactions among variables, variables with absolute correlations greater than 0.1 were retained. Additionally, all visual-spatial indicator variables were retained for the subsequent clustering analysis to fully capture detailed spatial patterns and subtle differences among clusters.

TOC

RF regression further supported these findings **(FIG. 4.7)**. Models for ESP and HAP achieved moderate predictive strength ($R^2 \approx 0.27–0.28$), while NFAP and ROAP remained weakly predicted ($R^2 < 0.20$). These values refer to the mean R^2 obtained through cross-validation, and complementary error metrics (MAE and MSE) showed similar trends, confirming model consistency. Key predictors for ESP included vegetation coverage, complexity, depth, and limited building dominance, whereas HAP was best explained by building structures, low vegetation, and openness extremes. These results reinforce that ESP is encouraged by layered, vegetation-rich, and visually diverse settings, whereas HAP emerges in simplified spatial conditions where architectural landmarks stand out.

Local analyses refined these insights by identifying thresholds and turning points. ESP was most prevalent in scenes with moderate openness (0.2–0.3), vegetation above 40%, high complexity (>0.6), and layered depth (>0.8). In contrast, HAP was concentrated in scenes with lower vegetation (<0.3–0.4), lower complexity (<0.6), and either highly enclosed (<0.1) or more expansive (>0.3) openness, conditions that accentuate singular focal points, and a nonlinear openness effect, whereby both highly enclosed (<0.1) and more expansive (>0.3) conditions accentuated single focal points **(FIG. 4.8, FIG. 4.9)**.

At the level of overall exploration strategies, RF classification identified orientation, complexity, vegetation, depth, and openness as the strongest discriminators between clusters **(FIG. 4.10)**. Lower values of these indicators were consistently associated with environmental exploration (Cluster 0), intermediate values with specific element attention (Cluster 1), and higher values with holistic appreciation (Cluster 2). Although predictive accuracy remained moderate, these variables clearly structured the transitions between different strategies.

In summary, the correlation analyses establish consistent, statistically supported linkages between visual-spatial features and perceptual behaviors. ESP is promoted by complex, vegetation-rich environments, while HAP is linked to architecturally explicit and simplified scenes. NFAP and ROAP showed weaker associations, reflecting their more context-dependent nature. At a broader level, gradients in orientation, complexity, and openness systematically differentiated the three exploration strategies.

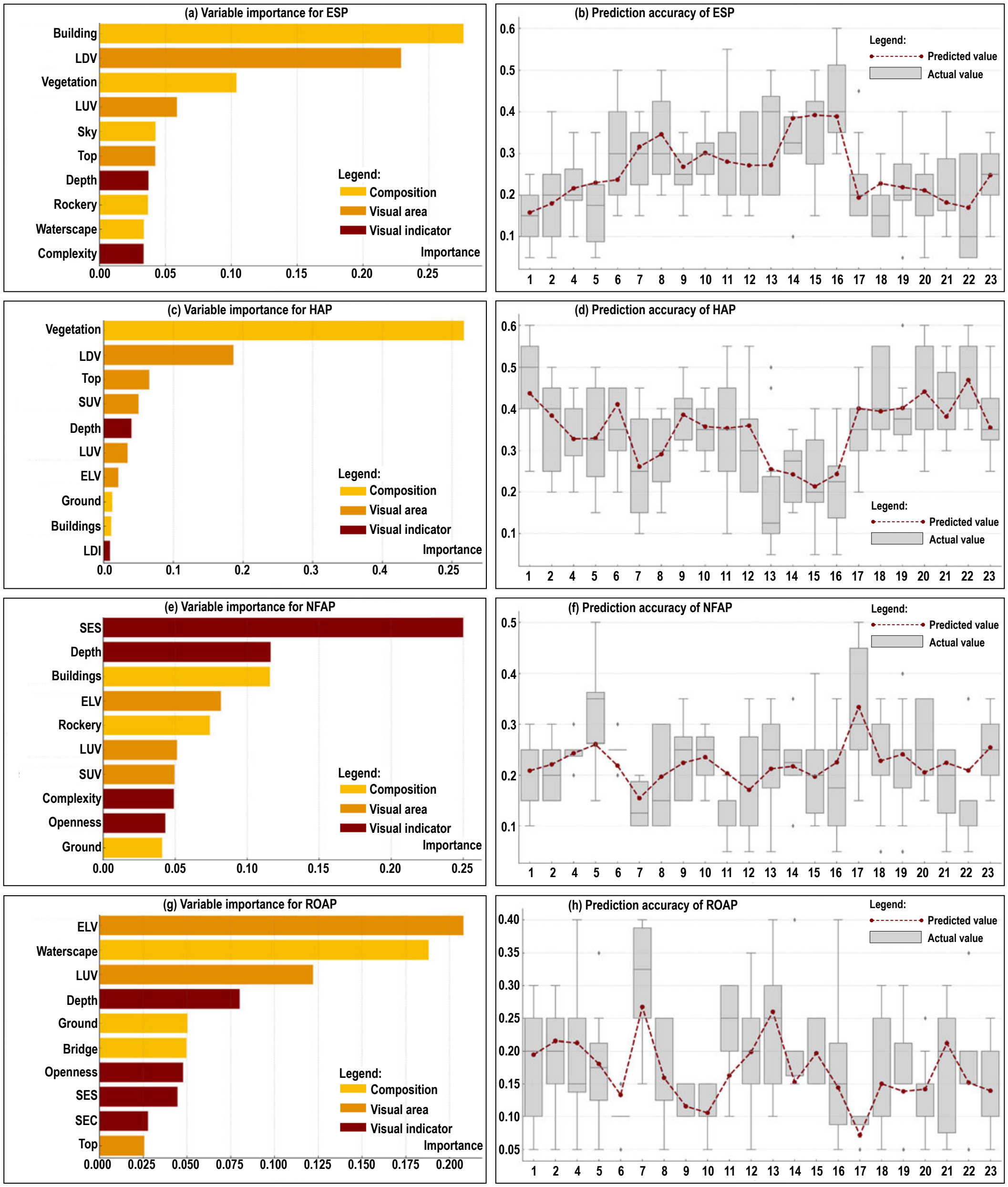


FIG. 4.7 Random Forest analysis results: (a), (c), (e), and (g) show factor importance analysis results for the four visual behavior patterns (Error bars are not applicable); (b), (d), (f), and (h) illustrate comparisons between predicted and actual values for the four perceptual behavior patterns using RF.

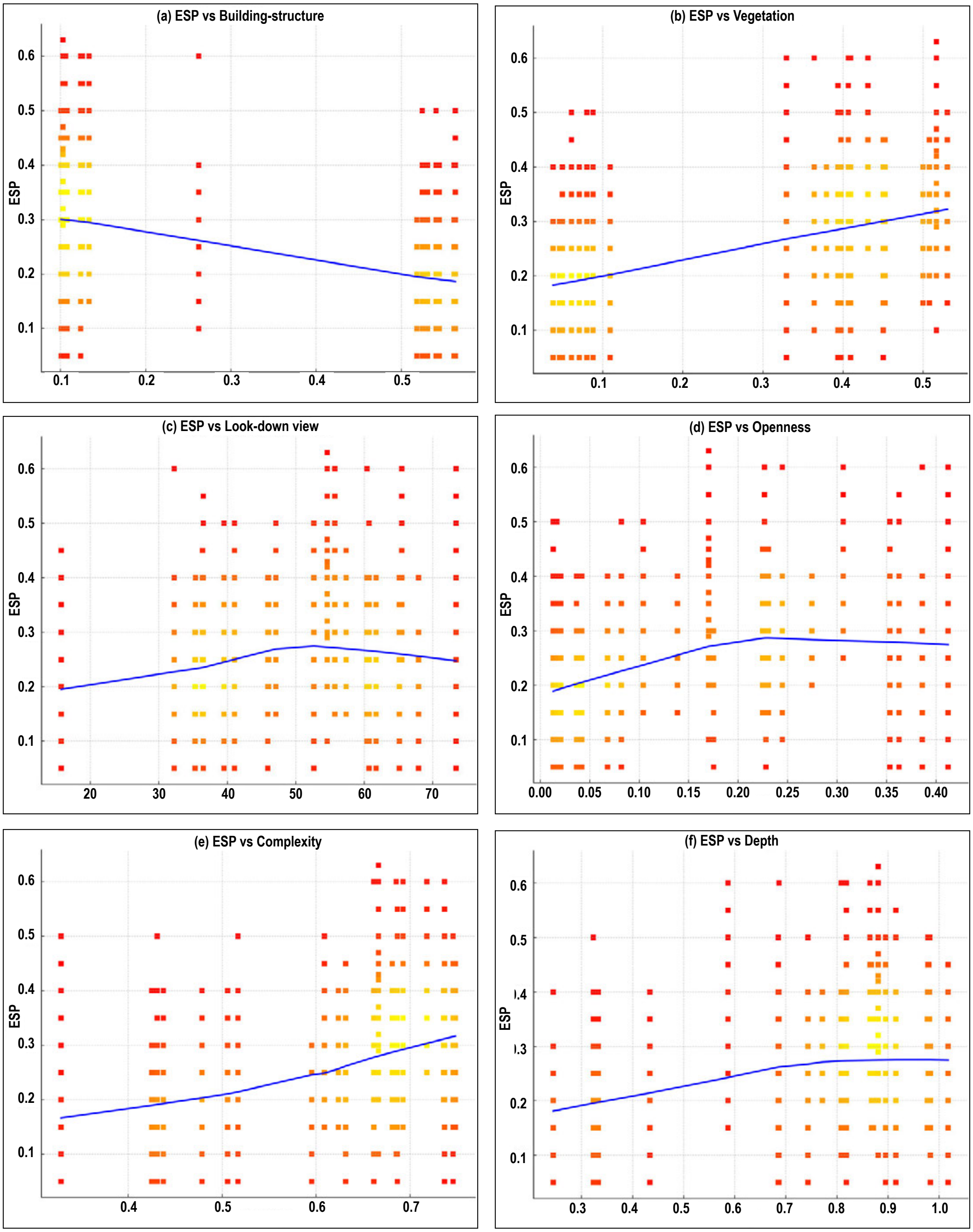


FIG. 4.8 Random Forest local analysis of important variables influencing ESP: (a) Building-structure; (b) Vegetation; (c) Look-down view; (d) Openness; (e) Complexity; (f) Depth.

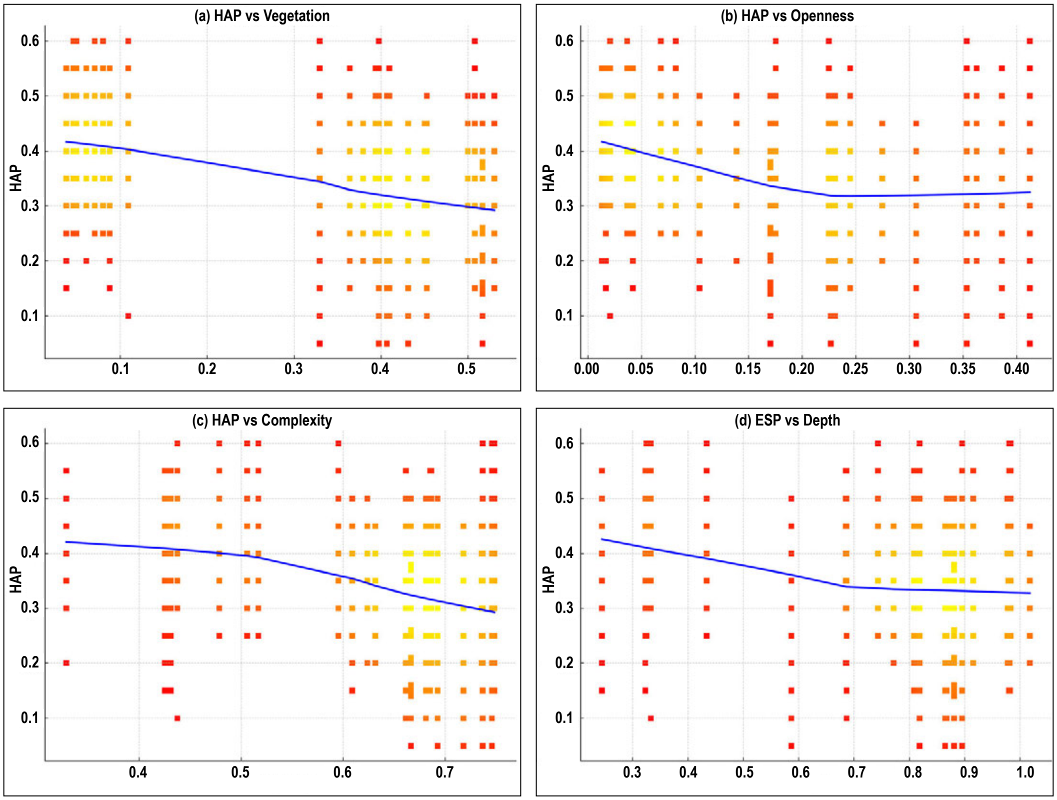


FIG. 4.9 Random Forest local analysis of important variables influencing HAP: (a) Vegetation; (b) Openness; (c) Complexity; (d) Depth.

TOC

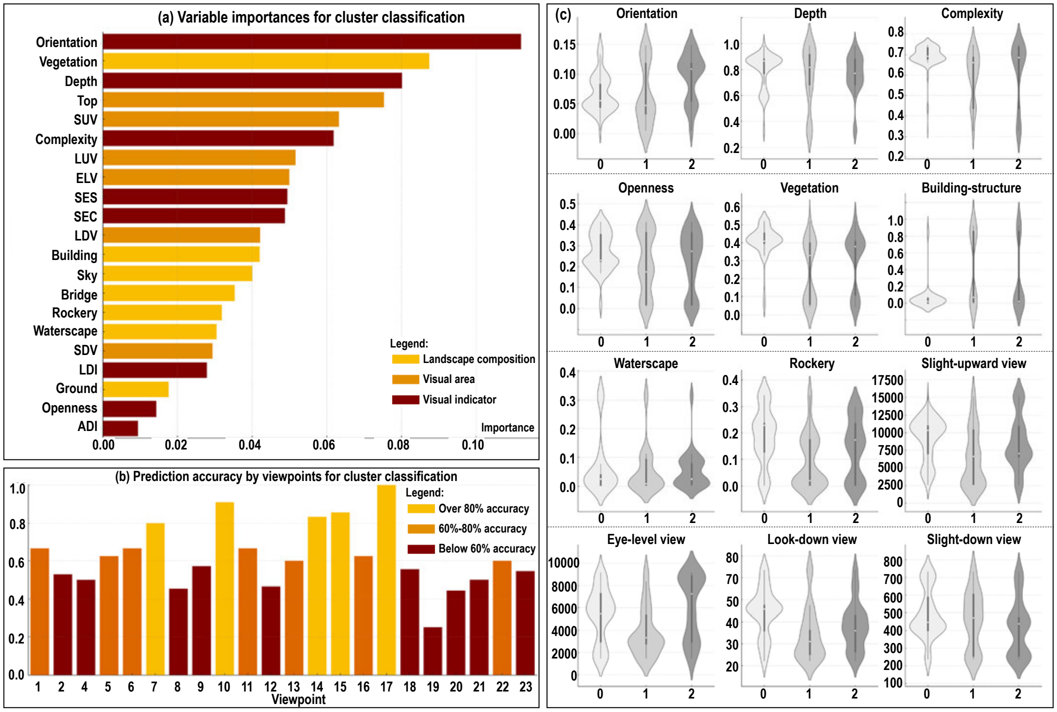


FIG. 4.10 RF analysis results for overall visual exploration strategies (Error bars are not applicable): (a) Factor importance; (b) Prediction accuracy and corresponding viewpoints; (c) Local analysis of effective variables.

TOC

4.3.4 Cultural-semantic validation

Post-experiment interviews provided cultural-semantic validation of the three exploration strategies identified in the eye-tracking analyses. Participants' accounts showed that each strategy is not only a perceptual mode but also embedded in culturally meaningful readings of landscape elements, clarifying how perceptual pathways combine with cultural semantics. Moreover, culturally salient cues often act as exogenous attention drivers, systematically biasing strategy selection away from the baseline implied by spatial features; thereby explaining model under-prediction in certain scenes.

a) **Environmental exploration:** Participants adopting exploratory scanning described vegetation-dominated or layered environments. They emphasized the restorative atmosphere created by abundant trees and shrubs, seasonal changes, and natural vitality, often noting koi as adding a lively presence. Without fixed focal points, attention was dispersed across the whole scene. Culturally, these experiences resonate with traditions of heritage landscapes as retreats for repose, where natural abundance sustains immersion and contemplation.

b) **Specific element attention:** When fixations clustered on single objects, participants consistently pointed to symbolic, culturally charged elements (distinctive plant forms, calligraphic inscriptions, unusual rockeries, koi, and water reflections). Façades and pavilions further anchored attention through historical associations, producing stable hotspots.

c) **Holistic appreciation:** In scenes where participants combined scanning with depth alternation, they emphasized the integrative harmony of the entire setting. Descriptions included "the scene unfolding layer by layer," "harmony between near and far," and the effect of reflections that made the whole scene "coherent and atmospheric."

d) **Cultural-semantic explanation of predictive gaps:** The cultural-semantic validation also clarified why certain viewpoints were poorly predicted by the RF models reported in **Section 4.3.3**. For instance, settings containing koi, calligraphic inscriptions, or distinctively shaped plants were often misclassified **(FIG. 4.11)**. Quantitatively, the first scene **(FIG. 4.11a-b)** resembled vegetation-dominated contexts expected to elicit exploratory scanning. However, participants explained that such salient cultural cues redirected their focus toward specific features, shifting their strategy toward specific element attention or holistic appreciation. Similarly, reflections on water surfaces and inscribed stones altered gaze behaviors in ways not anticipated by spatial indicators alone. Considering that overall classification accuracy remained at about 60%, these cases demonstrate that spatial features alone cannot fully explain perceptual strategies.

Instead, the combined influence of spatial morphology and cultural-semantic triggers determines whether an environment is experienced as free exploration, focused attention, or integrated appreciation. These discrepancies typically occurred where symbolic cues (e.g., inscriptions, unusual rockery forms, water reflections, or koi) redirected attention in ways not fully captured by geometric indicators. In such scenes, cultural salience overrode spatial regularities, producing gaze concentrations that the models underpredicted.

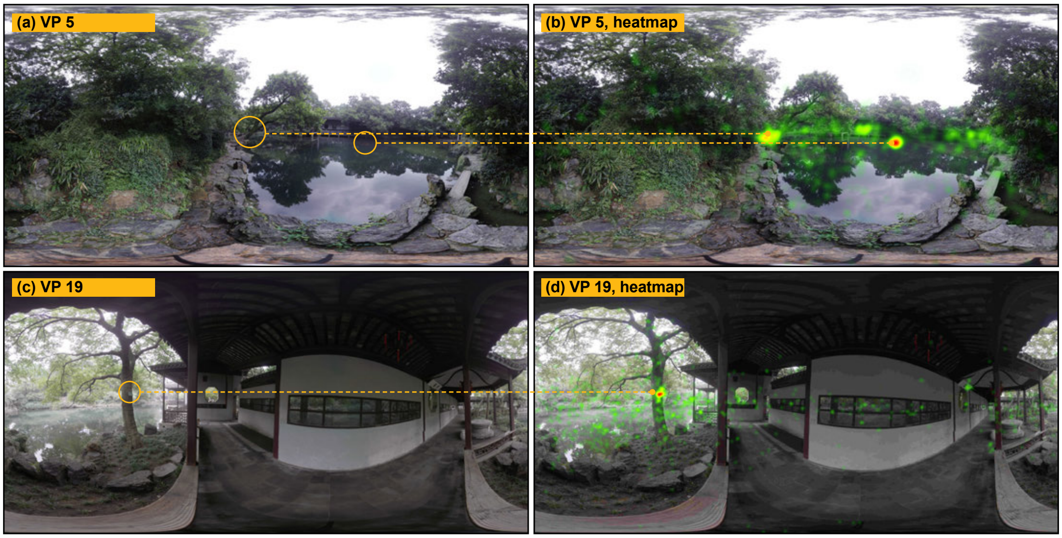


FIG. 4.11 Cultural–semantic explanation of mismatches between predicted and observed perceptual strategies: (a), (b) Viewpoint 5 (VP 5) predicted as Cluster 2: Holistic appreciation based on spatial indicators (e.g., high depth and layered openness), but participants' gaze shifted to Cluster 1: Specific element attention due to a culturally salient tree and the presence of koi fish; (c), (d) Viewpoint 19 (VP 19) shows a similar deviation, where inscriptions hung on a tree redirected attention away from spatially predicted holistic appreciation.

TOC

4.3.5 Integrated mapping of visual-spatial features and visual perceptual behaviors

Building on the quantitative correlations **(Section 4.3.3)** and cultural-semantic validations **(Section 4.3.4)**, the results were integrated into a comprehensive mapping framework **(TABLE 4.7)**. This framework demonstrates that quantitative indicators derived from point cloud analysis (e.g., openness, complexity) provide the baseline conditions shaping perceptual tendencies. In addition, as highlighted in **Section 4.3.4**, cultural-semantic triggers played an essential role in shaping perceptual strategies, particularly in cases where the statistical models showed limited accuracy.

TABLE 4.7 Integrated mapping of visual-spatial features, cultural-semantic triggers and perceptual behaviors.

Overall strategies	Visual-spatial features	Cultural-semantic triggers
Cluster 0: Environmental exploration	**Openness** 0.20–0.30; **CI** >0.60 (typically 0.60–0.75); **DI/LDI** ≈0.80–0.90; **Vegetation** >0.40; **Building** low–moderate (<0.25–0.30); **Viewing angles:** SDV and LDV high (downward ground visibility supports locomotion), LUV/Top elevated (sky and upward openness encourage scanning), ELV moderate	**Elements:** Seasonal/ornamental plants, natural greenery, sky light and cloud shadows. **Composition:** These scenes are characterized with vegetation-dominant with supporting waterscape/rockery layers (background waterscape/rockery provides depth cues).
Cluster 1: Specific element attention	**Openness** extremes <0.10 or >0.30 (U-shaped effect); **CI** (complexity)<0.60; **DI/LDI** (depth)<0.70; **Vegetation** <0.30–0.40; **Building** >0.50–0.60 (dominant); **Viewing angles:** ELV dominant (but not too high); LDV moderate-low; LUV/Top low (limited upward openness)	**Elements:** Historic façades, pavilions, calligraphic inscriptions, symbolic rockeries, unusual plants, animals, water reflections **Composition**: Usually, building-dominated with a few other elements.
Cluster 2: Holistic appreciation	**Openness** >0.25 (moderate–high); **CI** (complexity) ≥0.70–0.80; **DI/LDI** (depth)>0.80 (pronounced layering); **Vegetation** 0.30–0.50 (intermediate); **Building** 0.20–0.40 (moderate share); **Viewing angles**: ELV high (eye-level anchors landmarks); SUV/LUV high (not firmly framed); SDV moderate; Top moderate-high	**Elements:** Water reflections, distant architectural silhouettes, symbolic inscriptions **Composition**: Balanced mix of vegetation, water, buildings, and rockeries (water reflections and distant silhouettes reinforce layered depth and alternation).

Notes: Depth and orientation showed only modest and context-dependent effects compared with vegetation, complexity, and openness. Higher depth values (DI/LDI > 0.8) are associated with slight increases in NFAP, consistent with NFAP, but effects on ESP and HAP are weak. Orientation exhibited negligible linear effects on single gaze patterns, yet emerged as a useful discriminator in RF classification of overall strategies (low values → exploratory scanning, higher values → more structured attention). These variables, therefore, act as secondary cues rather than as primary drivers of gaze allocation.

4.4 Results-2: Design interpretation of Jichang Garden

The computation generated two graphical outputs: the accumulated viewshed map, in which the red represents the highest visibility while the green represents the lowest **(FIG. 4.12a)**, and the “times seen” map for the pond, in which the red represents the most visible potions while the blue represents the least visible potions **(FIG. 4.12b)**. In addition, the **FOVs** for the visual-composition analysis have been calculated.

4.4.1 How the waterscape organizes the garden’s visual-spatial structure

Many literature sources indicate that the landscape elements surrounding the *Jinhuiyi* pond, such as buildings, rockeries, and plants, are organized about its water surface. Moreover, the *Jinhuiyi* pond serves as the visual centerpiece of the garden and even creates an illusion of a larger space than its actual scale (DONG, 2014; Eunyeong, 2017; Shu et al., 2018). This centrality was also corroborated by our VR-based perceptual experiment: participants frequently focused on water-related elements, including the water surface, reflections, and koi. How, then, is this spatial effect achieved? The following analysis addresses this question through two complementary lenses: the overlooking (vertical) perspective and the eye-level (horizontal) perspective.

4.4.1.1 “Overlooking” mapping analysis results

The visibility map showcases the comprehensive coverage of the pond’s viewsheds over essential sites, pathways, and significant buildings within the garden, highlighting its centrality in the sightseeing experience. This indicates that the garden designers deliberately arranged these leisure objects around the pond **(FIG. 4.12b, FIG. 4.12c)**. Furthermore, evidence supports this notion by observing the axial lines of several main buildings in a bird’s-eye view **(FIG. 4.12d)**. Due to such spatial arrangement, the water surface naturally becomes the visual core. The “times seen” map also indicates a higher likelihood of the central regions (rather than central points) of the pond being visible, further emphasizing the pond’s significance as the organizing element for the garden’s views.

Moreover, other noteworthy phenomena are still on the "times seen" map: Two core areas on the water surface can be noticed **(FIG. 4.12e)**. This can be explained as the garden's designer employed an ingenious strategy by shaping the pond as an "8-like" shape, completing with a peninsula (*Hebutan*) and a building (*Zhiyujian*), which create two open central spaces with the pond. The southern core region is more concentrated, while the northern core region tends to split into two. By examining the bare earth model, it is apparent that there are two other corresponding peninsulas on both banks of the northern water area **(FIG. 4.12f)**. The difference lies in the influence of vertical elements such as plants and buildings. From an "overlooking" perspective, it is also noticeable that the water surfaces are divided into two parts by a large tree located on *Hebutan* **(FIG. 4.12g)**. The northeastern boundary of the northern core area did not continue to extend. The reason for this phenomenon is that the *Qixingqiao*, a bridge spanning the water surface at this location, divides the water surface **(FIG. 4.12h)**.

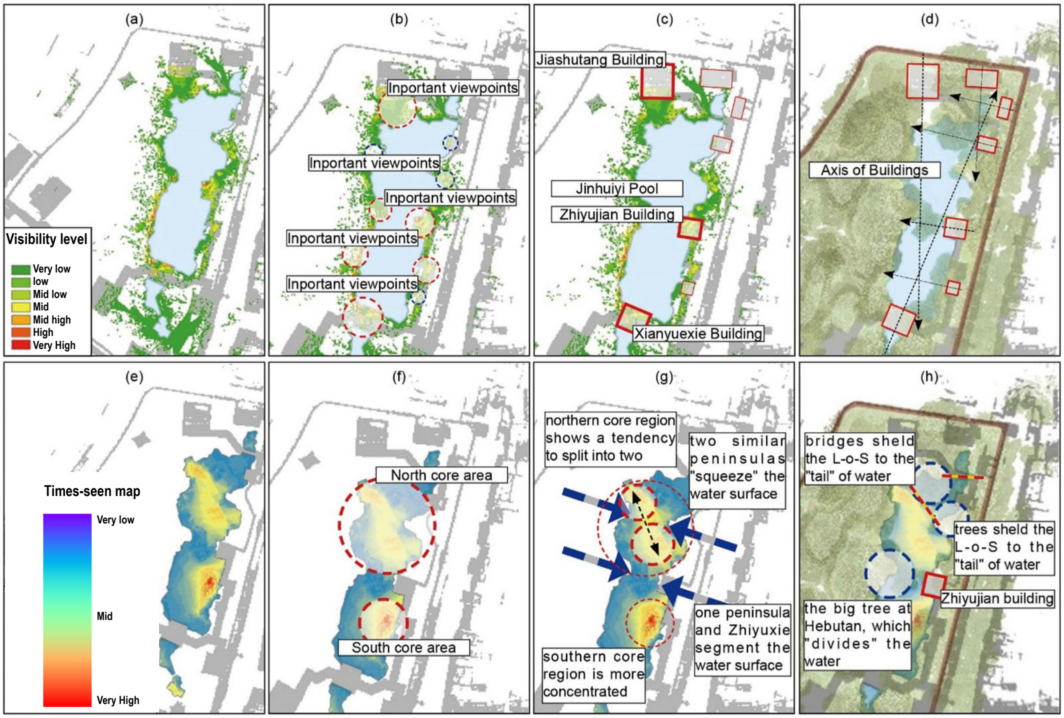


FIG. 4.12 "Overlooking" analysis: (a)Viewsheds map; (b) important viewpoints around the pond and their spatial relationship with the viewsheds map; (c) the same for the main buildings around the pond; (d) main buildings' axes are set to point to the pond; (e) "times seen" map; (f) two central areas accessible to be viewed; (g) the shape of the pond is composed with three adjacent spaces rather than two ("8" shaped); (h) The explanation for the central areas' formation.

4.4.1.2 “Eye-level” perspective analysis results

Through the “overlooking” analysis, it becomes evident that the garden designers have implemented a series of spatial arrangements to enrich the perceptual environment of the garden. As a result, the viewpoints surrounding the pond offer various framed views, presenting diverse perspectives on the pond, vegetation, and built structures. However, what influences do these designs have on the FOV, and how are these arrangements accomplished to create the visual illusion of expanded space? Answering these questions requires an analysis from an “eye-level” perspective.

In Jichang Garden, one of the most famous viewpoints is from the terrace near the *Xianyuexie* building. This viewpoint and its vision of the pond will be utilized for a detailed analysis. By capturing images from the viewpoint, a perspective view close to human vision can be obtained **(FIG. 4.13a)**. Building upon the overlooking analysis, we will focus on the plants, buildings, and the bridge spanning the water’s surface. The large tree at *Hebutan* is observed to be farther from this viewpoint than several trees on the eastern bank. The *Zhiyujian* building is relatively closed, and a few trees are visible behind it, but at a greater distance (detail of the distance can be seen in **FIG. 4.13b**). Consequently, the arrangement of plants and buildings (both are semi-transparent) forms a spatial composition of overlapping and occlusion, creating a powerful sense of depth in the visual perception of space. The placement of *Qixingqiao* bridge is located at the far end of this vision, whose presence prevents a clear view of where the water flows **(FIG. 4.13c)**. The vegetation on both sides stimulates the imagination of a larger space beyond the visual boundaries. This further expands the perceived space.

This design interpretation is consistent with the earlier analysis of perceptual pathways. At viewpoint 23, the spatial configuration supports holistic appreciation: sufficient openness enables exploration, while a rich set of salient elements sustains focused attention. The indices: LDI = 2.6352 (relatively high), ADI = 1.0000 (very high), and DI = 0.8084 (relatively high), indicate physical conditions conducive to gradual exploration. Eye-tracking results show a median NFAP share of approximately 0.25 at this viewpoint, second only to VP-17, further corroborating near-to-far exploratory behavior and the underlying design logic of the garden **(FIG. 4.14)**.

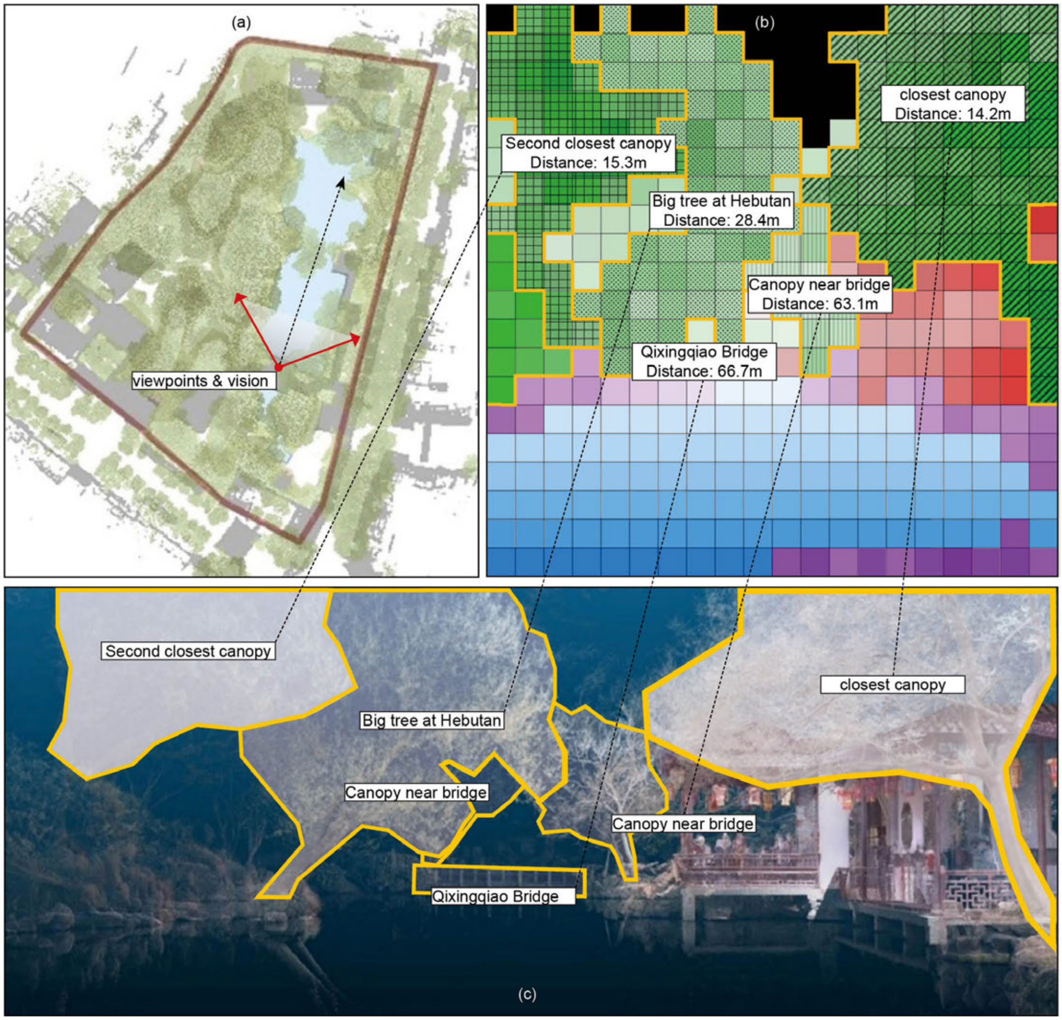


FIG. 4.13 "Eye-level" analysis for the viewpoint: (a) Location of the viewpoint; (b) Segment of the vision (horizontally ranges 100° and vertically ranges 100°, and the accurate distances (in average for the voxels) among the objects to the viewpoint; (c) the same vision visualized with 3D true-color point cloud.

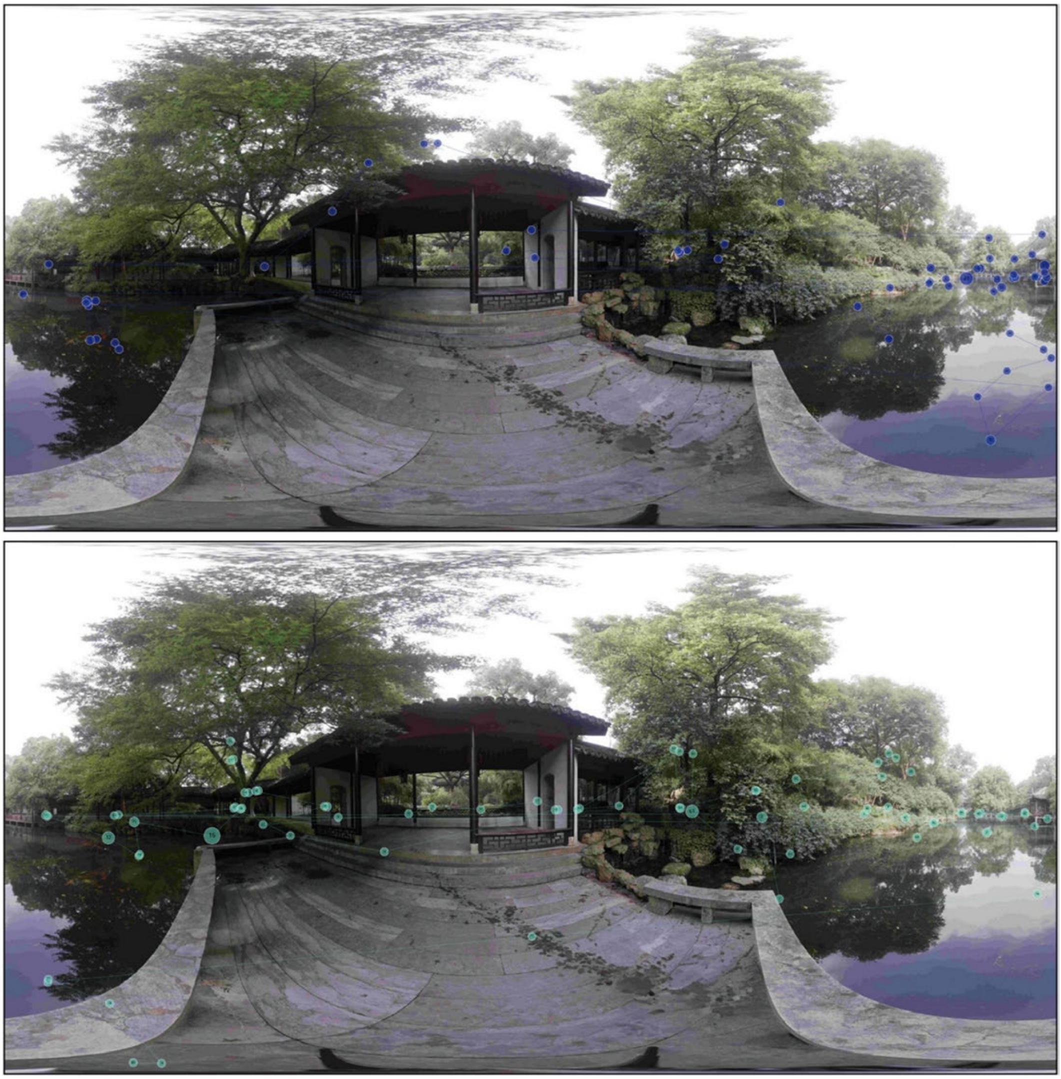


FIG. 4.14 Direct evidence from experiment participants: More than half of the participants exhibited NFAP, such as alternating fixations between nearby plants and the water surface, and distant elements including the Qixingqiao bridge and Zhiyujian building.

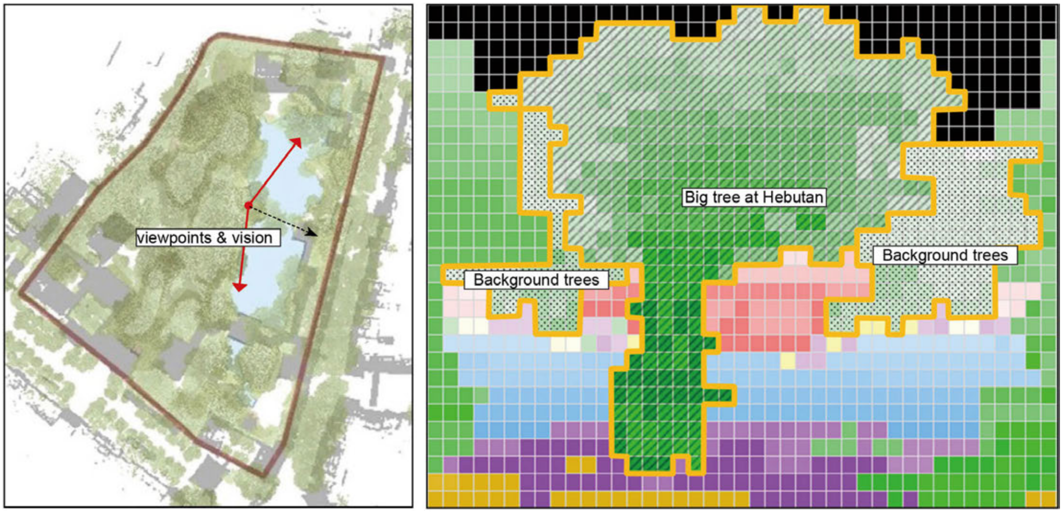


FIG. 4.15 “Eye-level” analysis for the viewpoint around the “Hebutan”: The big tree has extended into the east and blended with the vegetation on the opposite bank.

It is noted that many studies analyzing Jichang Garden point out that the “trick” of the perceived extension of space was constructed by creating the shape of an “8” on the water’s surface with *Zhiyujian* and *Hebutan* (Shu et al., 2018; Zhou et al., 2018). However, the contour of the *Jinhuiyi* pond’s water surface resembles three interconnected spaces stretching from north to south. What causes people, including professional researchers, to have such a misled impression? The author believes this is also a visual-spatial design “trick” involved. The FOV from the viewpoint of *Hebutan* showcases that the aforementioned large tree, due to its eastward growth orientation, gradually blends with the vegetation on the opposite bank in the depth map **(FIG. 4.15)**. Through this “trick”, visitors are led to perceive a false impression of the two banks being very close to each other.

Similarly, the perception analysis reinforces this conclusion. At VP-7 near the selected location, behavior indicates the highest ROAP (median ≈ 0.30), suggesting that vision extends along linear elements. Beyond following the path itself, observers’ gaze also extends from vegetation toward *Zhiyujian*, indicating a tendency to project attention toward the architecture. Meanwhile, NFAP is compressed (lowest among all viewpoints), largely supplanted by ROAP, thereby producing a shortened perceived viewing distance in the observed perceptual pattern.

4.4.2 How do the routes make visitors' perceptual experiences interesting?

The garden path is one of the central locations for visitors to engage in recreational activities and is a physical manifestation of the designer's concept of the garden space. Therefore, studying route-based visual space is also essential for understanding and revealing the essence of historic gardens.

4.4.2.1 "Overlooking" mapping analysis for the route

The "overlooking" viewshed map is applied to reveal the relationship between the route and the *Jinhuiyi* pond. The spatial relationship between the route and the pond is of interest: (a) the route covers terrain with different ranges of visibility for the pond, and (b) the distance between them also varies. Consequently, the designer deliberately crafted this visual-spatial arrangement to generate distinct perceptual experiences for visitors, enhancing the overall sightseeing entertainment.

4.4.2.2 "Eye-level" perspective analysis for the route

The analysis of selected viewpoints on this route reveals that the buildings occupy a significant portion of the visual field when people look at the water, indicating that they play a crucial role in the landscape design. Specifically, the *Xianyuexie* building is located on the south side of the pond, the *Jiashutang* building on the north, and the *Zhiyujian* building in the center. The relationship between the building and the landscape can be illustrated using FOV below:

a) **In the first stage of the journey from *Xianyuexie* to *Hebutan*:** The FOV maps reveal a noticeable trend in which the *Zhiyuejian* building gradually approaches the observer's viewpoint and becomes increasingly dominant in the FOV. The building of *Jiashutang* also slowly appears in the direction of walking. Conversely, the *Xianyuexie* building diminishes in size and prominence in the observer's FOV **(FIG. 4.16)**.

b) **In the second stage of the journey from *Hebutan* to *Jiashutang*:** The FOV map indicates a reduction in the proportion of the *Zhiyuejian* building visible in the observer's FOV. The presence of the *Qixingqiao* bridge assumes greater prominence in the observer's view of the water surface and serves as a directional guide towards the *Jiashutang* building **(FIG. 4.16)**.

TOC

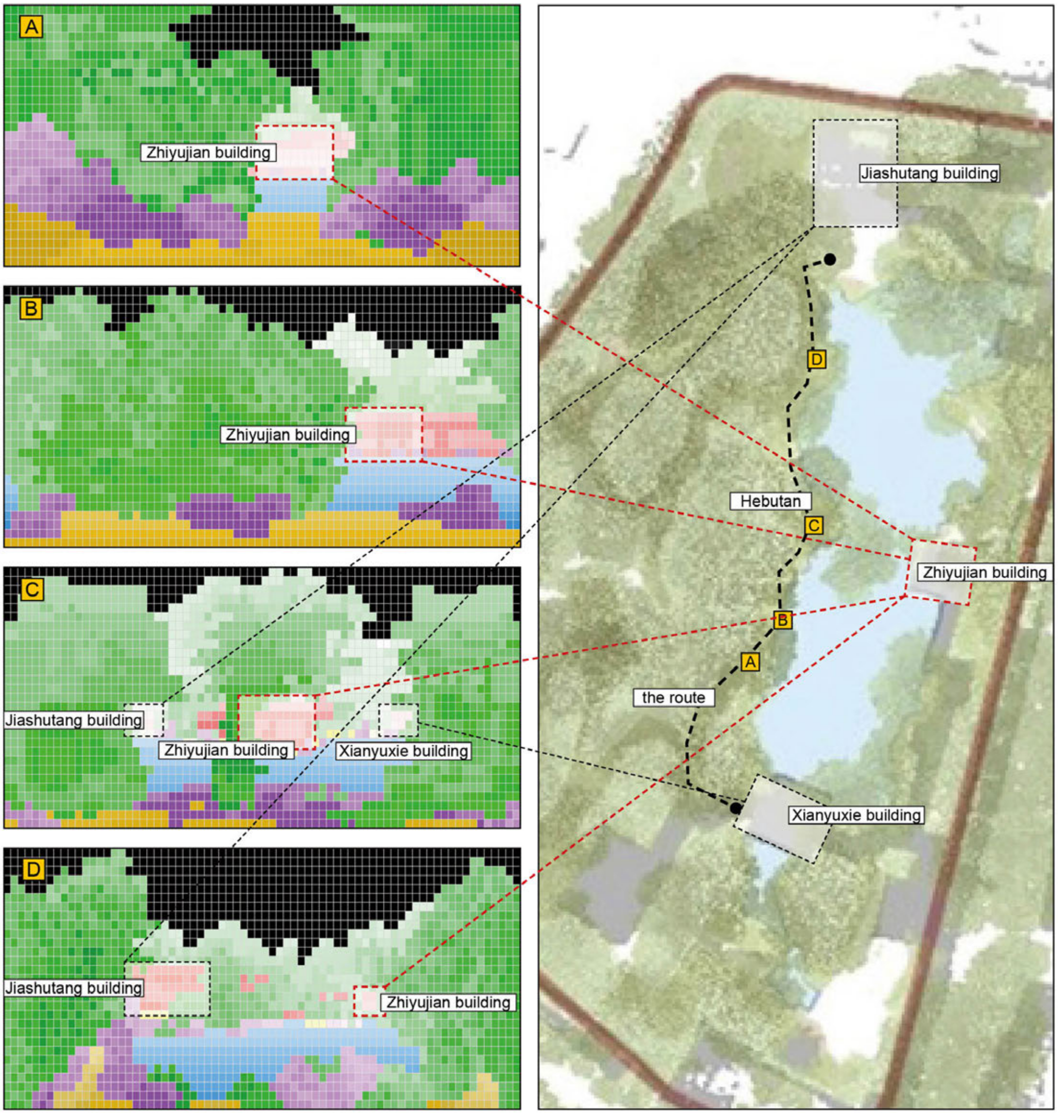


FIG. 4.16 How does the “Zhiyujian” building play a crucial transitional role in linking the preceding and subsequent spaces?

Throughout the entire process, it is evident that the *Zhiyujian* building has played a crucial transitional role in linking the preceding and subsequent spaces. The designers have strategically utilized various techniques to visually accentuate the *Zhiyujian* building, such as elevating the building vertically, protruding it towards the water on the plane, and employing color contrasts to enhance its prominence. This reading is further corroborated by the perceptual pathway analysis: perceptual activity patterns shift among three overall strategies across adjacent viewpoints, a finding supported by changes in spatial metrics and by heat-map visualizations **(FIG. 4.17)**.

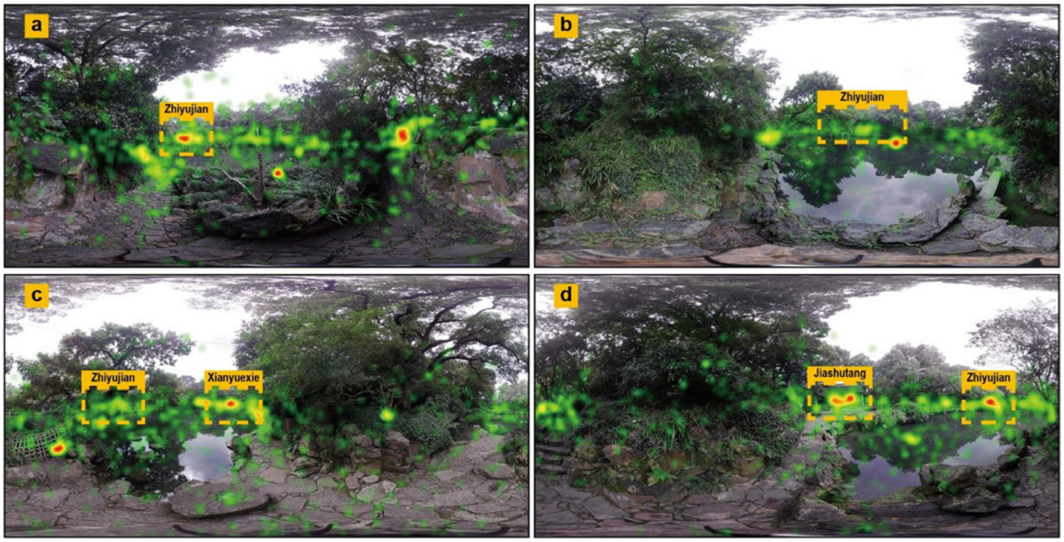


FIG. 4.17 Gaze heatmaps of the four selected viewpoints: the arranged buildings function as perceptual anchors, guiding and structuring participants' exploratory activities.

TOC

4.4.3 Conservative managing strategies for Jichang Garden

The analysis above identifies many core spatial-visual characteristics within the Jichang Garden and the landscape elements involved in achieving them. Conversely, we can better maintain the spatial-visual features of the Garden. As the architecture, topography, rockery, and embankments of the garden cannot be easily adjusted, the suggested protective management focuses on plants and replaceable elements:

a) The health of the big tree on *Hebutan* must be prioritized for maintenance **(FIG. 4.18b & c)**. This tree serves as an essential object that facilitates the formation of multiple visual centers on the water surface. It also contributes to shortening the east-west distance and increasing the north-south depth perception. If the tree disappears, it will significantly diminish the core visual-spatial characteristics of Jichang Garden. Even with salvage replanting, restoring the visual and spatial environment would still require considerable time.

b) To ensure relatively unobstructed north-south visibility within the site while still providing some plant coverage, it is important to control the growth of the plants shown in the diagram within manageable limits to maintain their "semi-transparent" characteristics. Additionally, if any of these plants die, they should be replaced.

c) The deciduous trees around the *Qixingqiao* bridge should have canopy sizes that effectively block many of the southern viewpoints, creating a visual barrier towards the water surface on the northernmost side (**FIG. 4.18b & c**). Furthermore, if the handrails on bridges like the *Qixingqiao* bridge need replacement, their height should match the existing ones, while maintaining a relatively airy to stay semi-transparent. This ensures that visitors perceive the presence of the water surface but without actually seeing its size, thus creating an illusion of expanded garden space through the viewer's imagination.

d) The "Zhiyujian" building should capture visitors' attention in the middle section of the path along the west of the pond (**FIG. 4.18b & c**). Methods to ensure this building is visually captivating are needed, including protecting the background plants create contrasting colors that make the *Zhiyujian* building stand out and controlling the scale of surrounding plants or newly added rockery stones.

e) The growth of woods on the pond's west does not require deliberate control, and the canopies must be dense. However, it is essential to ensure that in the critical visual "corridor" areas (**FIG. 4.18a**). This ensures the variability of spatial-visual characteristics during the stroll, providing a rich and interesting visitor experience.

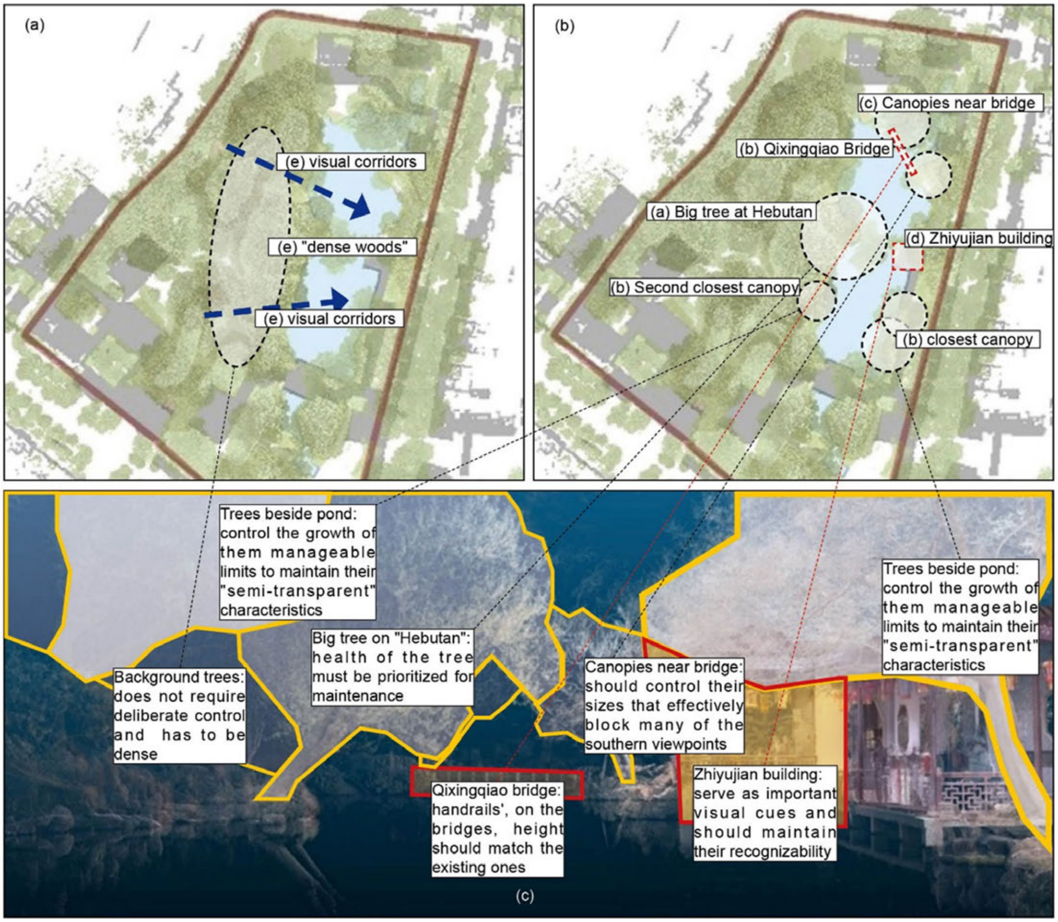


FIG. 4.18 Conservative managing strategies: (a) region of the trees' growth does not need stringent control and the visual corridors; (b) the distribution of the management strategies on a "vertical" map; (c) the visualization of the management strategies in a "horizontal" perspective view.

TOC

4.5 Discussions

4.5.1 Core findings

This chapter quantitatively establishes how specific visual-spatial features of heritage gardens shape visitor visual behaviors in immersive contexts. By integrating point cloud analytics with VR eye tracking, we identified four behavior patterns: ESP, HAP, NFAP, and ROAP. From these patterns, three exploration strategies emerged, namely environmental exploration (cluster 0), specific element attention (cluster 1), and holistic environmental appreciation (cluster 2). In addition, the chapter demonstrates how this knowledge can be used for design analysis and interpretation of heritage gardens.

Visual-spatial indicators exerted partly non-linear effects on visual perception behaviors and overall strategies. Complexity and vegetation increased ESP and attenuated HAP, and together with moderate openness, they also favored the holistic environmental appreciation strategy because visitors could look widely and then return to a few clear anchors. Openness showed a U-shaped role. Very low openness created tight framing that concentrated attention, and very high openness produced clear sightlines to distant anchors, so both ends of the range tended to strengthen HAP. In contrast, moderate openness, especially when paired with textured vegetation and water edges, supported holistic exploration by coupling ESP with NFAP. Apparent depth further differentiated strategies. Moderate to high depth encouraged exploratory sampling and near-to-far comparison and therefore promoted holistic appreciation and environmental exploration, whereas shallower depth below about 0.70 reduced layering and made single objects stand out, which concentrated attention and increased HAP.

Viewpoint sensitivity was pronounced. Differences in the size and shape of the visible region under different viewpoints altered perceptual behavior and the choice of overall strategy. In particular, the downward visible area LDV, which has often been overlooked or treated only anecdotally, is here quantitatively shown to be a strong predictor. Larger LDV reliably increased exploratory scanning and route-oriented attention and, when combined with moderate openness and depth, favored the holistic environmental appreciation strategy by allowing viewers to sample widely and then return to a few stable anchors, while it reduced pure hotspot attention.

We speculate that this occurs because a larger downward visible region makes locomotion affordances and constraints explicit, increases the density of near-field cues on the ground plane, and lowers occlusion uncertainty, which together encourage route probing, near-to-far alternation, and periodic confirmation on landmarks rather than prolonged fixation on a single target. These effects are consistent with affordance-based accounts of perception and with theories of attention that link clear goal states to focused viewing and diffuse information fields to exploration (Gibson, 2014; Greeno, 1994). More broadly, the results indicate that manipulating viewpoint geometry and its visible field metrics can reorganize visual strategies under otherwise comparable spatial conditions.

After controlling for scene and viewpoint, we did not observe reliable between-participant differences. This should not be taken to mean that individual variation does not exist. Rather, the strong spatial structure of the settings and the standardized VR procedures likely guided participants in similar ways, reducing between-participant variability. The sample was relatively homogeneous and modest in size, which also limits sensitivity to small effects. In eye-tracking data, variance is often dominated by scene and viewpoint, and our results are consistent with that pattern. Accordingly, the non-significant findings are best interpreted as attenuation due to design and context, not as evidence of no true individual differences.

In this chapter, we also propose a combined analysis from vertical (overlooking) and horizontal (eye-level) perspectives to link metrics to design intent. Applying this to Jichang Garden, the waterscape organizes centers of visual attention at the garden scale, while the west-side path sequences eye-level views that enrich near-to-far alternation. *Zhiyujian* acts as a transitional node that connects preceding and subsequent spaces and stabilizes attention through elevation, projection toward the water, and color contrast. Cross-validation between vertical visibility products (accumulated viewsheds and times-seen maps) and horizontal FOV-perception profiles supports these interpretations and clarifies how the designers, by orchestrating perceptual pathways, enriched the garden's visual-spatial experience. These findings demonstrate that integrating perception-informed visual analysis across the two perspectives yields design-relevant interpretations that are empirically grounded and transferable.

4.5.2 Mechanisms and theoretical alignment

The findings align closely with established theories in environmental psychology and ecological perception, while also extending them through quantitative evidence from immersive settings. By linking three-dimensional spatial metrics and viewpoint geometry to observed gaze patterns, this study moves classic ideas beyond descriptive plausibility toward empirically testable regularities.

a) **Information seeking and cognitive load:** Consistent with environmental preference theory, higher complexity and vegetation elevate informational yield and the density of peripheral candidates, which sustains exploratory scanning. Simpler and clearly framed compositions reduce cognitive load and funnel attention into hotspots, thereby increasing HAP (Kaplan et al., 1989; Kaplan, 1987).

b) **Depth and perceptual organization:** Moderate apparent depth promotes perceptual layering and figure-ground comparisons, which support near-to-far alternation. When depth becomes large, distal structure behaves as an explicit visual object and draws longer fixations, increasing HAP. These effects are compatible with cognitive mapping processes that test spatial hypotheses across layers (Briggs, 1973).

c) **Viewpoint and affordances:** In line with affordance theory, downward visible regions make the ground plane, obstacles, and route options legible, which amplifies ESP and, where corridors are readable, ROAP. Eye-level views aligned with framed targets stabilize landmark fixations and strengthen HAP (Gibson, 2014; Greeno, 1994).

d) **Openness as a moderator:** Openness operates through visibility and framing. With salient anchors along the view axis, increased openness reduces visual competition and prolongs dwell, which favors HAP. Without anchors, openness broadens the search field and sustains ESP. Vegetation interacts with openness by generating occlusion bands and micro-windows that invite near-to-far alternation and thus support NFAP (Nasar, 1994; Stamps, 2013).

e) **Affective tuning and micro-dynamics:** Vegetation-rich and softly articulated settings elicit low-effort soft fascination that sustains relaxed exploration, whereas distinctive architectural features prompt rapid engagement and focused dwell associated with HAP. Early gist extraction biases the priority map. Under high complexity, it remains diffuse and sustains sampling, whereas strong framing collapses it onto one or two candidates and lengthens dwell (Basu et al., 2019; Kaplan, 1995).

4.5.3 Theoretical contributions

This research strengthens and extends established theoretical frameworks by translating qualitative claims into quantitative and predictive relationships. The explicit link between LDV and exploratory scanning provides quantitative support for affordance-guided exploration, and the dual role of openness refines attention and cognitive load accounts that have traditionally relied on descriptive observations rather than model-based tests. The findings also enrich environmental preference and cognitive mapping theories by showing how depth and complexity shape the balance between search and focus in a way that depends on viewpoint and target salience (Briggs, 1973; Kaplan et al., 1989).

Methodologically, integrating point cloud technology with immersive VR eye-tracking advances environmental perception research from image and planar proxies to in situ three-dimensional spatial cognition (Adhanom et al., 2023). This shift improves spatial validity and enables advanced analytics. Machine learning can support tasks such as discovering scanpath motifs (Cheekaty & Muneeswari, 2025), linking them with image semantics, and modeling multivariate relations beyond traditional segmentation, which is a promising direction for landscape planning and environment psychology research workflows (Bibri et al., 2024).

Translating these insights to practice should begin with the primary constraint of heritage work, namely, preserving the historic fabric while managing the perceptual qualities that shape visitor experience (Bell, 2019; Jani et al., 2015). Within that constraint, viewpoint-aware choreography is an effective and low-impact lever because it alters what visitors see rather than the underlying structure. When the goal is to stimulate exploration and route probing, reveal or curate a small number of look-down vantage points along legible paths. When the goal is to consolidate focus at key anchors, frame a limited set of eye-level vistas with appropriate openness and clear sightlines. Minor adjustments to vegetation layering and to the visual salience of existing landmarks can then be used to fine-tune the balance between exploration and focus without structural change.

For heritage landscape management, this means acknowledging that landscapes are dynamic systems and moving away from a strict fixation on preserving a single moment’s appearance. Instead, stewardship should be perception-informed and structure-oriented, managing the landscape’s visual-spatial framework and its culturally meaningful cues. Although surface forms will inevitably change, if these structural characteristics and cultural semantics are safeguarded and carefully refreshed, visitors’ perceptual experience will remain recognizably similar, which is the core of the heritage landscapes (Nijhuis, 2015; Peng et al., 2024).

4.5.4 Practical applications

Insights obtained from this research have significant practical potential for the analysis, management, and design of historic gardens, particularly in optimizing visitor experiences through spatial planning.

4.5.4.1 Analysis and extraction of historic gardens' design knowledge

The analytical approach employed in this chapter effectively captures the core visual-spatial characteristics of historic gardens, exemplified by Jichang Garden. Notably, the garden's spatial configurations, such as alternating openness and enclosure, winding pathways, and visually guided layouts, significantly shape visitor visual behaviors. Several key visual-spatial techniques emerge clearly from Jichang Garden, reflecting historic designers' sophisticated understanding of visual guidance. Firstly, strategic vegetation placement enhances depth perception and spatial layering, providing smooth visual transitions between foreground and background. Secondly, iconic landmarks and distinct vegetation serve as visual anchors, naturally attracting focused visual attention. Thirdly, central water bodies function as focal points, leveraging reflections to reinforce visual interest. Lastly, thoughtfully crafted sequential experiences around water features promote dynamic and engaging visual experiences, demonstrating effective spatial interaction techniques.

This methodological framework visually analyzes historic gardens and systematically extracts practical design knowledge. By uncovering how historic designers anticipated and shaped visitors' visual experiences, this research offers contemporary designer valuable theoretical insights and actionable tools for informed landscape design decisions (Bell, 2019; Jani et al., 2015).

4.5.4.2 Management and conservation of historic gardens

Given the dynamic nature of historic gardens—continuously shaped by human activities, vegetation dynamics, and environmental changes—conservation efforts should prioritize preserving core visual-spatial qualities rather than rigidly maintaining static physical conditions (Nijhuis, 2015; Peng et al., 2024). Drawing on the visual-spatial characteristics identified in this study (as detailed in section 4.1), this chapter advocates adaptive management approaches not only for Jichang Garden but also as a guiding principle for managing and conserving other historic gardens. Such an approach emphasizes recognizing, preserving, and thoughtfully enhancing essential visual and experiential values within dynamic heritage landscapes (Nijhuis, 2021; Storms-Smeets et al., 2023).

4.5.4.3 Perception-driven heritage landscape design

This chapter establishes a potential analytical pathway linking visual-spatial characteristics and visitor perception patterns, thus making objective, perception-driven heritage landscape design feasible. While the current predictive accuracy remains moderate, this methodological approach explicitly identifies key spatial-perceptual mechanisms, paving the way for more data-driven and visitor-oriented design practices. By clarifying these mechanisms, the proposed structured workflow becomes viable for landscape architects:

Design goals → Visual behavior patterns/exploration strategies → Visual-spatial features (e.g., 3D Viewsheds, landscape compositions, visual indicators) → Specific landscape element and arrangements

For instance, **FIG. 4.19** illustrates several practical examples demonstrating how various design goals can be systematically achieved through precise adjustments in visual-spatial features and landscape elements, including vegetation density, landmark placement, and the shaping of visible spaces.

In addition, integrating immersive technologies, high-precision modeling, advanced visualization tools, and participatory design methods can significantly enhance and support this workflow (Gordon et al., 2011). These technologies enable precise spatial interventions tailored explicitly toward desired perceptual experiences, bridging theoretical insights with practical landscape management and design strategies.

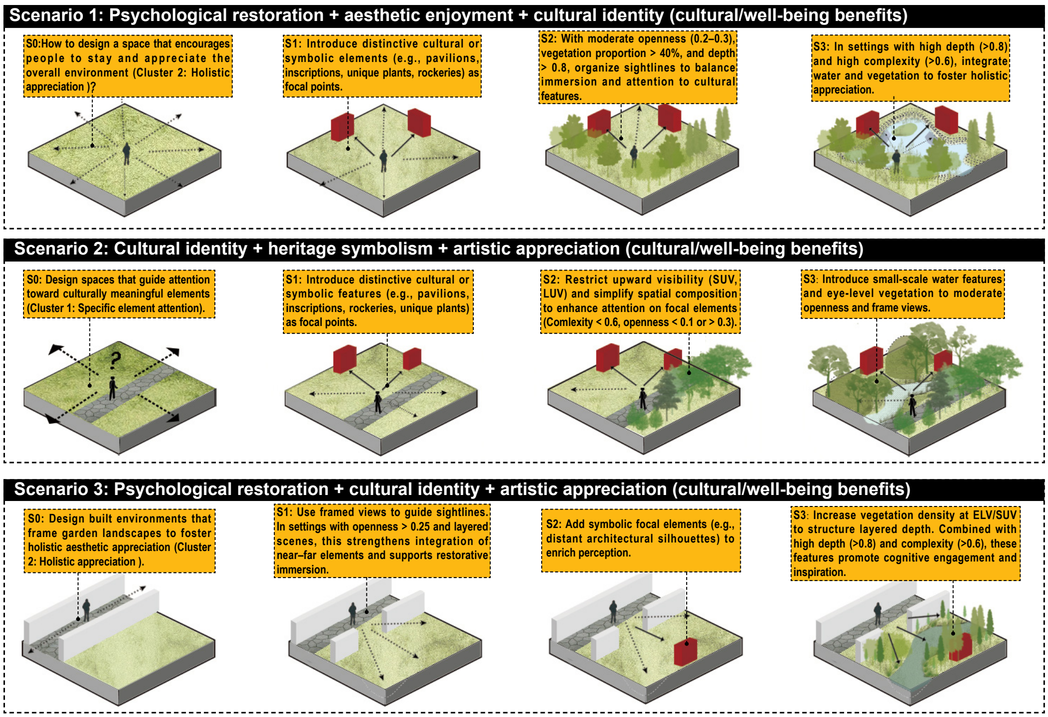


FIG. 4.19 Examples of “perception-driven” landscape design: Three different scenarios showcase the chain of “from design goals to specific landscape design”.

TOC

4.5.5 Limitations and outlooks

Several limitations warrant caution. A single site constrains generalizability, and simplifications of vegetation and architectural detail in the virtual environment may attenuate fine-grained cues. Although the sample size (N = 53) is consistent with prior VR-based eye-tracking research in environmental psychology, no formal a priori power analysis was conducted. Thus, statistical power may be limited for detecting small effect sizes. These points motivate larger and cross-contextual studies with improved scene fidelity in future work (Gomm et al., 2000). Many dynamic and contextual factors remain difficult to capture through point-in-time scans, including seasonality, blooming cycles, changing light and sky conditions, moving water and reflections, wildlife, culturally meaningful signage, distinctive plant species, and small architectural details. These elements enrich visitor experiences but are not fully predictable within a static analytical framework, and they also intersect with cultural and historic meanings that require qualitative and mixed methods to document and interpret (Lawrence et al., 2020).

Looking forward, research should diversify samples across age, expertise, and cultural background, and should preregister power analyses that target person-level effects. Modeling should employ multilevel and Bayesian approaches with cross-classified scene-by-person structures in order to partition variance more precisely and to estimate individual differences that may be conditional on viewpoint. Experimental designs should include finer manipulations of orientation and elevation and should record micro movements to map trait-by-viewpoint interactions. Scene fidelity should be improved through denser vegetation models and dynamic lighting and water, and temporal coverage should be expanded through multi-season and time-of-day scans. Mixed methods, such as in-depth interviews, can recover meaning-laden cues beyond geometry.

4.6 Conclusions

This chapter quantitatively elucidates how visual-spatial features and semantic-cultural cues relate to visitor perceptual behaviors in heritage gardens, addressing a core gap in landscape visual-perception research, while advancing methods for historic garden analysis and design translation. The contributions are fourfold:

a) **Methodological advancement:** We present an integrated framework that couples point cloud–based three-dimensional visibility analyses with immersive VR eye tracking, yielding spatial metrics and gaze measures suitable for hypothesis-driven testing.

b) **Empirical insights:** We identify four visual behavior patterns (ESP, HAP, NFAP, ROAP) and three visual exploration strategies (environmental exploration, specific-element attention, holistic appreciation), and relate them quantitatively to visual-spatial features, including visual indicators such as complexity and openness, viewing angles such as LDV and ELV, and landscape-element proportions such as vegetation and buildings. In addition, interviews and immersive records indicate that culturally meaningful features, including inscriptions, emblematic architectural details, and symbolic plantings, can function as attentional anchors that co-shape gaze patterns and the adoption of broader perceptual strategies.

c) **Design analysis and translation:** Building on perception-supported evidence, we introduce a multi-perspective analytic procedure that integrates vertical (overlooking) and horizontal (eye-level) readings, with cross-validation between visibility maps and FOV-perception profiles. This procedure explains how the perceptual pathway in historic gardens and it translates findings into design-relevant interpretations and actionable guidance for sequencing vistas, calibrating enclosure, positioning anchors, and curating culturally salient cues.

d) **Theoretical and practical contribution:** Aligning the results with classic theories in environmental psychology and perception, this chapter provides a quantified basis that links theory to practice. For management and design, the refined quantitative relations among visual-spatial features offer a practical foundation for perception-informed and precise spatial stewardship and planning in heritage landscapes, while culturally meaningful cues should be identified and curated as complementary levers that modulate attention over time.

Overall, this work demonstrates a reproducible way to link high-resolution visual-spatial features with immersive, trajectory-level gaze behaviors and to convert perception-based evidence into transferable, decision-ready knowledge for historic-garden analysis, design interpretation, and design guidance.

Author's contribution in this case study

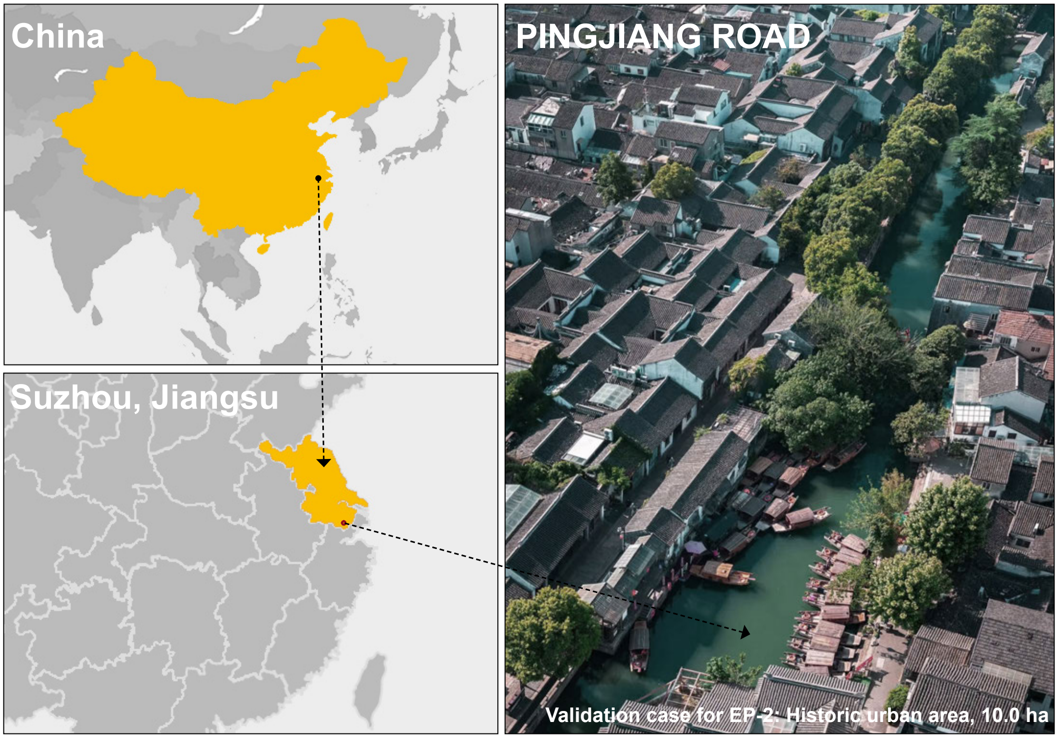
This case study of Jichang Garden was conducted by the author under the supervision of the TU Delft promotors. The author led the research design and analytical framework, processed and analysed the datasets, and developed and wrote the methodological section. The author prepared and presented the ethics application, designed and carried out the interviews, and produced the visualizations of the point-cloud-based analyses and empirical results. The author also drafted the initial version of this case-study chapter and undertook the subsequent rounds of review and editorial refinement. The co-author contributed by performing part of the point cloud computations and visualizations, recruiting participants and coordinating the on-site experiment, and conducting the on-site acquisition of point cloud data in Jichang Garden.

5 EP-2: Case study of historic urban area

Seeing heritage through green and blue: Assessing the visual influence of Blue-Green Infrastructure (BGI) in Historic Urban Areas (HUAs)

This chapter is based on a published paper.
Peng, Y.*, Li, W., Nijhuis, S., Yu, Y. & Wu, Z. (2026). "Seeing heritage through green and blue: Assessing the visual influence of Blue-Green Infrastructure (BGI) in Historic Urban Areas (HUAs)". *Environmental Impact Assessment Review.*

This chapter aims to examine how blue-green infrastructure (BGI) shapes everyday heritage experience in a dense historic urban area, and how visually oriented methods can support planning-sensitive interpretation. Taking Pingjiang Road as a representative HUA, the chapter constructs a pathway that links streetscape-scale visual exposure with experience-oriented evidence, enabling the assessment of how green and blue elements appear, cluster, and vary along pedestrian routes. By integrating street-level imagery, spatial context data, and visual indicators, the study identifies where BGI contributes to visual comfort, legibility, and heritage ambience, and where it may compete with or obscure key heritage attributes. The chapter emphasizes the value of combining perceptual proxies and spatial interpretation to move beyond purely aesthetic judgement, and to generate practical insights for heritage-sensitive BGI strategies in living historic districts.



Contents	Methods	Data
A. Object: historic district, area scale; B. Theme: The visual perception of historic landscape from different audience groups	A. Horizontal FOV analysis B. Modeling with multi-view image C. Eye-tracking D. Survey and questionnaire E. In-depth interview	A. UAV imagery B. Eye-tracking data C. Interview and survey data

FIG. 5.1 Summaries for the case study.

TOC

Abbreviations used in Chapter 5

Abbreviation	Full term	Meaning in Chapter 5
EP-2	Expanded Pathway 2	Digitally supported, multi-perspective perception evaluation pathway implemented in Chapter 5.
BGI	Blue-Green Infrastructure	Combined blue (water) and green (vegetation) elements assessed for their visual influence in historic streets.
HUA / HUAs	Historic Urban Area(s)	Heritage-sensitive urban environments used as the study context.
BI	Blue Infrastructure	Water-related elements (e.g., canals) used in exposure computation and perception analyses.
GI	Green Infrastructure	Vegetation-related elements used in exposure computation and perception analyses.
UAV	Unmanned Aerial Vehicle	Platform for aerial image capture supporting photogrammetric 3D modeling.
DJI	Da-Jiang Innovations (DJI)	UAV manufacturer (e.g., Phantom series) used for aerial imaging.
SfM	Structure-from-Motion	Photogrammetric step for feature matching and camera alignment.
MVS	Multi-View Stereo	Photogrammetric step for dense point cloud generation.
3D semantic mesh	Three-dimensional semantic mesh model	Photorealistic mesh annotated with semantic labels (BI, GI, others) for exposure analysis.
LoS	Line of Sight	Ray casting used to sample visibility/exposure of BI and GI from viewpoints.
FOV	Field of View	Human visual coverage used to define the sampling range for exposure and image-based classification.
VP	Viewpoint	Pedestrian observation location used for exposure computation and for selecting stimulus scenes.
AOI / AOIs	Area(s) of Interest	Semantic regions in stimuli images used for eye-tracking aggregation (e.g., buildings, sky, GI, BI).
N / L / M / H	None-very low / Low / Medium / High	Four-level exposure scale used to classify BI/GI visibility in image stimuli.
G1–G4	GI exposure categories	Threshold-based GI exposure levels (high, medium, low, none-very low).
B1–B4	BI exposure categories	Threshold-based BI exposure levels (high, medium, low, none-very low).
T1–T3	Interview themes 1–3	T1 historical & cultural atmosphere; T2 spatial aesthetics; T3 spatial functionality.
LMM / LMMs	Linear Mixed-effects Model(s)	Models used to test BI/GI effects while accounting for participant and scene-level variance.
RF	Random Forest	Machine-learning model used to estimate relative importance of BI vs GI for perception factors.
MDI	Mean Decrease in Impurity	Feature-importance metric used within RF models.

5.1 Introduction

The concept of “historic urban areas” (HUAs) was introduced in 1987, defining these areas as: “*regardless of size, any area including cities, towns, historic centers, and residential districts, as well as their natural and constructed environments* (Washington Charter, 1987).” HUAs are a crucial part of humanity’s cultural heritage, playing a vital role in preserving and continuing traditional cultural history and providing unique cultural experiences over time (UNESCO, 2021). As “living” heritage, HUAs not only accommodate activities such as commerce and tourism but also increasingly incorporate urban blue-green infrastructure (BGI), including green spaces, parks, and waterways. While numerous studies have examined the effects of human activities on the visual character and experiential quality of HUAs (Dinçer, 2011; Ferreira & Ramírez Eudave, 2022; Sastre et al., 2013), the role of BGI in shaping human visual perception remains underexplored. This chapter addresses this gap through an integrated approach that combines empirical perception-based methods (e.g., eye-tracking, questionnaires, interviews) with digital spatial analysis techniques, including UAV (Unmanned Aerial Vehicle)-based photogrammetry and view-based BGI quantification. To ensure diverse perspectives, participants in the perception experiments include both experts (primarily architects and landscape architects) and the general public without relevant educational backgrounds.

5.1.1 Blue-green infrastructure and HUA

BGI refers to the integration of natural and artificial ecosystems, including urban green spaces, parks, gardens, wetlands, rivers, and lakes (Escobedo et al., 2019; Liao et al., 2017). It contributes to climate regulation, biodiversity, flood mitigation, and enhances physical, mental, and environmental well-being (Li et al., 2025; Macháč et al., 2022; Zhang et al., 2025).

In the context of HUAs, BGI is often an essential component. Blue infrastructure (BI), such as the waterways that permeate Venice (Vallerani & Visentin, 2018), Amsterdam (Pruijt, 2004), and ancient cities in the Jiangnan region of China (Zuo & Zhang, 2023), serves as a defining visual and spatial feature of these HUAs (Vallerani & Visentin, 2018). Green infrastructure (GI), including green spaces, parks, and urban greenery within HUAs, contributes to urban livability and reinforces cultural character (Hua et al., 2022; Stanley et al., 2012). Additionally, special vegetation, such as ancient and heritage trees, can further enrich the historical and cultural atmosphere of these sites (Haneca et al., 2009; Rostami et al., 2015).

Previous studies on HUAs have primarily focused on two aspects of BGI: (a) its spatial integration with historic fabric and landscape evolution (Halbac-Cotoara-Zamfir et al., 2021; Wang et al., 2020); and (b) its functional roles in urban resilience and well-being (Yang et al., 2020; Zhao et al., 2024). However, despite BGI's prominence in heritage landscapes, systematic investigations into its role in shaping human visual perception and experiential qualities are almost absent. Addressing this gap is crucial for advancing heritage-sensitive landscape assessment and planning.

5.1.2 Visual perception research on HUAs

Visual perception plays a critical role in evaluating the environmental and cultural quality of HUAs. As carriers of cultural memory and landscape identity, HUAs have increasingly been examined in terms of how users visually engage with their spatial environment (Deghati Najd et al., 2015; Ren, 2024). Existing research can be broadly grouped into two complementary streams: perception-based and geo-spatial analytical approaches.

a) **Perception-based approaches** emphasize subjective and experiential dimensions. Two primary directions are evident: *(i) User-group differences*, exploring how perceptions vary among stakeholders such as heritage professionals, planners, and the general public. These studies highlight socio-demographic factors, including age, gender, and cultural background, as key influences on visual evaluations. (Pendlebury & Townshend, 1997; Remoaldo et al., 2014). *(ii) Aesthetic and emotional responses,* investigating how urban form and landscape settings evoke feelings of beauty, nostalgia, or belonging (Chen et al., 2015; Deghati Najd et al., 2015; Jenks, 2008; Nasar, 1989; Smardon, 1988). These insights are valuable for understanding user preferences and acceptance of conservation or redevelopment strategies.

b) **Geo-spatial and computational approaches** rely on digital tools to assess visual characteristics from a performance perspective. Key directions include: *(i) Visual impact assessments* of new architectural insertions or infrastructure projects, evaluated for compatibility with historic contexts using simulation and modeling techniques (Bu et al., 2022; Jiang et al., 2022; Serra et al., 2021). *(ii) Spatial cognition and visibility analysis*, using tools like spatial syntax, viewshed modeling, and GIS to understand how people navigate and perceive historic environments (Esposito et al., 2020; Tan & Ujang, 2012; Wang et al., 2022). Both approaches increasingly benefit from recent advancements in high-resolution spatial data acquisition technologies, such as UAV-based photogrammetry and point clouds derived from scanning devices (e.g., LiDAR), significantly enhancing visibility analysis and spatial cognition modeling in HUAs (Curcio et al., 2022; Zhang et al., 2021).

Although both perception-based and geo-spatial analytical approaches have yielded valuable insights, they remain largely separated in methodology and scope. In particular, little attention has been paid to how BGI structures visual experiences in HUAs through integrated spatial and perceptual analysis. Given the growing relevance of ecosystem-based design and nature-based solutions in impact assessment, embedding BGI within perception research frameworks presents a timely and underexplored direction for heritage-sensitive urban analysis.

5.1.3 Research gaps and research questions

Although BGI is widely acknowledged for enhancing both visual quality and ecological function in urban environment (Li et al., 2025; Macháč et al., 2022; Zhang et al., 2025), its specific impact on human visual and spatial perception in HUAs remains insufficiently understood. While previous research has recognized BGI as a product of historical processes with aesthetic and environmental value (Haneca et al., 2009; Rostami et al., 2015), few studies systematically assess how users perceive it or how it contributes to experiential qualities in heritage contexts. Another gap lies in the methodological fragmentation of visual perception studies. Research typically relies either on empirical user-based methods (e.g., surveys, interviews, behavioral observation) or on digital spatial techniques (e.g., GIS, viewshed analysis, photogrammetry), with limited integration between the two.

TOC

Recent advances in multi-view photogrammetric modeling technologies, such as Structure-from-Motion (SfM), combined with increasingly accessible and affordable UAVs, now enable the acquisition of high-resolution spatial data suitable for detailed visual analyses (Berra & Peppa, 2020; Fernández-Hernandez et al., 2015). These advancements significantly lower the technical and financial barriers for integrating empirical and digital spatial methods. UAV-based digital models can thus be effectively embedded within perception-driven research frameworks, providing reliable data support for initial scene selection and subsequent generalization of findings.

Therefore, this chapter proposes an integrated framework that combines digital modeling techniques, including UAV-based 3D reconstruction and human-scale view extraction, with multi-layered perception methods including eye-tracking, questionnaires, and semi-structured interviews. The goal is to investigate how BGI influences visual perception in HUAs and how such effects vary between expert and public users. Accordingly, the study addresses the following research questions: (RQ1) How can BGI exposures and spatial characteristics be effectively measured from pedestrian perspectives in HUAs? (RQ2) How can integrated, multi-layered methods combining spatial modeling and empirical perception analysis be applied to assess BGI's visual impacts? (RQ3) How does BGI influence visual attention patterns, perceptual evaluations, and cognitive interpretations across expert and general public user groups?

This chapter contributes to the field of heritage-sensitive urban visual impact assessment in two key ways: **(a) Novel thematic focus**: While previous studies have explored BGI's ecological and functional roles, this research is among the first to systematically examine its influence on human visual perception within HUAs, addressing an important and underexplored dimension in heritage landscape evaluation. **(b) Integrated framework and cross-group analysis**: The study develops an integrated approach combining UAV-based spatial modeling and multi-layered perception analysis, and systematically compares expert and general public responses to reveal differentiated perceptual structures related to BGI in HUAs, advancing methodological practices and stakeholder-informed assessment.

5.2 Reviewing visual perception analysis methods in urban contexts

This section reviews two complementary methodological domains that have been widely used in visual perception research related to HUAs: digital geo-spatial approaches, and perception-based methods. While the former focuses on modeling spatial structure and visibility, the latter emphasizes users' cognitive and emotional engagement. Reviewing both domains provides a foundation for identifying opportunities for methodological integration in the context of evaluating BGI in urban heritage settings.

5.2.1 Digital geo-spatial approaches

Geo-spatial and computational approaches often utilize spatial data and simulation techniques to analyze visibility, spatial composition, and structural patterns of HUAs, which can be categorized as:

a) **GIS-based methods:** Used to quantify land cover, vegetation, hydrology, and built structures, GIS enables mapping and modeling of spatial patterns in historic contexts. Also, GIS-based viewshed/visibility analysis tools calculate the spatial visibility of elements from a given observer's location (Jerpåsen & Larsen, 2011; Sarihan, 2021), simulating what is seen from specific points in 2D or 3D terrain environments. They are useful for assessing visual accessibility and the prominence of landscape elements across an urban environment (Florio et al., 2017; Zhou et al., 2023).

b) **3D modeling visual analysis:** Using photogrammetry or LiDAR data, urban scenes can be reconstructed in 3D to simulate human viewpoints. Field of view (FOV) analyses within these models help determine the relative exposure of various visual components, such as vegetation, water, built heritage (Balsa-Barreiro & Fritsch, 2018; Prechtel et al., 2013). Recently, UAV-based photogrammetry has increasingly been employed due to its flexibility, cost-effectiveness, and ability to produce detailed, high-resolution spatial models (Berra & Peppa, 2020; Fernández-Hernandez et al., 2015). UAV-derived point clouds provide accurate spatial relationships between elements, capture complex urban morphology, and offer perspectives unavailable through traditional ground-based observations, making them particularly suitable for heritage-sensitive urban contexts (Lo Brutto et al., 2014; Pepe et al., 2022).

c) **Street-level and image-based analysis with computer vision:** Techniques using street view imagery (e.g., Google Street View) combined with semantic segmentation and deep learning allow for automatic classification and quantification of visual elements like trees, sky, water, or building façades (Gao et al., 2025; Li et al., 2017; Zhang et al., 2023). These methods approximate human perspectives at the street level and have been applied to both modern urban studies and heritage districts.

The strengths of these methods lie in their objectivity, repeatability, and ability to capture spatial complexity. However, they often lack sensitivity to human perception, emotion, and cultural meaning. While they provide precise accounts of what is spatially present or visible, they reveal little about how these environments are actually perceived. This underscores the need to complement geo-spatial analysis with user-centered perception methods—particularly when evaluating the visual role of BGI in culturally significant urban settings.

5.2.2 Perception-based methods

Perception-based approaches explore the cognitive, emotional, and sensory dimensions of how people engage with urban spaces—revealing not just what is seen, but how it is interpreted, evaluated, and remembered. In the context of historic urban areas (HUAs), these methods are especially valuable for capturing the layered experiences shaped by spatial form, cultural memory, and atmospheric qualities. These methods can be broadly classified into three complementary strands:

a) **Psychophysical approaches** examine the physiological basis of perception, using biometric tools such as eye-tracking, EEG, or heart rate monitoring to capture unconscious reactions to visual stimuli (Braddick, 1997; Bruce et al., 2014; Xiao et al., 2024). Among these, eye-tracking has gained prominence in landscape and urban research as a non-intrusive method to analyze attention distribution and visual salience (De Lucio et al., 1996; Fang et al., 2024; Ye et al., 2022).

b) **Psychological approaches** focus on how individuals evaluate and emotionally respond to environments (Leventhal & Scherer, 1987; Moser & Uzzell, 2003). Techniques such as questionnaires, semantic differential scales, and image-based scoring help measure aesthetic preferences, perceived atmosphere, and affective responses (Brosch et al., 2013; Gifford et al., 2011).

c) **Phenomenological approaches** delve into the interpretive and experiential layers of perception, using interviews, self-reports, and narrative observations to explore how people assign personal and symbolic meaning to spaces (Albertazzi, 2013; Merleau-Ponty et al., 2013; Ohta, 2001; Santo-Tomás Muro et al., 2020). These methods are especially relevant in HUAs, where individual lived experience is often entangled with historical identity and cultural memory.

Together, these approaches offer a multilayered understanding of perception, tracing how people see, feel, and make sense of their surroundings. However, when used in isolation, perception-based methods present two critical limitations. First, they lack the capacity to quantify what is spatially visible from different viewpoints. Without geo-spatial data on visual exposure, such as which elements are actually seen and how prominently, subjective evaluations risk being disconnected from the physical environment. Second, the fragmented nature of perceptual data—spread across physiological signals, survey responses, and qualitative insights—makes it difficult to synthesize findings into a coherent, spatially grounded interpretation. These limitations highlight the need for integration with geo-spatial approaches. Only by combining the spatial precision of modeling tools with the experiential richness of perception-based methods can we fully understand how blue-green infrastructure (BGI) influences visual experience in culturally significant urban settings.

5.3 Methods

Building on the methodological insights outlined in the previous section, this study applied an integrated framework that merged the spatial precision of geo-spatial modeling with the interpretive depth of perception-based analysis to systematically examine the influence of BGI on visual experience in HUAs. The framework comprised three complementary modules **(FIG. 5.2)**:

a) **Digital modeling module**: A high-resolution 3D mesh model of the case site was reconstructed using Unmanned Aerial Vehicle (UAV)-based photogrammetry combined with ground-level imaging. Eye-level panoramic viewpoints were then extracted to quantify the exposure levels of GI and BI from pedestrian perspectives. These quantified spatial representations informed the selection of representative scenes for the perception experiments.

b) **Perception analysis module**: This module was structured into three layers: **"seeing"** (physiological attention), **"feeling"** (subjective preference), and **"understanding"** (cognitive interpretation). It integrated eye-tracking experiments, structured questionnaires, and semi-structured interviews, providing a holistic framework for assessing the perceptual effects of BGI across user groups.

c) **Integration and generalization module:** This module combined empirical results from the perception analysis with the spatial exposure levels of BGI derived from digital modeling. By establishing relationships between BGI exposure and perceptual responses, it enabled integrated assessments at the street level and predictive modeling of visual perceptual impacts in areas not directly examined through experiments.

This framework bridged digital modeling with human-centered perception research, enabling both objective spatial quantification and subjective evaluation, an essential step toward integrating subjective visual perception with objective spatial attributes in the visual impact assessment of HUAs.

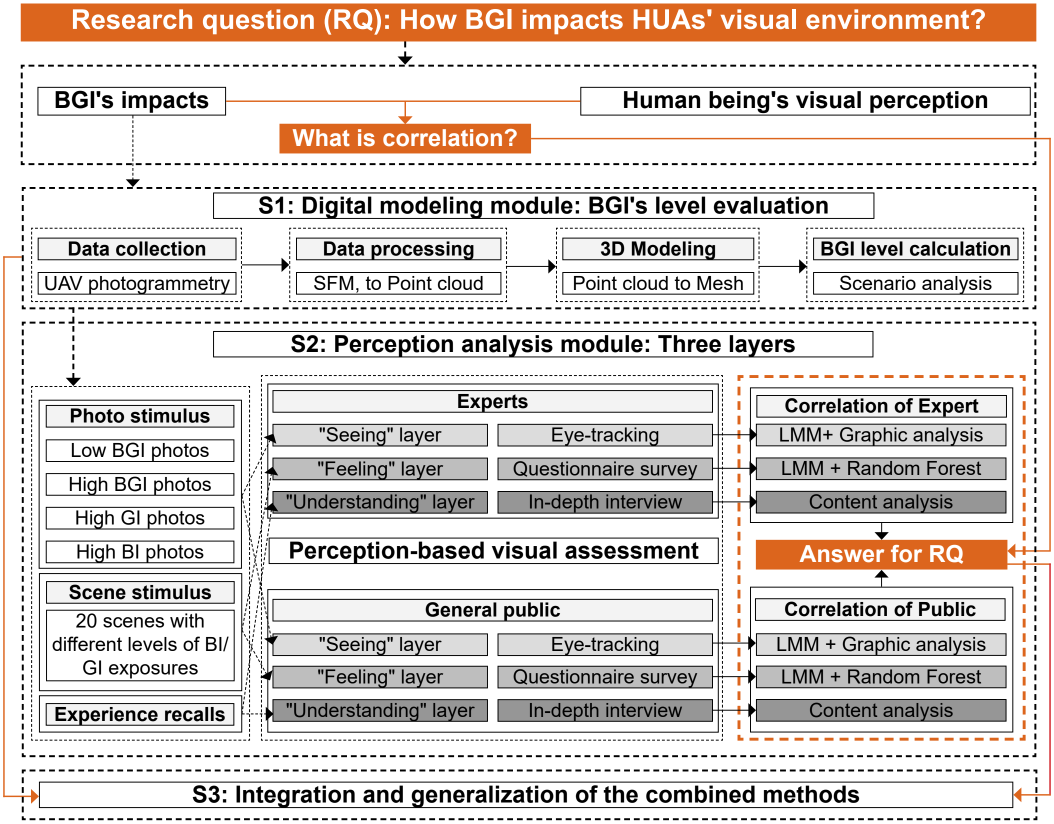


FIG. 5.2 The workflow of this research

5.3.1 Case study site

Pingjiang Road area in Suzhou, China, was selected as the case study site. As a nationally protected historic street situated within the buffer zone of the UNESCO World Heritage Site "Classical Gardens of Suzhou" (Wang et al., 2015), Pingjiang Road exemplifies the Jiangnan water town typology, characterized by its linear canal-side layout, traditional architecture, and abundant greenery **(FIG. 5.3)**.

TOC

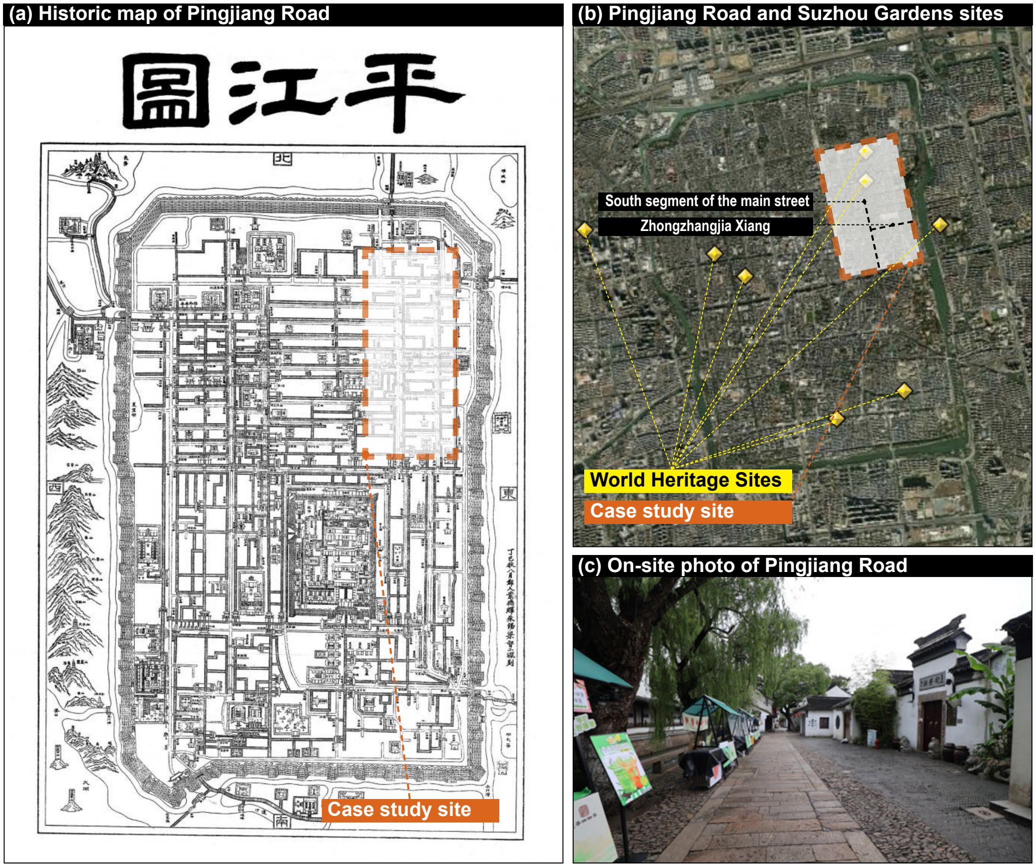


FIG. 5.3 The location and historic map of Pingjiang Road.

These features make it a representative example of historic urban areas (HUAs) in East Asia and culturally transferable to similar water- and vegetation-integrated heritage environments worldwide. Within this area, the primary street can be divided into two main segments (north and south). Five lateral streets connected with water channels branch off from these segments. The selected study fragment comprises the southern segment, specifically chosen due to its proximity and direct connection to Zhongzhangjia Xiang, a street whose original water channel was recently restored. This restoration differentiates Zhongzhangjia Xiang from other BGI conditions within the Pingjiang Road area, providing unique comparative value. Thus, the southern segment was selected to capture this distinctive transitional context.

5.3.2 3D modeling and BGI exposure computation

To quantify the spatial exposure of BGI from a pedestrian perspective, a high-resolution 3D semantic mesh model of Pingjiang Road was created through a combined aerial and ground-level photogrammetry workflow. This model served as the analytical base for evaluating the exposure of BI and GI within the human visual field. Image acquisition was conducted in December, 2024, using two complementary modes **(FIG. 5.3)**:

a) **Aerial imaging**: Low-altitude photographs were taken using a DJI Phantom 4 Pro UAV at heights ranging from 2 to 10 meters, capturing rooftops, tree canopies, and canal structures.

b) **Ground-level imaging**: Manual photos were captured at approximately 1.6 meters, the average eye level of pedestrians, focusing on façades, vegetation, and water features within narrow alleys and walking paths.

The photogrammetric processing pipeline involved: (a) feature matching and alignment via Structure-from-Motion (SfM); (b) point cloud generation using Multi-View Stereo (MVS); (c) mesh surface reconstruction; and (d) texture mapping to retain photorealistic detail. The resulting mesh was annotated with semantic labels, assigning each surface element to one of several categories: BI, GI, or other urban components. This enabled spatially explicit quantification of BGI exposure without the need for post-rendered segmentation.

To quantitatively assess BGI exposure, pedestrian-level viewpoints were placed at 1-meter intervals along the primary walking route. At each viewpoint, lines of sight (LoS) were systematically constructed horizontally at 5-degree intervals over a full 360-degree field-of-view, and vertically from 30 to 175 degrees relative to the ground plane, approximating human visual coverage. When an LoS intersected with a semantic mesh surface labeled as BI or GI, the intersection was recorded (Peng et al., 2025; Peng et al., 2024). The proportions of BI and GI visible surfaces within each viewpoint's visual field were then calculated.

Due to accuracy constraints associated with consumer-grade UAV equipment, exposure levels (visibility levels of BI/GI) in the resulting semantic mesh model were simplified into categorical rankings rather than precise numeric intervals. Exposure thresholds for BI and GI were defined separately based on their distinctive visibility characteristics in urban setting. For GI, higher thresholds were applied, defined as high (G1, ≥25%), medium (G2, 15–24.9%), low (G2, 5–14.9%), and none/very low (G4, <5%), consistent with its relatively greater coverage in urban environments

TOC

(Aoki, 1987; Li et al., 2021). For BI, given the absence of established thresholds in the existing literature, a proportional scaling factor of 0.3—derived from observed relative exposure ratios between BI and GI—was applied to define exposure categories (Peng et al., 2025). Therefore, thresholds were set as high (B1, ≥7.5%), medium (B2, 4.5–7.4%), low (B3, 1.5–4.4%), and none/very low (B4, <1.5%), reflecting the typically lower yet perceptually significant presence of water elements.

Based on combinations of these BI and GI exposure categories, the street was segmented into 16 distinct BGI typologies (e.g., G1B2 refers to a scene with 5–14.9% GI exposure and 4.5–7.4% BI exposure). Representative scenes covering diverse spatial and environmental conditions were subsequently selected from these typologies to serve as visual stimuli in the subsequent perception experiments. At last, to verify the accuracy of this custom approach, selected viewpoint results were validated through panoramic camera simulations within the Unity environment.

5.3.3 Multi-layered perception-based experiments

To examine how BGI influences visual perception in HUAs, this study adopted a three-layered experimental framework that integrated physiological, psychological, and cognitive dimensions of human experience. The framework is structured as follows **(FIG. 5.2)**:

- **“Seeing”:** early-stage visual attention, assessed using eye-tracking technology;
- **“Feeling”:** intuitive preferences and evaluative judgments, measured through structured questionnaires;
- **“Understanding”:** interpretive and reflective responses, explored via semi-structured interviews.

These methods were selected for their complementarity. Eye-tracking captures unconscious attentional patterns and perceptual salience; questionnaires elicit subjective appraisals of environmental quality across multiple dimensions; and interviews reveal deeper meanings and contextual interpretations associated with BGI in heritage settings. Together, they provide a multi-faceted and integrative perspective on perception—bridging the gap between observable behavior and experiential understanding.

5.3.3.1 Recruitment of participants

Participants underwent the experimental tasks in a sequential manner, progressively refining the sample size at each stage. First, structured questionnaires were administered to all recruited participants (80 valid responses per group, **TABLE 5.1a**), enabling rapid collection of subjective appraisals. Based on questionnaire quality and participant engagement, suitable candidates (40 valid participants per group, **TABLE 5.1b**), who met standard visual acuity requirements (corrected or uncorrected between 0.8 and 1.5), proceeded to the eye-tracking experiment. Finally, representative participants who successfully completed the eye-tracking tasks were invited to participate in semi-structured interviews (20 per group, **TABLE 5.1c**).

TABLE 5.1 Participants' information

Variables	Features	Sum	Expert (80,)	General public (80)
a) Participants for questionnaire survey:				
Age	18-22	38	11	17
	23-25	57	24	33
	26-30	44	26	18
	31-40	31	19	12
Gender	Male	83	42	41
	Female	77	38	39
b) Participants for eye-tracking experiment:				
Age	18-22	17	8	9
	23-25	26	13	13
	26-30	26	14	12
	31-40	11	5	6
Gender	Male	38	20	18
	Female	42	20	22
c) Participants for in-depth interview:				
Age	18-22	9	4	5
	23-25	11	6	5
	26-30	13	7	6
	31-40	7	3	4
Gender	Male	19	9	10
	Female	21	11	10

Note: Participants who did not meet the inclusion criteria have been excluded from the table (including those with poor-quality eye-tracking data or participants who completed questionnaires carelessly or randomly). For the expert group, participants were required to have academic backgrounds in architecture, landscape architecture, urban planning, or closely related fields, with at least senior-level undergraduate standing or higher. Additionally, considering that questionnaires were administered electronically and the eye-tracking experiment required familiarity with computer operations and equipment calibration, tasks potentially difficult for middle-aged and older adults, all participants were limited to individuals aged 40 or younger.

This sequential and layered approach ensures efficient data collection, enhances data quality through rigorous participant screening, and reduces potential interference between experimental stages. By structuring the methods sequentially, the potential influence of later tasks on participants' initial responses is minimized. Furthermore, the gradual refinement of participant pools based on task-specific inclusion criteria ensures that each experimental stage involves individuals suited to provide meaningful and reliable insights.

5.3.3.2 Questionnaire survey ("feeling" layer)

To assess users' intuitive responses to BGI in HUAs, a structured questionnaire survey was conducted as the basis for the "feeling" layer. This layer focuses on affective and evaluative judgments, capturing how different types of scenes influence participants perceived aesthetics, cultural atmosphere, and functional value. The web-based questionnaire was organized around three dimensions, each composed of multiple relatively independent items to capture distinct aspects within the same domain:

- **D1: Historical and cultural atmosphere**; Derived from cultural memory theory (Assmann, 2011b), genius loci theory (Norberg-Schulz, 1976), and place attachment frameworks (Lewicka, 2013). These theories collectively emphasize *cultural symbolics (F11)*, *spatial memory (F12)*, and *genius loci or spirit of place (F13)*, acknowledging that cultural and spatial atmospheres form crucial perceptual foundations that must not be overlooked in heritage contexts.

- **D2: Spatial aesthetics;** Based primarily on the classical urban aesthetics and landscape preference theories (Kaplan et al., 1989; Nasar, 1994), emphasizing *visual aesthetics (F21)* such as form, material, and color, and *ecological aesthetics (F22)* concerning the harmonious integration of natural elements. These aesthetic dimensions are vital as visual attributes fundamentally shape heritage landscapes' experiential quality.

- **D3: Spatial functionality;** Encompasses *ecological functions (F31)*, *recreational and well-being functions (F32)*, and *spatial function (F33)*. This dimension integrates established theoretical perspectives from ecosystem services literature (Assessment, 2005), restorative environment theory (Hartig et al., 1997; Kaplan, 1992), and spatial coherence and legibility principles (Kaplan et al., 1989; Nasar, 1994). These functional aspects are critical in determining how effectively BGI enhances ecological resilience, user comfort, recreational value, and spatial legibility in heritage areas.

Each item was rated using a 1–5 interval scale with 0.5-point increments (e.g., 1.0, 1.5, ..., 5.0), allowing for moderate resolution in perception-based scoring while retaining comparability across items. The questionnaire was scene-based: a total of 20 representative viewpoint scenes were selected, each accompanied by 3–5 stimulus images and corresponding map locations to help participants accurately identify spatial context. The questionnaire survey was conducted in March, 2025. This ensured that evaluations were grounded in place-specific memory and spatial experience rather than abstract visual judgment.

Responses were first analyzed using descriptive statistics (mean and median scores) to identify perceptual trends across scenes and user groups. To further assess the influence of BGI variables, two complementary analytical methods were employed: **(a) LMMs** evaluated the influence of BI and GI exposure levels on each perception item while accounting for inter-individual variability and repeated scene measures; **(b) Random Forest (RF)** was used to quantify the relative influence of BI and GI, with separate models for expert and public groups. Feature importance scores were calculated using Mean Decrease in Impurity (MDI). Together, these two methods provide complementary insights: LMMs establish statistically significant effects of BGI exposure, while RF analysis identifies which variables exert the strongest practical influence on perceptual variation.

5.3.3.3 Eye-tracking experiment (“seeing” layer)

To capture unconscious visual responses to different BGI configurations, an eye-tracking experiment was conducted as the basis for the “seeing” layer. This method focuses on early-stage visual attention and perceptual salience, providing objective data on how users scan and prioritize landscape elements in HUA environments (Dupont et al., 2014). Participants were selected and contacted based on questionnaire responses and sequentially invited for the eye-tracking experiment between March and April of the same year. Participants were presented with a series of static images simulating pedestrian views of the case site. A total of 24 images were used as stimuli: 20 images were captured at representative viewpoints previously identified in the spatial analysis, and 4 additional images were selected to diversify the stimulus pool and enhance the range of visual BGI exposure. Each viewpoint was represented by only one image. Since these images presented only a partial field of view rather than full 360-degree panoramas, the visual composition did not fully correspond to the modeled BGI exposure values. To ensure consistency, each image was independently reclassified based on the visible proportion of GI and BI within the photo frame, using a four-level scale: none/very low (N), low (L), medium (M), and high (H). This image-based classification was used to guide subsequent analysis and group comparison.

Each image was displayed for 20 seconds, preceded by a central fixation point to standardize attention. Participants were instructed to view the images naturally, simulating spontaneous observation. To support visual analysis, eight Areas of Interest (AOIs) were defined for each image, corresponding to semantic categories: *(a) historical and cultural elements, (b) commercial elements, (c) paved ground, (d) sky, (e) perspective focal points, (f) buildings and structures, (g) green infrastructure (GI),* and *(h) blue infrastructure (BI).*

Visual attention was analyzed through fixation duration and gaze heatmaps (de la Fuente Suárez, 2020). Group-level heatmaps were generated to visualize attention distribution across AOIs. Fixation data were then analyzed using linear mixed-effects models (LMMs), which allowed for the evaluation of BGI exposure effects on visual attention while accounting for group, AOI category, and scene-level variance. Descriptive statistics such as mean and median fixation durations were also examined to support trend interpretation.

5.3.3.4 Semi-structured interviews ("understanding" layer)

To capture the cognitive and interpretive depth of user responses to BGI, semi-structured interviews were conducted as the foundation of the "understanding" layer. This method aimed to uncover how different user groups conceptualize the spatial, symbolic, and functional roles of BI and GI within HUAs. The interview protocol was structured around three open-ended thematic prompts, corresponding to the three perception dimensions explored in the survey: *T1 – Historical and cultural atmosphere, T2 – Spatial aesthetics*, and *T3 – Spatial functionality*.

To support memory recall and contextual grounding, participants who successfully completed the eye-tracking experiment and expressed willingness were invited to participate in the semi-structured interviews. Gender and age ratios were controlled within both participant groups. Participants were shown selected photographs from the previous eye-tracking and questionnaire experiments. This multimodal cueing method was designed to evoke both affective and analytical reflections anchored in place-based experience. All interviews were audio-recorded, transcribed verbatim, and analyzed using a frequency-based thematic coding approach. The analysis followed a structured four-step process:

a) **Open coding:** Initial concepts and expressions were tagged line-by-line from the transcripts without pre-imposed categories.

b) **Subdimension classification:** The open codes were then grouped into eight perception subdimensions (the same as the questionnaire), including Genius loci, Ecological aesthetics, Recreational and well-being function, among others.

c) **Infrastructure attribution:** Each coded phrase was linked to either BI or GI stimuli, based on contextual references in the participants' statements.

d) **Cognitive activation modeling:** Final frequencies were synthesized into two user-specific models (expert and public), mapping the perceived activation paths from infrastructure contact through subdimensions to the three thematic categories (T1–T3).

This coding structure enabled the reconstruction of distinct perceptual pathways for each group, revealing both shared cognitive patterns and key divergences in how BGI is interpreted in a HUA setting.

5.3.4 Spatially explicit cross-layer integration at the street level

To systematically evaluate the visual impact of BGI at the street scale, this section integrates empirical findings from all three perceptual layers ("seeing," "feeling," and "understanding") with the UAV-derived spatial exposure data described in **Section 3.2**. The goal is to clearly link spatial exposure levels (high, medium, low, none/very low) of BI and GI at street-level viewpoints to corresponding perceptual outcomes.

For the "seeing" and "feeling" layers, eye-tracking data (fixation duration) and questionnaire scores were explicitly structured around scenes selected based on UAV-derived exposure categories. Thus, perceptual variations inherently corresponded with these spatial categories, enabling two types of flexible, spatially explicit assessments that surpass the limitations of traditional point-based perception studies:

a) **Street-level integrated assessment:** By aggregating perceptual outcomes (e.g., mean fixation duration, mean preference ratings) according to the proportional distribution of exposure categories along the entire street, it is possible to systematically evaluate the cumulative perceptual impact of BGI across the full spatial extent. This approach provides a holistic, spatially integrated evaluation of how varying BGI exposures collectively influence visual attention and environmental preferences along the street.

TOC

b) **Localized impact predictions:** Using the established empirical relationships between perceptual outcomes and BGI exposure categories, perceptual impacts can be flexibly predicted at smaller scales—whether specific street segments or individual viewpoints—even if empirical data at these locations have not been explicitly collected. Such predictive capability facilitates targeted planning and enables scenario-based evaluations of BGI impacts at specific spatial locations.

For the "understanding" layer, interpretive qualitative responses from semi-structured interviews were mapped via cognitive pathways linking BGI exposure categories to specific perceptual subdimensions (e.g., ecological function, spatial memory), and subsequently to overarching themes (T1–T3). Although qualitative in nature and less directly integrated with quantitative spatial modeling, these cognitive insights were systematically anchored in the UAV-derived exposure typologies, ensuring consistent spatial referencing and coherent interpretation of cognitive meanings attributed to BGI.

Together, this spatially explicit cross-layer integration approach not only establishes a rigorous analytical linkage between spatial exposure and perceptual responses but also significantly enhances the flexibility, depth, and practical applicability of visual impact assessments within historic urban contexts.

5.4 Results

5.4.1 Digital model-based classification of BGI exposure

A detailed digital model of the case area was first constructed, incorporating surface-level detail and basic semantic distinctions (BI, GI, and others) to support visibility-based analysis **(FIG. 5.4a)**. Based on this model, a spatial classification was conducted to evaluate the distribution and intensity of BGI across the case area. At each observation point, the proportion of visible surfaces occupied by GI and BI was calculated. The results reveal a highly heterogeneous spatial pattern of BGI distribution **(FIG. 5.4b)**: **(a) High BI** exposure was concentrated along the central, eastern and northern segments of the street, where proximity to primary canal zones resulted in extensive water visibility. These areas were characterized by strong waterfront spatial identity. **(b) High GI** exposure occurred primarily in the southern segments and northern side alleys, typically associated with street vegetation, courtyard greenery, and vertical plantings. **(c) High BGI scenes**, characterized by the simultaneous visual dominance of water and greenery, were spatially scattered across the area. These scenes typically appeared at locations where canal-edge vegetation and historic structures intersected. **(d) Low BGI** scenes were generally located in densely built-up commercial segments with limited open space or vegetation, producing enclosed and visually hardened environments.

The resulting classification map identified 15 BGI composition types based on the cross-combination of BI and GI exposure levels. From this spatial dataset, a set of representative scenes was selected to serve as the basis for subsequent perception experiments. These scenes reflected diverse combinations of water–vegetation composition and spatial context while avoiding overrepresentation of any single exposure condition **(FIG. 5.4b-c)**.

TOC

FIG. 5.4 (a) Visualization and modeling results; (b)-(c) Scene type classification based on BI and GI exposure.
Note: Seasonal variations were not specifically considered in this study, as the study area experiences minimal seasonal water-level fluctuations, and the dominant vegetation comprises subtropical evergreen species with negligible phenological changes (see in FIG 5.4).

5.4.2 Results of eye-tracking experiments (seeing layer)

Eye-tracking data was collected from 40 participants in each group, using 24 images that were independently reclassified based on their visible GI and BI proportions, and focusing on two metrics: gaze heatmap and fixation duration.

5.4.2.1 Gaze heatmap

Gaze heatmaps overlay participants' fixation locations and durations on the image, with warmer colors indicating longer fixation time **(FIG. 5.5)**. Although no dominant preference for BGI-related AOIs is observed in the overall heatmap patterns, scenes with salient vegetation still exhibits moderate visual attraction. In addition, the focus is higher on *(a) historical and cultural elements*. Notably, both groups demonstrate higher fixation on *(e) perspective focal points*. Differences emerge in the professional group, which disperses more warm areas and a varied fixation sequence, suggesting an irregular pattern rather than a uniform pattern.

5.4.2.2 Fixation duration

Fixation duration data were analyzed after removing outliers above 3 seconds. Results are averaged across all 24 photos for 8 predefined AOI categories **(FIG. 5.6)**. Overall, *historical and cultural elements* received the longest average fixation time across both user groups (professionals: 0.64s; public: 0.78s), followed by *perspective focal points* and *buildings/structures*. In contrast, *paved ground* had the shortest fixation durations. *GI* shows moderate attention, with higher durations in scenes where vegetation is visually salient. *BI* demonstrates more variable results, influenced by scene composition. The total fixation time on *GI* is lower than that on cultural or architectural features, but still notable in scenes classified as high-GI. These findings indicate that while BGI elements can draw visual attention, particularly when prominent in the frame, cultural and architectural components remain the primary visual anchors in the historic environment.

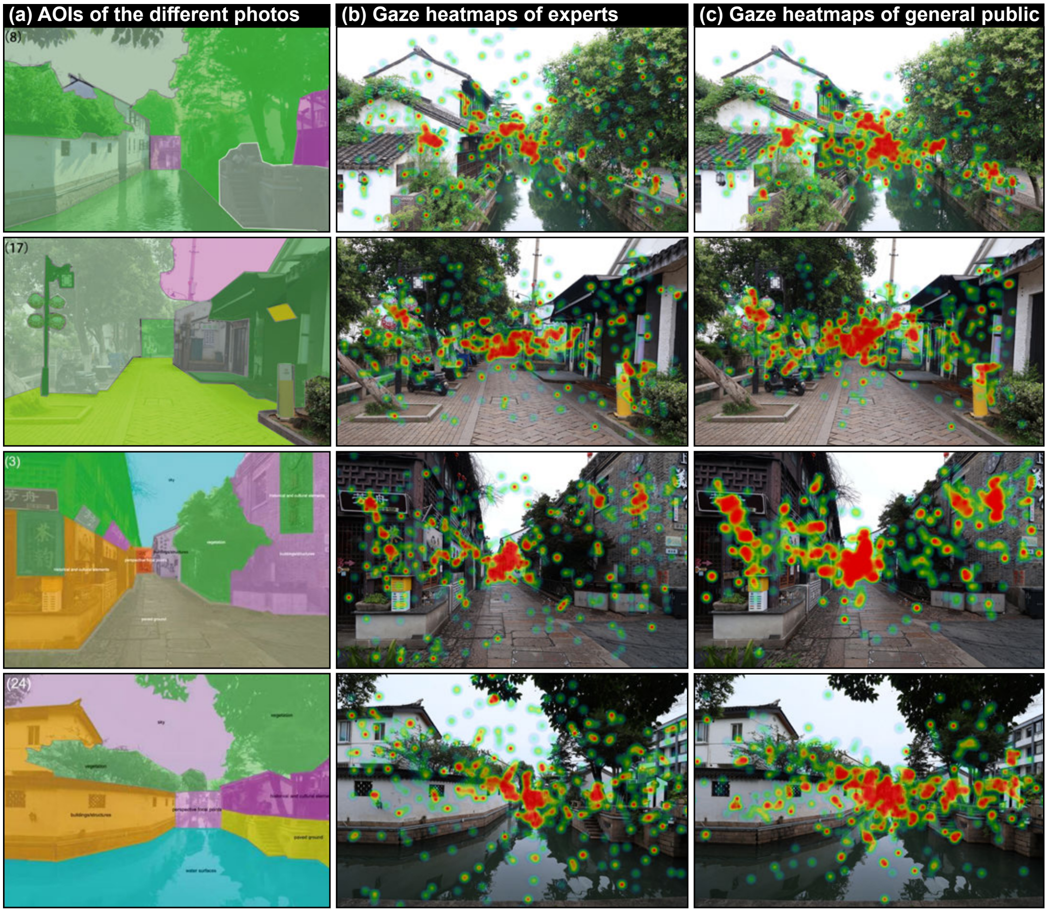


FIG. 5.5 Eye-tracking heatmaps: The examples of the two groups.
Note: Other heatmaps from the two groups can be found in Appendix C1.

TOC

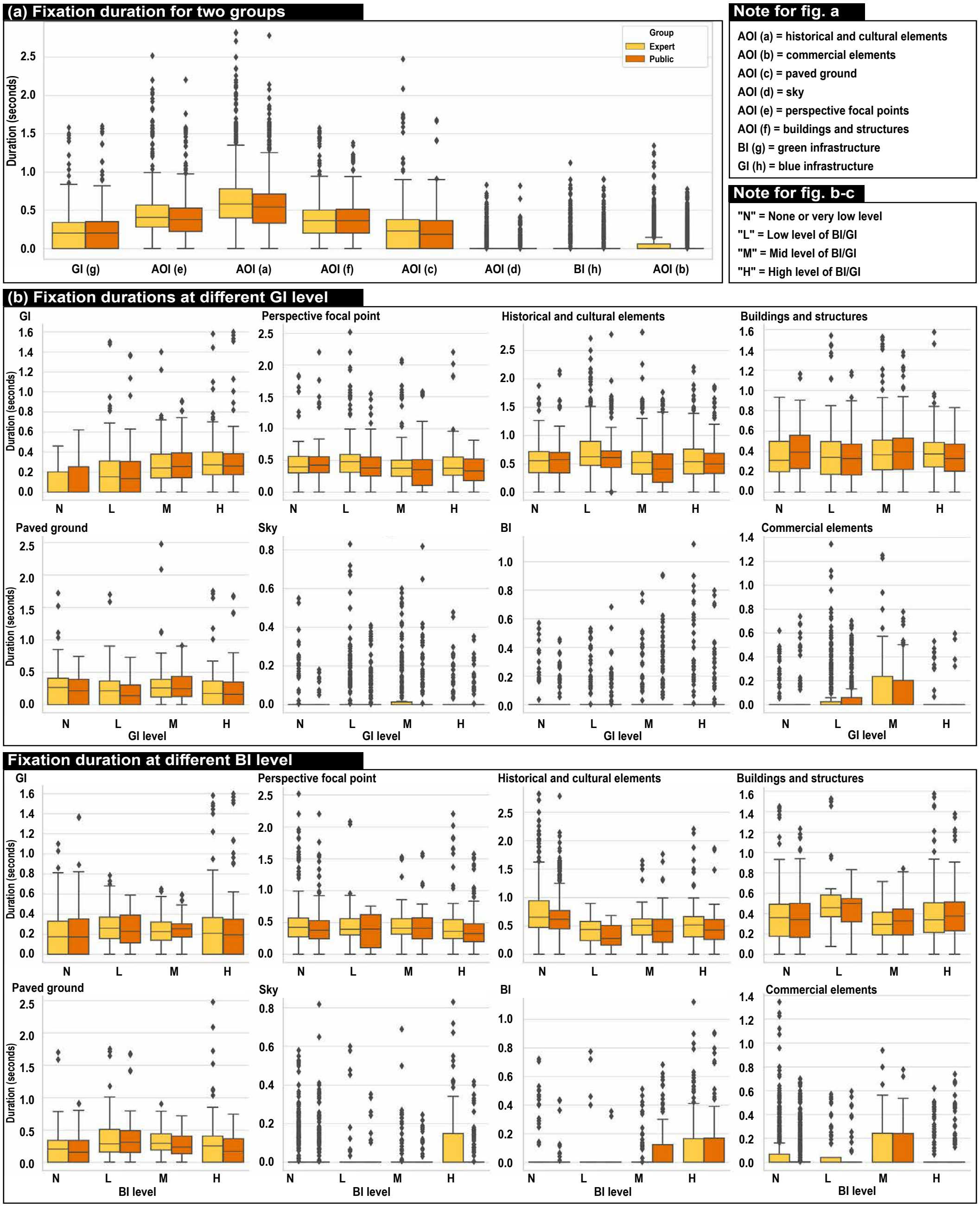


FIG. 5.6 Analysis results of fixation duration.

Note: Additionally, fixation durations for each AOI category under different BI/GI exposure levels are also computed for reference at (b)-(c). In addition, the table of fixation duration for each participant can be found in Appendix C2. Details of the fixation duration for each participant can be seen in Appendix C3.

TOC

5.4.2.3 Effect of BI and GI Levels on fixation duration

The LMM results demonstrate that various types of AOIs exert distinct influences on visual attention in HUA environments. Among all AOIs, *historical and cultural elements* yield the highest fixation durations (Coef = 0.784, $p < 0.001$), followed by *perspective focal points* (Coef = 0.517) and *buildings/structures* (Coef = 0.318). These findings underscore the central role of culturally and compositionally salient features in shaping gaze behavior. In contrast, natural elements such as BI and GI receive less attention, while paved ground (Coef = 0.213) displays a moderate but significant effect **(FIG. 5.7a)**. Beyond main AOI effects, the interaction between infrastructure exposure levels and AOI categories reveals nuanced perceptual dynamics:

a) **A negative interaction between *BI* and *historical and cultural elements*** (Coef = -0.124, $p < 0.001$) indicates that increasing BI may visually compete with or overshadow cultural and historical features, reducing attention to them **(FIG. 5.7b)**.

b) ***GI* positively influences attention to *GI*** ($p < 0.001$), suggesting a reinforcing effect between perceptual salience and visual exposure **(FIG. 5.7b)**.

c) Additional significant interactions include *GI/BI*× *perspective focal points* and *GI* × *paved ground*, illustrating that ***GI/BI* may enhance or redirect spatial cognition depending on scene composition**, because the gaze on *perspective focal points* and *paved grounds* always relates to spatial cognition **(FIG. 5.7b)**.

The analysis also reveals notable group-level differences. Public participants exhibit significantly lower attention to *historical and cultural elements* (Coef = -0.087, $p = 0.017$) and *perspective focal points* (Coef = –0.079, $p = 0.030$) compared to professionals. This suggests that professionals are more attuned to symbolic and visual-spatial features. Interestingly, under higher GI Level conditions, the general public group demonstrates greater engagement with *paved ground* AOIs (Coef = 0.043, $p = 0.042$) **(FIG. 5.7c)**.

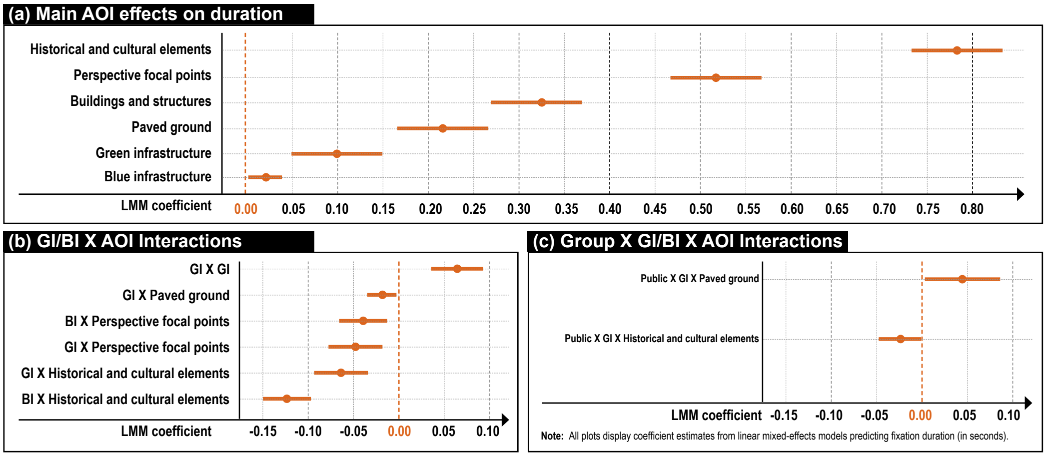


FIG. 5.7 Results of the LMM analysis.
Note: Details of the LMM results can be seen in Appendix C4.

5.4.3 Questionnaire results (feeling layer)

5.4.3.1 Overview of response patterns

To ensure internal consistency across repeated scene evaluations, Cronbach's Alpha was computed for each perception factor (F11–F33) separately within the expert and public groups. All 16 (8 factors, 2 groups) coefficients exceeded 0.92 **(Appendix C4)**, confirming the reliability of responses and the stability of factor structures across 20 spatial scenarios. Descriptive analysis reveals a clear alignment between perceived environmental quality and infrastructure exposure. Scenes with high combined infrastructure levels—particularly Scene 10 (BI=1, GI=1) and Scene 8 (BI=1, GI=2)—consistently received the highest average ratings from both groups. Scene 10, for example, yields mean scores of 4.73 (experts) and 4.87 (public), the highest across all evaluated scenes. In contrast, scenes with minimal infrastructure receive noticeably lower ratings, often falling below 4.0. These trends are robust across factors and user groups, indicating that both experts and non-experts consistently associate greater infrastructure presence with higher perceived value in historic urban settings. While GI exhibits a broad positive effect, particularly on ecological aesthetics and spatial memory, BI displayed more focused influence. Among public participants, BI strongly enhances perceptions of visual aesthetics and genius loci, producing mean score differences of 0.3–0.5 points between low- and high-BI scenarios **(FIG. 5.8a)**.

5.4.3.2 BGI influence analysis: LMM and RF

All LMM analyses accounted for inter-individual variability and repeated scene measures to ensure robustness of estimated effects. LMM results revealed that both BI and GI have significant positive effects across nearly all perception factors, though with distinct patterns between expert and public groups **(FIG. 5.8b)**: For *historical atmosphere-related factors* (F11–F13), both BI and GI are highly significant ($p < 0.001$). In the public group, GI has a stronger effect on F11 (*cultural/symbolics*) (coef = 0.25) than in the expert group (0.15), while BI more strongly influences F12 (*spatial memory*) among experts (coef = 0.27 vs. 0.18 in public). For *spatial aesthetics* (F21–F22), experts are more influenced by *GI*, particularly for *ecological aesthetics (F22)* (coef = 0.23). Conversely, public participants are more responsive to *BI*, especially on *visual aesthetics* (F21) (BI coef = 0.25 vs. GI = 0.21), reflecting a more visually driven perception. In functionality-related factors (F31–F33), *GI* is the dominant predictor in both groups, especially for *recreational and well-being* (F32) and *spatial function* (F33). BI shows positive but generally weaker effects.

RF analysis assesses the contribution of BI and GI without relying on statistical thresholds **(FIG. 5.8c)**. Importance scores, calculated using MDI, further confirm the differential impact of BI and GI across perception factors: In the expert group, *GI* consistently ranks higher than *BI* in importance scores, averaging 0.63 across all factors. It is particularly dominant for F22 (*ecological aesthetics*) and F11 (*cultural/ symbolics*), where importance reaches 0.92 and 0.88, respectively. Among public participants, *BI* emerges as a stronger predictor for specific factors, namely F21 (*visual aesthetics*) and F13 (*genius loci*), where its importance surpasses that of *GI* (0.56 vs. 0.44 and 0.52 vs. 0.39, respectively).

The convergence of LMM significance and RF importance highlights the robustness of these findings: GI has a broad and stable influence, especially among experts, while BI's impact is more factor-specific and visually driven, especially in the public group.

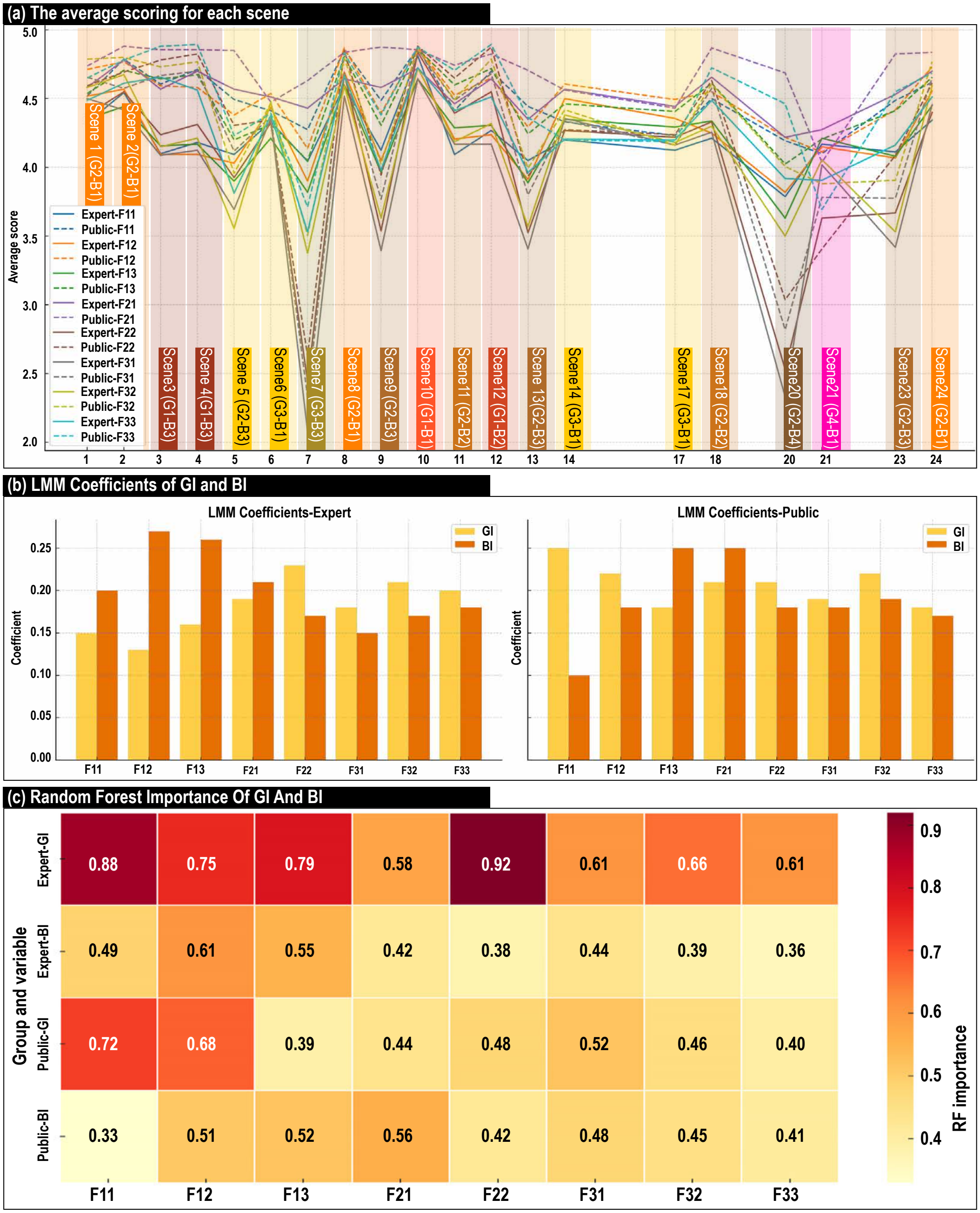


FIG. 5.8 Results of the questionnaire-based analysis.

Note: Details of the questionnaire results can be seen in Appendix C5.

5.4.4 Interview-based perception analysis (understanding layer)

In total, a combined 620 coded pathways have been identified across both groups, comprising 264 codes from the public group and 356 from the expert group **(FIG. 5.9)**. Across all interview responses, both public and expert groups exhibit a general preference for GI over BI, though the distribution is relatively balanced. The public group records 115 GI-related mentions and 102 for BI, while the expert group registers 119 for GI and 106 for BI.

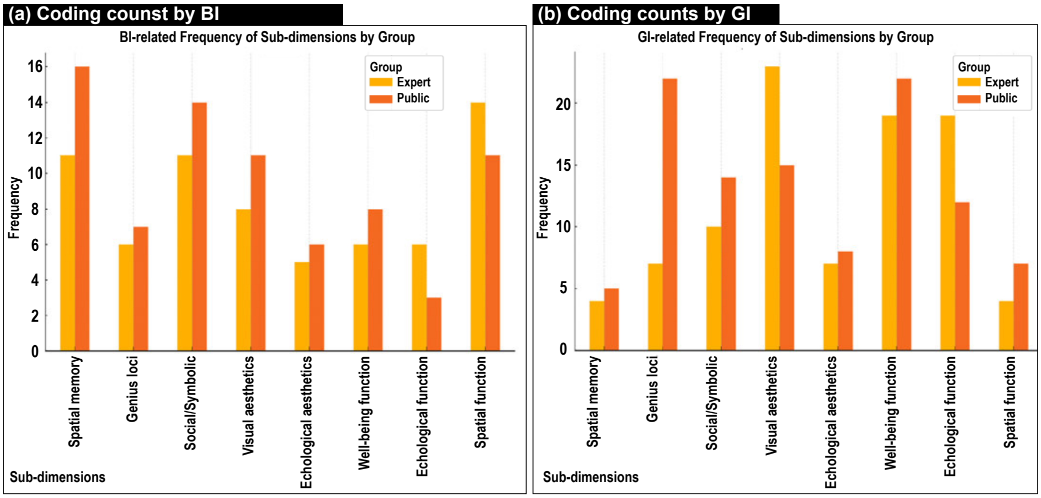


FIG. 5.9 Results of coding analysis.

The two groups demonstrate distinct patterns in how each infrastructure type is cognitively linked to specific subdimensions. For the public group, GI is most strongly associated with *Recreational and well-being functions* (37 mentions), followed by *Visual aesthetics* (18) and *Genius loci* (21). BI is linked primarily to *Visual aesthetics* (21) and *Recreational and well-being functions* (23), with some mention of *Ecological function* (15). The expert group exhibits a more functionally and ecologically integrated mapping. GI is most commonly linked to *Ecological function* (31) and *Recreational and well-being functions* (23), whereas BI is associated with *Ecological aesthetics* (11), *Ecological function* (18), and *Spatial function* (18).

TOC

At the subdimension level, the most cited categories for the public group are *Recreational and well-being functions* (60), *Genius loci* (44), and *Visual aesthetics* (39), highlighting an affective and sensory-driven mode of engagement. Experts emphasize *Ecological function* (49), *Recreational and well-being functions* (39), and *Spatial function* (33), reflecting a more analytic, systems-based framework. These findings underscore fundamental differences in how public and expert groups interpret BGI in HUAs at the “understanding” layer.

5.4.5 Cross-layer visual enhancement from BGI on HUA

This section integrates findings from all three perceptual layers with UAV-derived BGI exposure modeling to assess how BGI enhances visual experience across multiple spatial scales along Pingjiang Road. Consistent with the methodology outlined in **Section 5.3.4**, the analysis is structured into the following three subsections:

a) **Integrated street-level analysis of visual attention and preference:** Aggregated perceptual outcomes from the eye-tracking (“seeing”) and questionnaire (“feeling”) experiments reveal a coherent spatial relationship between BGI exposure and perceptual impacts at the street level **(FIG. 5.10a, b)**.

Specifically, street segments characterized by higher combined GI and BI exposure exhibit systematically modified visual attention distributions, reducing fixation intensity on historically dominant AOIs (such as cultural elements and perspective focal points) and slightly shifting visual attention toward GI elements. This attentional redistribution implies subtle attentional competition effects, where increased BGI exposure may moderately draw gaze away from traditional heritage focal points. Notably, these attentional shifts remain consistent across both expert and general public groups, suggesting a generalized attentional impact of BGI exposure.

In parallel, the street-level integrated analysis of affective preference consistently demonstrates positive perceptual uplift associated with increased BGI exposure. Higher exposure levels of GI and BI strongly correlate with elevated environmental preference ratings across all perceptual factors. GI emerges as a particularly consistent and influential factor, especially among experts who link it with ecological aesthetics and spatial coherence. In contrast, BI’s perceptual contribution is more nuanced and context-specific, exerting a somewhat stronger influence among the public, particularly concerning visual aesthetics and symbolic resonance (genius loci). Collectively, this integrated analysis clearly demonstrates that the high spatial exposure to BGI significantly enhances perceptual quality across the street, simultaneously promoting broader visual exploration and elevated environmental preferences.

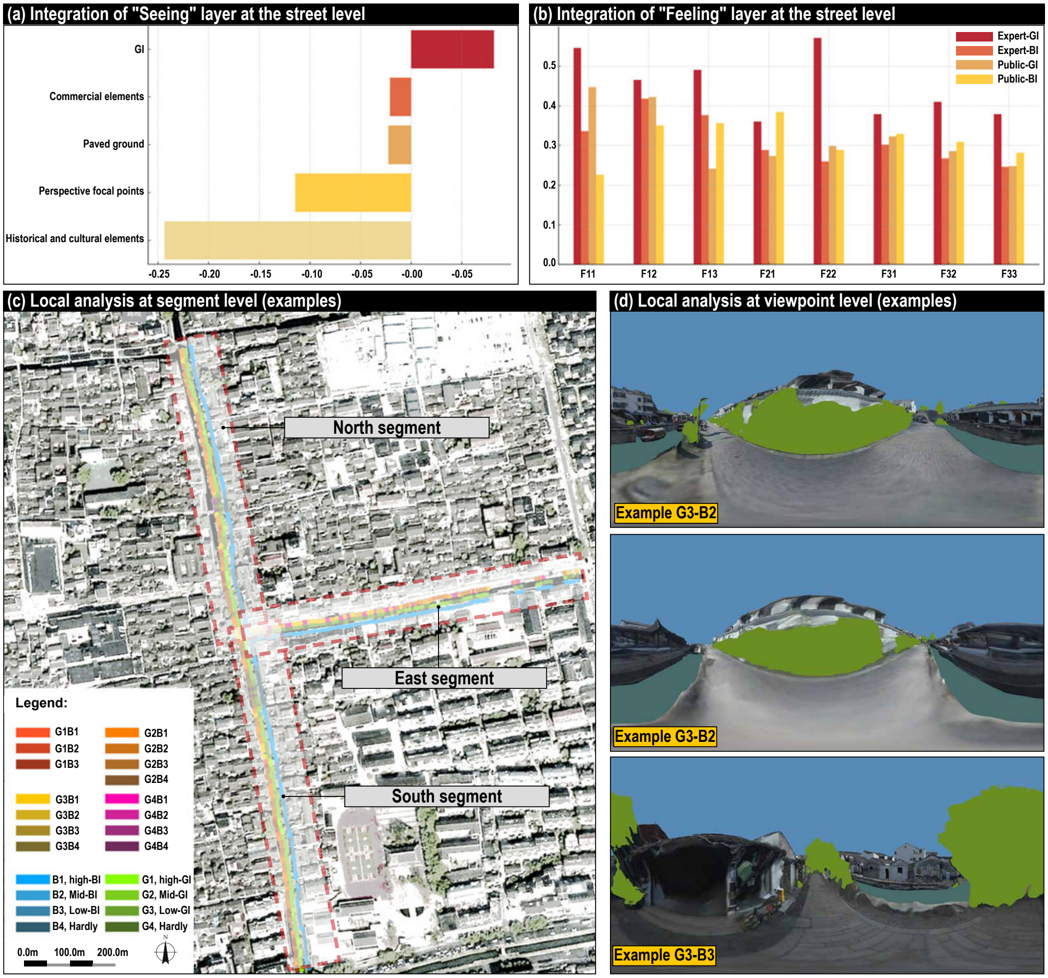


FIG. 5.10 Integration and generalization at "seeing" and "feeling" layer: (a) Visual attention weights by integrating LMM and BGI exposure; (b) Preference scores enhancing estimation for the entire street by integrating RF and BGI exposure; (c) The local analysis for the different segments; (d) The local analysis for the viewpoints.

b) **Localized predictions of BGI impacts:** Building upon UAV-derived spatial exposure modeling, this study further conducted detailed perceptual assessments for different segments of the street, specifically divided into the southern, northern, and eastern segments **(FIG. 5.10c)**.

In the southern segment, the area toward the south exhibited high levels of GI exposure and moderate BI exposure, contributing to a positive distribution of visual attention and significantly enhancing perceptual evaluations across *ecological aesthetics (F22)*, *visual aesthetics (F21)*, and *spatial functionality (F33)*, resulting in high overall preference scores (approximately 4.6–4.8). Conversely, the northern area of the southern segment, characterized by generally low levels of BGI exposure, exhibited notably lower preference ratings (approximately 3.8–4.1).

Similarly, in the northern segment, the central area demonstrated low BGI exposure levels, corresponding with reduced overall perceptual preference ratings (approximately 3.8–4.0). However, the southern and northern ends of the northern segment presented moderate BI exposure and relatively higher GI exposure, substantially improving environmental perceptions and spatial quality ratings (approximately 4.2–4.5), though still slightly below those of the southern portion of the southern segment.

For the eastern segment, high levels of BI exposure significantly elevated perceptual ratings for *visual aesthetics (F21)* and *genius loci (F13)*. Specifically, the western area of the eastern segment, with relatively lower GI exposure, exhibited somewhat reduced ratings for ecological aesthetics and spatial coherence, though overall preference scores remained relatively high (approximately 4.4–4.6). Meanwhile, the eastern area, characterized by both high GI and BI exposure, further enhanced ratings across visual and ecological aesthetics, leading to overall spatial perception scores of approximately 4.5–4.7, approaching the highest levels observed in the southern portion of the southern segment.

In addition, the environmental impact of BGI can also be assessed based on the specific areas of different viewpoints. For instance, the three viewpoints depicted in the figure show relatively low impacts of BGI on visual attention and preference, resulting in slightly lower preference scores **(FIG. 5.10d)**. This UAV-based spatial-perceptual analytical approach not only facilitates systematic evaluation at the overall street scale but also enables targeted assessments and predictions for specific points or segments of varying lengths and detail. Compared with traditional perception studies based solely on individual scenes or viewpoints, this method offers significantly greater flexibility and generalizability, providing robust support for spatial planning and design decisions in heritage areas.

c) **Understanding Layer: Divergent cognitive structures anchored in BGI:** At the understanding level, both user groups construct distinct cognitive pathways from BGI to perceptual meanings **(FIG. 5.11)**. Experts show a more comprehensive and balanced structure, linking both BI and GI to all three major themes, historical/cultural atmosphere, spatial aesthetics, and spatial functionality. Their interpretation is systematic, combining ecological, spatial, and symbolic dimensions. In contrast, the public group focuses more on affective and sensory experiences. Their pathways concentrate on visual aesthetics, cultural identity (genius loci), and recreational and well-being functions, reflecting a perception mode rooted in personal emotion and visual impression rather than systemic reasoning. These results highlight that while both groups recognize the value of BGI, experts approach it through functional and integrated thinking, whereas the public engages through aesthetic and experiential dimensions.

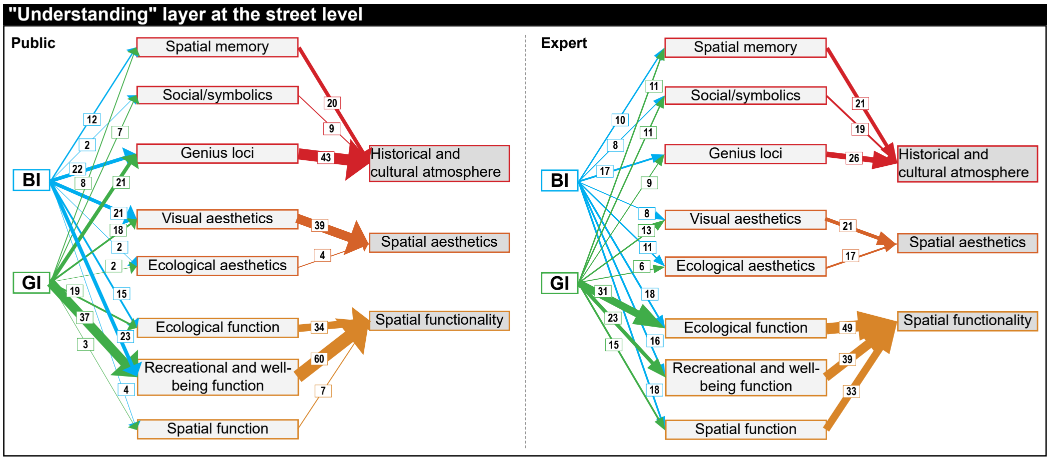


FIG. 5.11 Understanding layer: Cognitive pathways for both groups.

TOC

5.5 Discussions

By integrating UAV photogrammetry with a three-layer perceptual framework (seeing, feeling, understanding), this study provides nuanced insights into how BGI influences visual experiences in HUAs. The findings confirm that BGI subtly diversifies visual attention, consistently enhances subjective perceptual quality, and activates distinct cognitive interpretations among experts and the general public. In the following sections, these insights are critically discussed in relation to methodological integration, perceptual layering, and group-based differences, highlighting theoretical implications and practical contributions. Limitations and future research directions are also addressed.

5.5.1 Cross methodological gaps: Combination of digital tools with empirical approaches

In recent years, the study of visual perception has been characterized by a methodological divide: quantitative, expert-driven tools such as GIS and 3D modeling dominate spatial analysis, while empirical, perception-based approaches focus on users' subjective experiences (Gulten et al., 2025; Nijhuis et al., 2011). Although both streams offer valuable insights, each has inherent limitations when used independently. Purely spatial analyses (e.g., digital modeling approaches evaluating visibility or exposure metrics) frequently neglect human subjective experiences and emotions, especially inadequate for environments embedded with complex historical or cultural meanings (Ervin, 2001). Likewise, AI-based analyses using Street View Imagery (SVI) are constrained by fixed viewpoints, coverage limitations, and inadequate adaptability to diverse historical urban settings (Fan et al., 2025; Peng et al., 2025). For instance, in many heritage-sensitive areas, comprehensive street-view datasets are unavailable, severely restricting analysis applicability. On the other hand, empirical perception/behavior-based methods alone often undervalue spatial or environmental characteristics, making their findings challenging to generalize or integrate at larger scales (Chhetri & Stimson, 2014).

This chapter contributes to bridging this gap by integrating UAV-based photogrammetry and 3D semantic modeling with a three-layer empirical framework—combining eye-tracking, questionnaire surveys, and interviews. Specifically, the UAV-based data acquisition presented here overcomes the viewpoint and coverage constraints inherent to SVI approaches, offering a non-intrusive,

TOC

flexible alternative ideal for analyzing sensitive heritage contexts. The digital modeling component enables spatially explicit visibility mapping of BGI, producing scene-specific exposure metrics from pedestrian perspectives. These serve as the foundation for selecting representative visual stimuli and calibrating perceptual data at a fine-grained level. Empirical methods validate and contextualize these spatial metrics through user responses. This hybrid approach provides triangulated evidence across methods and links the objective spatial attributes of visual impact sources with the comprehensive spectrum of human perceptual responses. By correlating measurable exposure metrics with layered user perceptions, it enables a nuanced evaluation of visual impact levels that extends beyond mere geometric analysis. Although demonstrated here through the case of BGI (the influence is in general positive), the framework is broadly applicable to assessing diverse visual impact sources in different urban heritage contexts.

By demonstrating the value of cross-methodological integration, this study advances current visual assessment practices in heritage planning and Environmental Impact Assessment (EIA) (Dentoni et al., 2023). It supports a shift from static visibility simulations or isolated surveys toward multi-methodological and perception-informed evaluations, offering a more realistic reflection of how people experience complex, visually sensitive environments.

5.5.2 Cross perceptual layers: Seeing, feeling, and understanding

This study advances the understanding of visual perception in HUAs by systematically integrating three complementary layers: seeing, feeling, and understanding, into a unified analytical framework. Previous perceptual assessments often focus exclusively on one isolated dimension, limiting their explanatory power. Physiological methods, such as eye-tracking, are precise in revealing patterns of visual attention at the neurological and behavioral levels. However, they inherently neglect the experiential complexity and interpretive richness of visual perception. Specifically, eye-tracking data alone cannot clarify whether visual attention reflects attraction, confusion, or even cultural significance, as identical visual attention patterns could emerge from vastly different perceptual motivations (Geise, 2011; McGrath et al., 2019). Surveys capturing aesthetic or emotional preferences rely on participants' retrospective self-reports, which are inherently influenced by memory biases, social desirability, or cultural framing effects. Nevertheless, subjective evaluations derived purely from surveys are detached from real-time perceptual experiences, making it difficult to reliably associate reported preferences with actual visual processing behaviors or spatial-environmental features (Bishop &

Rohrmann, 2003; Vo et al., 2024). Qualitative cognitive studies, such as in-depth interviews or discourse analyses, excel at uncovering rich narratives and interpretive frameworks through which people understand visual environments. Yet, without grounding in measurable physiological data or systematically collected subjective ratings, these qualitative interpretations can remain speculative, contextually bounded, and difficult to generalize or systematically integrate into spatially explicit analyses (Lloyd & Gifford, 2024).

By merging physiological (seeing), affective (feeling), and cognitive (understanding) dimensions, the present study moves beyond these limitations, achieving a comprehensive and integrative analysis of visual perception. Each layer captures a distinct but interconnected facet of human experience, offering a progressively deeper view into how BGI shapes the visual environment. The seeing layer captures the immediate physiological responses through eye-tracking (Liu & Nijhuis, 2020), showing that BGI subtly diversifies visual attention without overriding cultural focal points. The feeling layer further reveals that greater BGI exposure consistently enhances subjective evaluations across aesthetic, atmospheric, and functional dimensions. Building on these sensory and affective responses, the understanding layer maps the cognitive pathways through which different user groups interpret BGI, from experts' functional-symbolic reasoning to the public's emotional and aesthetic engagement.

Together, these layers form a complementary and hierarchical structure, where sensory perception (seeing) initiates emotional appraisal (feeling), which subsequently supports deeper cognitive interpretation (understanding). This structured integration allows a multi-dimensional reading of visual experience and a gradual unfolding from surface-level impressions to meaning-making processes. Such an approach highlights both the analytical complementarity—each layer offering distinct but interconnected insights—and the progressive depth of perception, reinforcing the value of layered frameworks for nuanced visual impact assessments in culturally significant environments.

Notably, in heritage-sensitive contexts, where spatial perception is deeply embedded in cultural memory, symbolic narratives, and emotional attachments, visual impact assessment must move beyond numerical measures of visibility or the physiological tracking of gaze patterns. It must also address the experiential and interpretive dimensions that shape how individuals and groups relate to historic spaces (Assmann, 2011a; Lowenthal, 1975). Interventions (such as BGI in this study), when introduced into such contexts, interact not only with the physical environment but also with collective memory and identity, making its visual impact inseparable from affective responses and cognitive constructions of meaning (McDowell, 2016). By systematically linking seeing, feeling, and understanding, the present framework captures this complexity, offering a more holistic, culturally attuned methodology. It thus provides a critical basis for future heritage visual impact assessments that aim to respect, preserve, and enrich the experiential authenticity of historic urban landscapes.

5.5.3 Cross groups differences: General public and experts

While the three-layer framework reveals certain cross-group differences between experts and the general public in terms of visual attention, affective evaluation, and cognitive interpretation, these variations are secondary to a more profound implication: the shifting paradigms in heritage value assessment. Briefly, experts tend to interpret BGI interventions through multidimensional functional, ecological, and symbolic frameworks, whereas the general public's engagement is anchored in aesthetic pleasure, emotional resonance, and immediate spatial experiences.

This divergence reflects a broader and increasingly recognized shift in heritage theory and practice. Traditional models of heritage evaluation, predominantly expert-driven and focused on formally recognized values, are now expanding to incorporate diverse public perceptions and everyday experiences (Jones, 2017). Concepts such as "everyday heritage (Atkinson, 2016)," "informal heritage (Barrère, 2016)," and participatory heritage management emphasize that cultural significance is not solely determined by expert authority but emerges through lived experience, emotional attachment, and collective memory within communities (Li et al., 2020). In this context, visual impact assessment for heritages landscapes must move beyond narrowly technical or professionalized perspectives. They must systematically account for the perceptual, affective, and cognitive frameworks through which non-expert users engage with interventions in the landscape. By capturing both expert and public pathways of meaning-making, assessments can better reflect the pluralistic nature of heritage value judgments and more effectively guide the design and management of culturally sensitive environments.

5.5.4 Insights for HUA development

Building upon the cross-layer and cross-group findings, several insights emerge for the future planning and visual management of HUAs, particularly where BGI forms an integrated part of the spatial and cultural experience.

First, the layered perception model demonstrates that BGI is not merely a functional or decorative component, but a perceptual agent that modulates attention, influences preferences, and shapes meaning. Even when not the primary visual focus, BGI supports more diversified and relaxed visual scanning, contributing to environmental legibility and psychological restoration. This suggests that strategic incorporation of BGI can enhance visual coherence without overwhelming the heritage character. For example, in newly reconstructed historic environment (Zhongzhangjia Xiang), higher levels of BGI exposure can effectively enhance people’s preference for the newly created spaces, as illustrated by Scene 20. Although its score is slightly lower than other scenes with similar BGI levels, the preference rating is still higher than many areas with lower BGI exposure.

Second, by linking BGI exposure to perceptual evaluations, the study provides a framework for evidence-based visual enhancement. Scenes with moderate to high BGI exposure consistently achieved higher perceptual scores, indicating that balanced integration (not excess) is key. Overdesign or uncontrolled vegetation growth, while not present in the case site, may lead to visual clutter or loss of historical legibility, a risk noted in other studies.

Third, the differentiated cognitive responses between experts and the general public underscore the need for multi-vocal design and evaluation processes. Experts seek systemic coherence and functional performance, while the public prioritizes sensory richness and cultural resonance. Planning strategies should therefore accommodate both analytical and experiential perspectives, facilitating broader public engagement and heritage appreciation.

Finally, the integration of digital modeling and empirical perception research offers a scalable and transferable approach to managing HUA visual environments. Recent advances in digital imaging technologies, many of which are now accessible through consumer-grade devices, combined with increasingly efficient modeling and rendering algorithms, such as 3D Gaussian Splatting, have significantly lowered the technical barriers for such integration. These developments make it feasible and highly desirable to more widely adopt hybrid approaches that blend digital techniques with traditional empirical methods, enhancing both the precision and the cultural sensitivity of visual impact assessments across diverse heritage contexts.

5.5.5 Limitations

Despite these contributions, several limitations must be acknowledged. First, the findings primarily apply to HUAs where BGI is already integrated into the urban fabric and moderate in scale. Therefore, the visual impacts identified here may not generalize to other contexts, such as arid regions, areas with minimal vegetation, or diverse heritage urban typologies. Future studies should systematically investigate these contexts. Second, the representativeness of the study sample was limited in terms of demographic variability, including gender, age, cultural background, and the structure of both general public and expert groups. These sampling limitations potentially constrain the broader applicability of perceptual and cognitive findings. Demographic factors (e.g., gender, age, culture) were intentionally not controlled, as the study focused primarily on perceptual differences between expert and public groups. However, future work should address these variables explicitly. Third, the integrated methodological approach employed in this study, including UAV-based data acquisition, eye-tracking, and qualitative assessments, is resource-intensive and logistically complex, limiting its immediate scalability beyond small-scale pilot studies. Future research could explore methodological simplifications or adaptations suitable for broader or larger-scale applications. Finally, the eye-tracking experiments utilized static photographs rather than mobile glasses in field settings, potentially reducing the ecological validity of perceptual data. Future research should consider employing mobile eye-tracking technology to capture more realistic perceptual responses.

5.6 Conclusions

This chapter investigates how BGI shapes visual perception in HUAs by integrating UAV photogrammetry with a perception-based framework encompassing three layers: seeing, feeling, and understanding. Combining spatially explicit modeling with empirical methods, including eye-tracking, questionnaire surveys, and in-depth interviews, the study assessed the perceptual influence of BGI across experts and the general public.

The findings reveal that BGI contributes to HUA perception in distinct but complementary ways. At the seeing layer, BGI moderates visual attention patterns, subtly reducing the dominance of traditional focal points and encouraging more diverse visual engagement. At the feeling layer, BGI exposure correlates with consistently higher user evaluations across historical atmosphere, aesthetics, and spatial functionality. At the understanding layer, BGI serves as a cognitive trigger, activating different interpretive pathways among user groups. GI exerts a more stable and broadly positive impact, while BI exhibits more context-dependent and group-specific effects. Professionals display a balanced and systemic interpretation of BGI, whereas the general public emphasizes emotional and aesthetic connections.

Methodologically, this study demonstrates the value of integrating digital spatial analysis with perception-based empirical approaches. By systematically bridging spatial quantification and multi-layered perception analysis, it offers a novel framework that advances visual impact assessment beyond traditional singular-method approaches. The proposed cross-method, cross-layer, and cross-group framework offers a practical, replicable model for perception-informed visual impact assessment in heritage contexts. This research is among the first to explicitly examine how BGI influences visual perception in HUAs, addressing a critical but previously overlooked dimension of heritage-sensitive landscape evaluation. Beyond BGI, the framework holds significant potential for broader applications in evaluating diverse spatial interventions in culturally sensitive environments, supporting more inclusive, evidence-based, and culturally attuned planning practices. By highlighting both spatial attributes and lived perceptual experiences, the study contributes new methodological pathways for advancing visual environmental assessments that respond to the pluralistic and evolving nature of heritage conservation demands.

Author's contribution in this case study

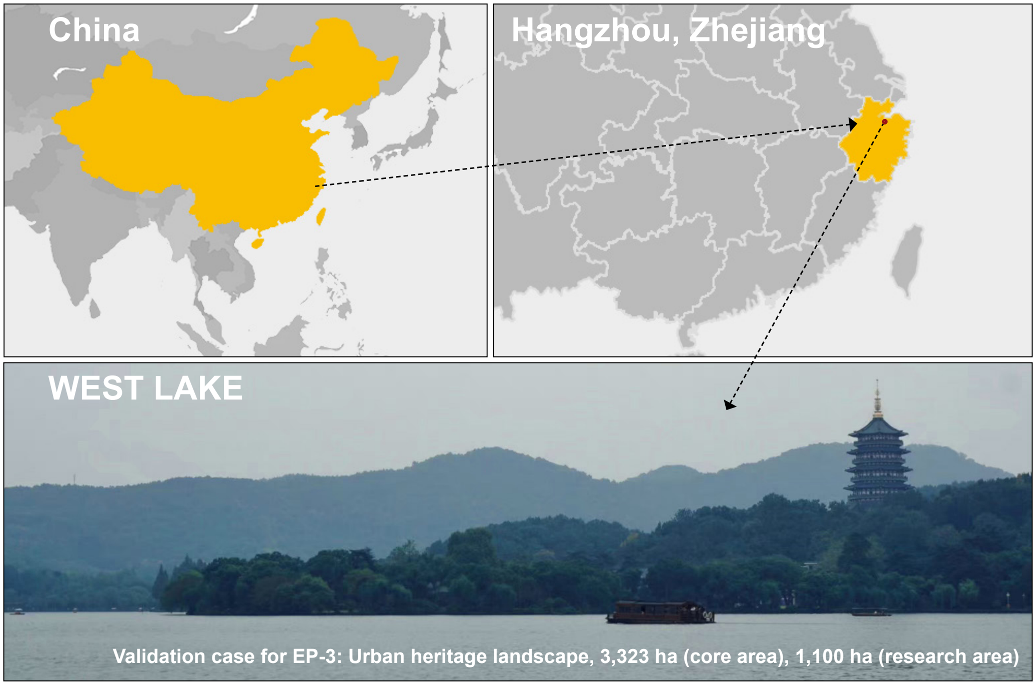
This case study of Pingjiang Road was developed by the author in consultation with the promotor Steffen Nijhuis, whose feedback helped refine the research design. The author was responsible for the overall research design and methodological framework, the writing and revision of the case-study text, and part of the data processing, modeling and analysis, as well as the visualization of the results. The co-author contributed by carrying out on-site UAV data acquisition along Pingjiang Road, recruiting participants, and conducting the on-site and online perception experiments (eye-tracking, interviews, and questionnaires), as well as part of the visualization and data processing tasks.

6 EP-3: Case study of an urban heritage landscape

Enhancing visual attribute comprehension of urban heritage landscapes using combined GIS-based visual analysis methods

This chapter is composed of three published papers.
Peng, Y.*, Nijhuis, S., Geng, M., & Yu, Y. (2025). "Enhancing visual attribute comprehension of urban heritage landscapes using combined GIS-based visual analysis methods: West Lake as a case study"; *Environmental Impact Assessment Review.*
Peng, Y.*, & Nijhuis, S. (2021). "A GIS-based algorithm for visual exposure computation: the west lake in Hangzhou (China) as example"; *Journal of Digital Landscape Architecture.*
Peng, Y.*, Nijhuis, S., Yu, Y. & Wu, Z. (2026). "From Comparison to Combination: Street View Imagery (SVI) and 3D Model-Based Analyses for Urban Visual Environment Assessment". *Landscape Architecture and Sustainability.*

This chapter aims to improve the comprehension of complex visual attributes in large-scale urban heritage landscapes through a multi-method GIS-based pathway. Using West Lake as the empirical setting, it integrates complementary visual analysis techniques to capture different dimensions of heritage visual structure, including exposure patterns, viewpoint logic, spatial sequence, and the distribution of visually significant elements. By combining multiple spatial analysis perspectives, the chapter shows how no single method is sufficient for describing urban heritage visual complexity, and how method combination can improve interpretability and robustness across scales. The results reveal key spatial regularities that organize visual experience and help explain why certain areas function as visual anchors, corridors, or transition zones. The chapter ultimately provides a structured analytical workflow that supports planning, conservation reasoning, and communication by translating complex urban heritage visual systems into interpretable spatial evidence.



Contents	Methods	Data
A. Object: urban heritage landscape, landscape scale; B. Theme: management of visual environment via understanding heritage's visual attributes.	A. Horizontal FOV analysis B. Vertical visibility analysis C. Sematic segementation D. Design diagramming	A. Surveying and mapping data (elevation data) B. Open-source geo-data for land use/routes/buildings C. Street view imagery (Baidu)

FIG. 6.1 Summaries of the case study.

List of Abbreviations

Abbreviation	Full Term	Explanation
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 Imagery	Panoramic images captured through street-view mapping services, used in spatial-visual analysis.
CV	Cumulative Viewshed	An analysis of 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.
DEM	Digital Elevation Model	A gridded representation of terrain elevation used for visibility modeling and viewshed computation.
LoS	Line of Sight	A straight ray from a viewpoint used to test visibility and derive field-of-view composition.
PSPNet	Pyramid Scene Parsing Network	A deep learning model used for semantic segmentation of street-view imagery.

6.1 Introduction

Urban heritage landscapes, located at the interface between historical environments and modern urban development, represent a critical category of cultural heritage (Veldpaus et al., 2013). 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...*" (European Landscape Convention, 2000), landscapes are inherently shaped by human perception, with vision serving as the dominant sensory modality (Bell, 2012; Liu & 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 et al., 2024). Unlike ordinary urban spaces, heritage landscapes interweave historical layers, symbolic meanings, and evolving urban dynamics (Bandarin & Van Oers, 2012; Worthing & 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, 2015b) 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 & Van Oers, 2012; Worthing & 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 & Meitner, 2013; Domingo-Santos et al., 2011; Ervin & Steinitz, 2003; Inglis et al., 2022; Liu & 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 & 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 chapter 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 (UNESCO, 2011). 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 chapter 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 chapter 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.

6.2 Review of GIS-based VAMs

GIS-based VAMs aim to investigate the relationship between landscapes and human perception (Chamberlain & 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. 6.2a)**, a category of methods that encompasses bird’s-eye-view visual analysis tools (Liu & Nijhuis, 2020; Nijhuis et al., 2011), like visibility assessment using viewshed-dominant algorithms/methods;

b) **Horizontal VAMs (eye-level, digital, FIG. 6.2b)**, 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. 6.2c**), 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 & Fukamachi, 2006; Sugimoto, 2018), among others.

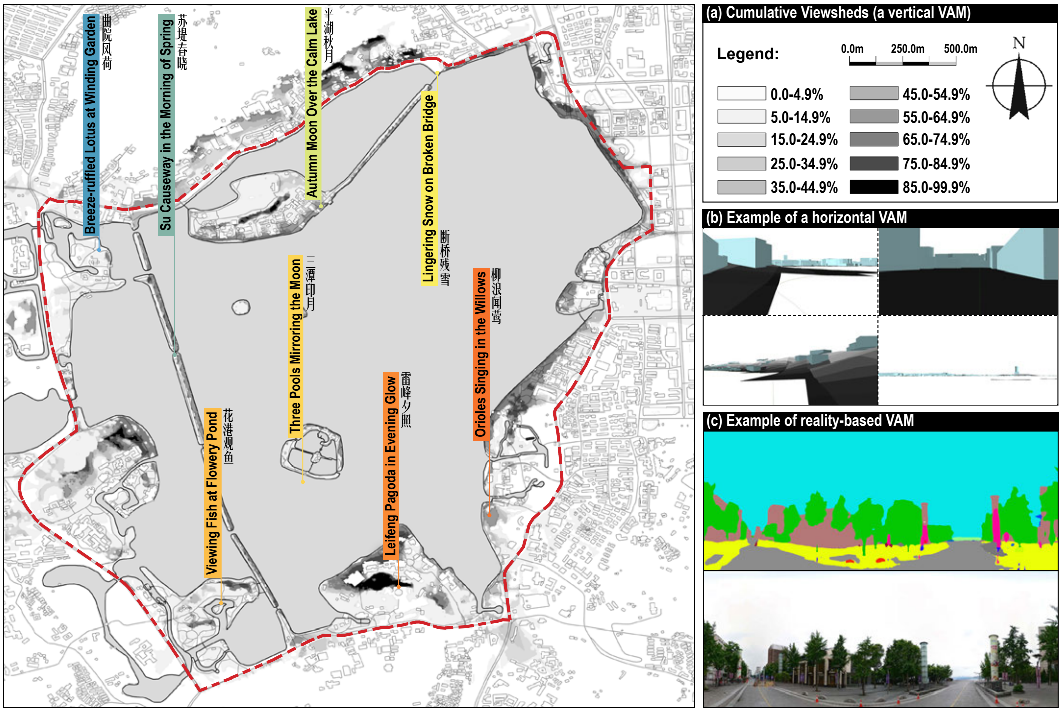


FIG. 6.2 Explanations for three categories of VAMs: (a) Example of vertical (bird's-eye) VAMs (Cumulative Viewsheds for West Lake, and the locations of the "Ten Scenic Places"); (b) example of reality-based VAMs; (c) example of horizontal (eye-level) VAMs.

TOC

6.2.1 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 & Blumentrath, 2022; Labib et al., 2021; Yu et al., 2016), visibility maps of landmarks (Bartie et al., 2008; Czyńska & 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 & Colby, 2002); The application of such methods extends beyond research on visual-spatial characterization (Van Eetvelde & Antrop, 2009, 2011; Yang et al., 2020), openness/enclosure (Wagtendonk & 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 & 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.

6.2.2 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 & Wee, 2009; Peng & 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 & Mérida-Rodríguez, 2017; Pardo García & 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.

6.2.3 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 & Antrop, 2011), video footage (Pardo-García & Mérida-Rodríguez, 2017; Sui et al., 2022), eye-tracking (Dupont et al., 2014; Dupont et al., 2016), and sketch-based analysis (Liu & 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 & 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 (Cavallo, 2015; Micusik & 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.

6.2.4 Summary

The reviewed visual analysis methods (classified as vertical, horizontal, and reality-based) demonstrate distinct perspectives and data foundations **(TABLE 6.1)**. 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.

TABLE 6.1 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.

6.3 Case study and data

A World Cultural Heritage Site, Cultural Landscape of West Lake, Hangzhou, has been selected as a case study **(FIG. 6.3c)**. 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.

6.3.1 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:

- **RQ6-1: What are the visual-spatial connections between the lake, the city, and the surrounding cultural landscapes?** This question 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.

- **RQ6-2: 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.

- **RQ6-3: 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.

TOC

6.3.2 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:

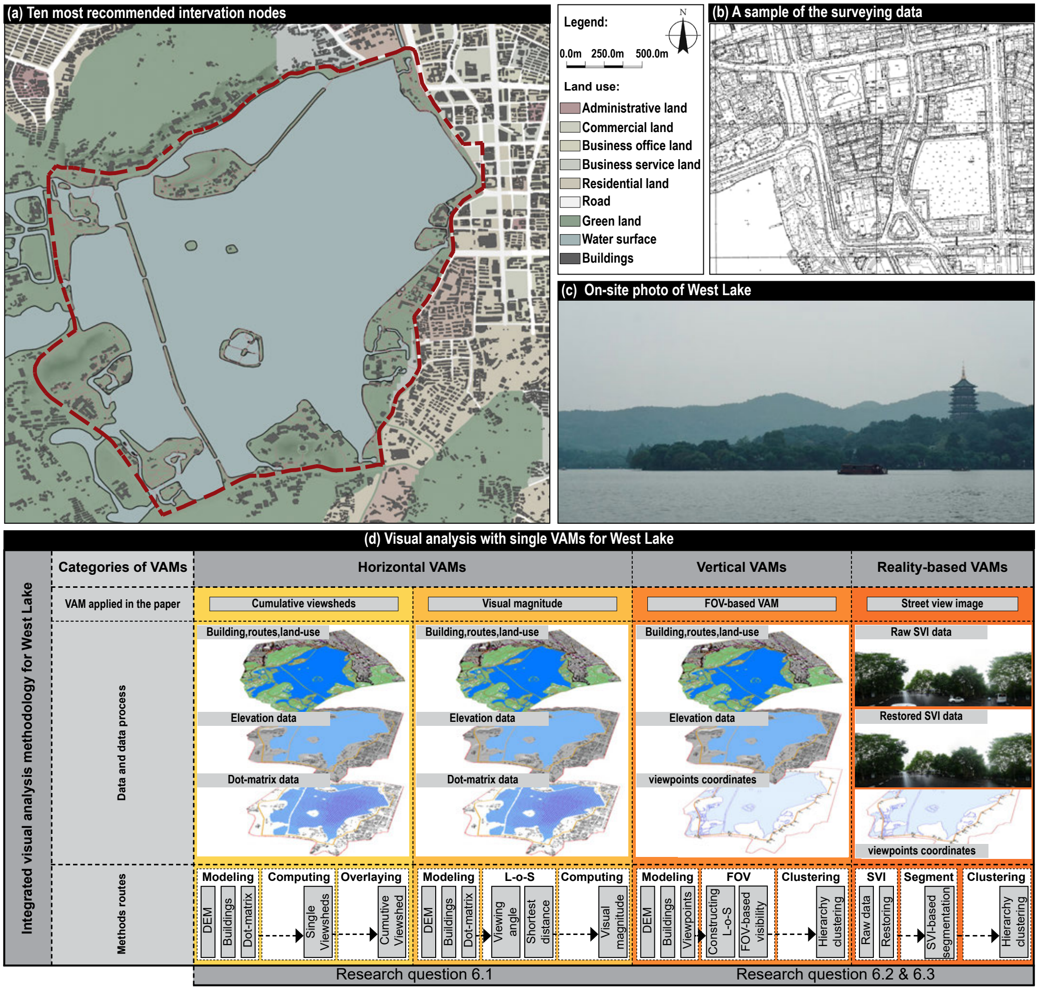
a) **SVIs:** The SVI data utilized in this chapter were sourced from Baidu Maps (https://map.baidu.com/) as panoramic views at various viewpoints on the roads near/surrounding West Lake (the coordinate data for each viewpoint has also been extracted, and the distance between two adjacent points is approximately 5 meters, 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. 6.3b):** These data, obtained from the local government surveying and mapping authority, consist of elevation points (approximately 100 points per hectare) and contour lines (with a contour interval of 1 meter). The lowest point in the study area is at an elevation of 3.8 meters, while the highest point is at a height of 48.3 meters, resulting in a vertical difference of 44.5 meters.

c) **Open-source data (FIG. 6.3a)** (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.

6.4 Methods



(e) Visual analysis with combined VAMs for West Lake

	Research question 6.1		Research question 6.2	Research question 6.3
	Lake-view landscapes	Visual corridors	Landscape classification	View analysis
Cumulative viewsheds	Applied	Applied	Applied	Applied
Visual magnitude	Applied			Applied
FOV-based VAM	Applied		Applied	Applied
Street view image		Applied	Applied	Applied

FIG. 6.3 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.

TOC

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. 6.3d, FIG. 6.3e)**.

6.4.1 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. 6.3d)**. 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 **RQ6-1**. 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 **RQ6-2**. Furthermore, these two methods are employed to analyze the visual composition of lake-view sites, offering insights into **RQ6-3**.

6.4.1.1 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-meter 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.

6.4.1.2 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.

6.4.1.3 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 meters.

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 meters.

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., 2023).

6.4.1.4 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., 2023).

6.4.2 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 S**ection 6.4.2.1** address **RQ6-1**, the VAM in **Section 6.4.2.2** responds to **RQ6-2**, and the VAM in **Section 6.4.2.3** answers **RQ6-3**.

6.4.2.1 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.

6.4.2.2 Classification of landscape types along the lakeside roads

This chapter 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).

6.4.2.3 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.

6.5 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.

6.5.1 Results from single VAMs

6.5.1.1 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. 6.4a).** 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. 6.4b)**. 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.

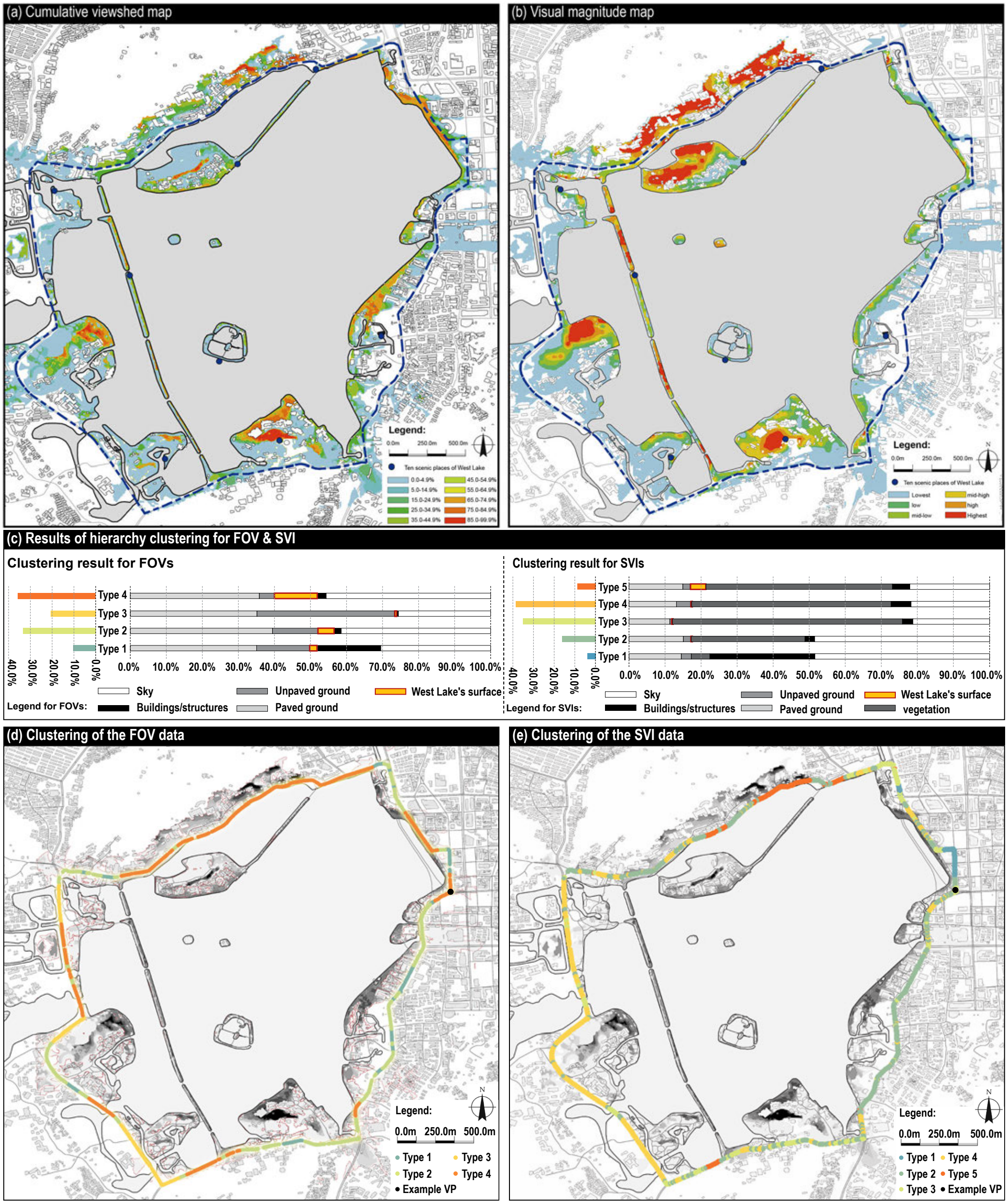


FIG. 6.4 Research findings of single VAMs: (a) CV maps; (b) VM maps; (c) clustering analysis for FOV and SVI; (d) FOV clustering; (e) SVI clustering.

Note: The continuous CV and VM values were classified by equal range of values between the observed minimum and maximum.

TOC

6.5.1.2 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. 6.4c)**. Hierarchical clustering revealed four distinct landscape types along the main roads surrounding West Lake **(FIG. 6.4d)**: **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) **(b)Analysis Results of SVI:** Six columns of colors represent the proportion for each landscape component within the SVI **(FIG. 6.4c)**. Hierarchical clustering method identifies five landscape types along the lakeside main roads **(FIG. 6.4e)**: **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** 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.

6.5.1.3 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.

6.5.2 Results from combined VAMs

6.5.2.1 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. 6.5a)**. 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. 6.5b)**. 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. 6.5a)** 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.

TOC

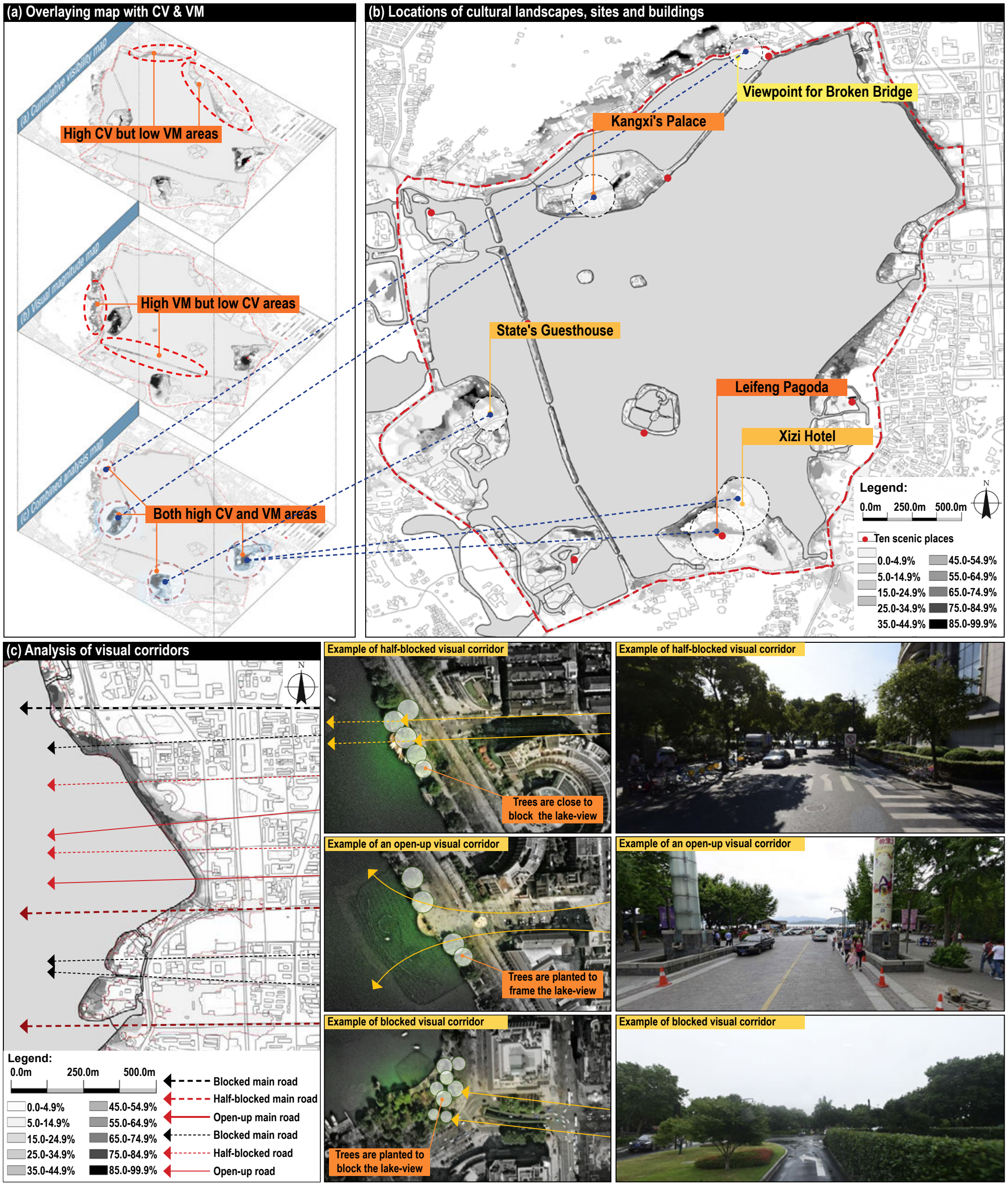


FIG. 6.5 The analysis results of the visual-spatial relationship between the lake and its surrounding environment using combined VAMs include: (a) overlaying CV and VM maps to identify high-quality lake-viewing spaces; (b) the spatial relationship between high-quality lake-view spaces and cultural landscapes/buildings; (c) visual corridors: visual and spatial connections between the city and the lake.

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. 6.5b)**. 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.

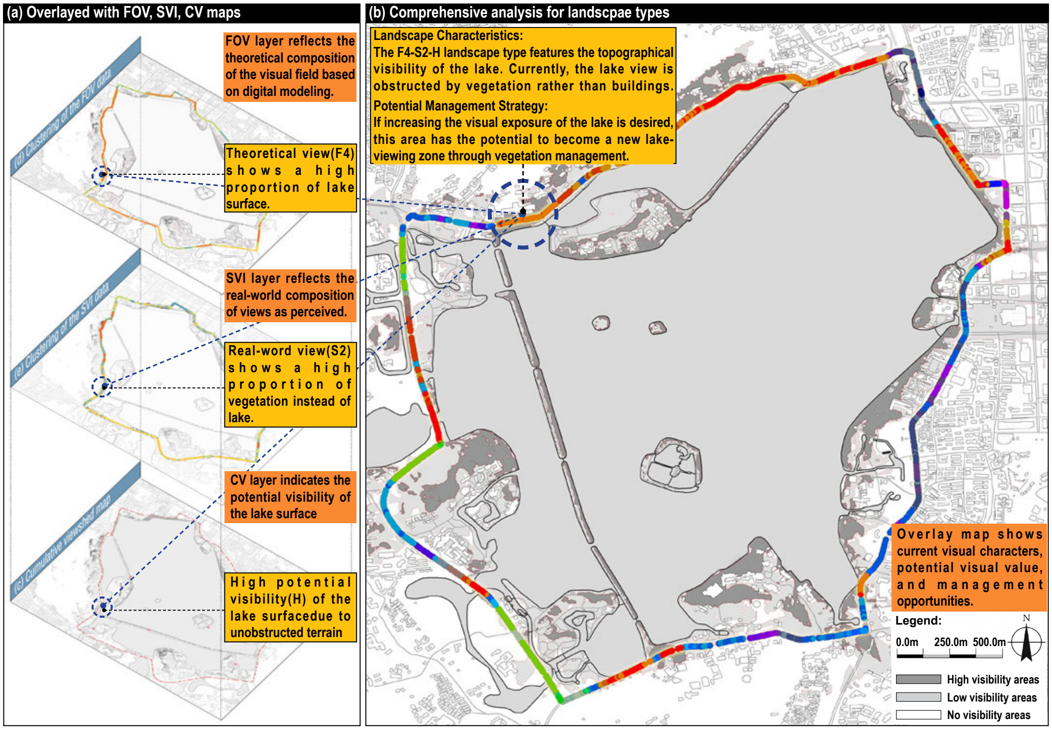
b) **Urban lake-view corridors:** The CV analysis identifies ten roads with the potential to establish lake-view corridors, connecting the city to the lake (**FIG. 6.5c**). However, SVI data reveals that most of these corridors are obstructed by vegetation. Among the three primary roads, two are partially 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.

6.5.2.2 Landscape types classification results of the lakeside roads

Thirty-seven different integral landscape types have been identified **(FIG. 6.6a, FIG. 6.6b)**. 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

TOC

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.



(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. 6.6 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.

TOC

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 & 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.

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.

6.5.2.3 Visual composition analysis of lake-view sites

This section uses two examples **(FIG. 6.7)** 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. 6.7a):** 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. 6.7b):** 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.

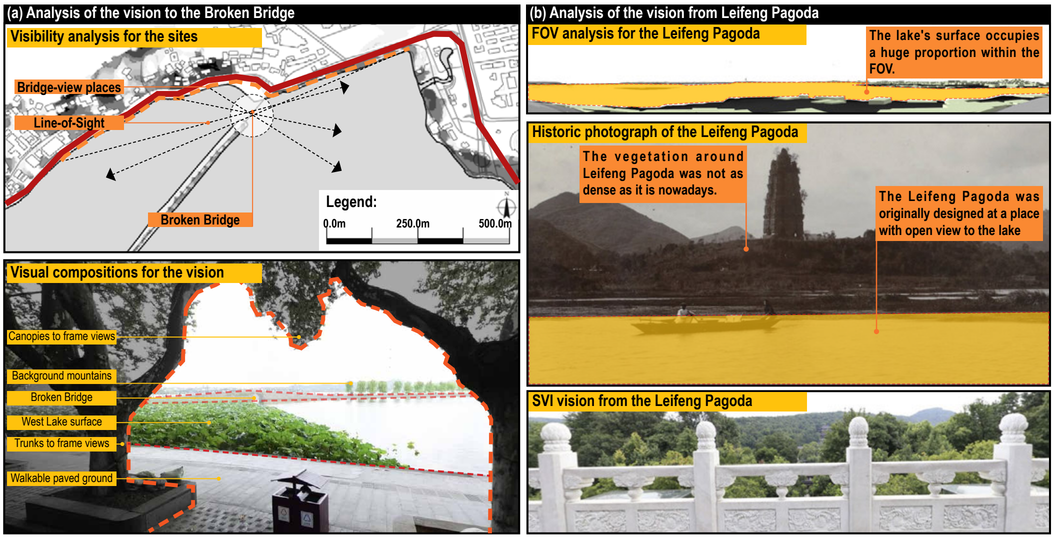


FIG. 6.7 Visual composition analysis of lake-view sites using combined VAMs: (a) the framing effect of vegetation in "Lingering Snow on the Broken Bridge"; (b) the complete obstruction of lake views by vegetation at the base of Leifeng Pagoda.

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.

TOC

6.5.3 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 6.2)**:

TABLE 6.2 Comparison between single and combined VAMs

Research question	Insights from single VAMs	Additional insights from combined VAMs
R6-1: Visual-spatial relation-ship between the lake and Its surrounding environment (dark orange and yellow boxes in)	- 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 man-agement improves visual corridors and enhances city-lake connectivity.
RQ6-2: Classification of lakeside road landscape types	- 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.
RQ6-3: Visual characteristics of lake-view sites	- 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.*"

— **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.

- **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.

- **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. 6.8)**.

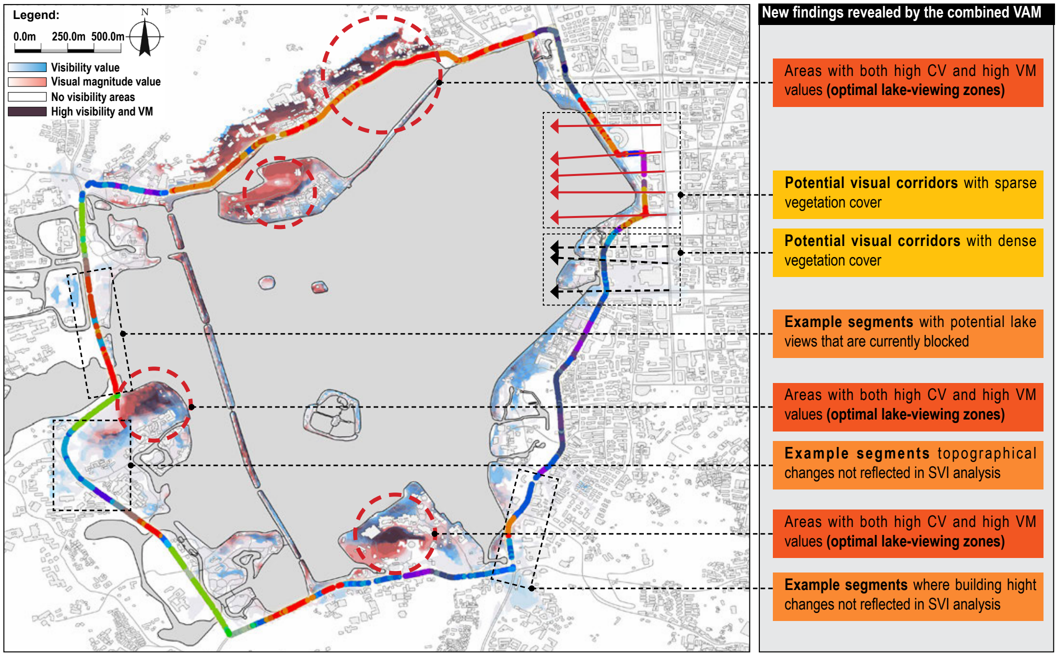


FIG. 6.8 The new findings derived from the combined VAMs.

6.6 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 & 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.

TOC

6.6.1 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. 6.9a):** The spatial 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. 6.9b)**. 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. 6.9a):** 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. 6.9c)**.

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. 6.9a):** 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. 6.9d)**.

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.

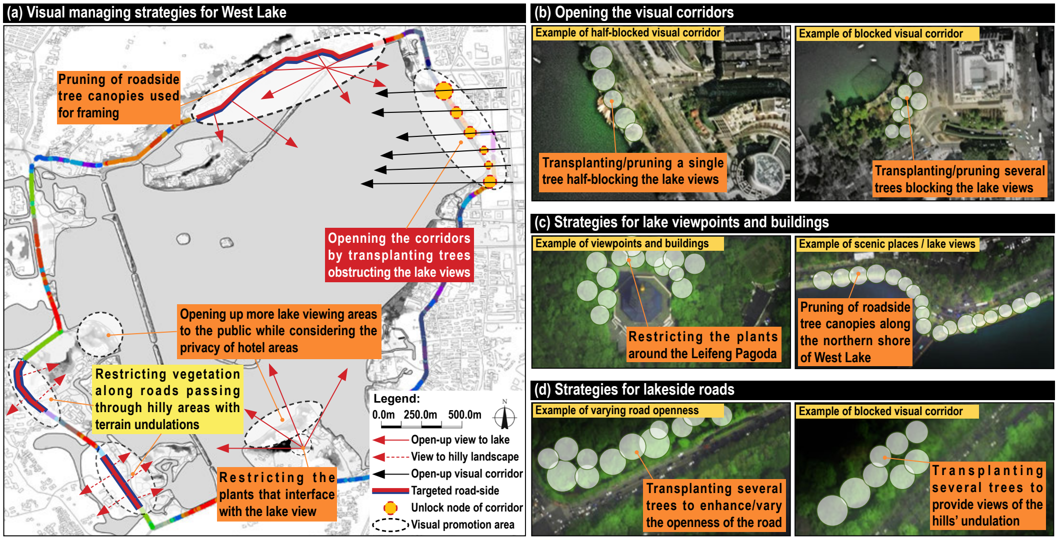


FIG. 6.9 Visual management strategies for West Lake: (a) overview of the strategies; (b) opening the visual corridors facing the lake; (c) strategies for managing the lake views from the scenic places and buildings; (d) strategies for managing the visual environments along the routes.

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, 2015a; 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 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 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.

6.6.2 Strengths and limitations of single VAMs

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

6.6.2.1 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 & Agur, 2021; Chamberlain & 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 & 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.

TOC

6.6.2.2 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 & 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. 6.9**).

6.6.2.3 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.

6.6.2.4 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:

TOC

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., 2021), were particularly problematic in heritage contexts where skyline and horizon perception play symbolic roles **(FIG. 6.10a)**.

b) The method was unable to detect buildings or terrain behind vegetative cover, even when clearly visible to human observers **(FIG. 6.10b, FIG. 6.10c)**. 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.

FIG. 6.10 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.

TOC

6.6.3 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 & Miller, 2007; Wróżyński et al., 2016). 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. 6.11)**. 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. 6.4)**, 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 & 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.

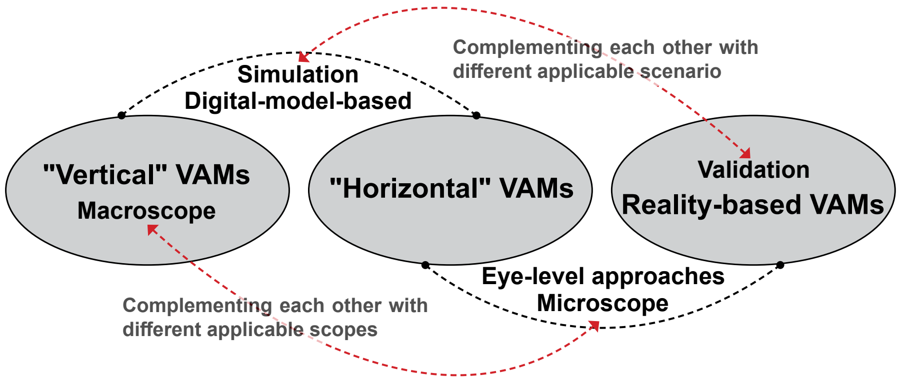


FIG. 6.11 Complementarity among different VAMs

6.6.4 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 chapter 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. 6.3)**. 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.

6.7 Conclusions

This chapter 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 chapter mainly cover three aspects:

a) **Insights into the methodologies of visual landscape research:** Building on the case study of West Lake, this study'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 study 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 study 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 chapter 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.

Author’s contribution in this case study

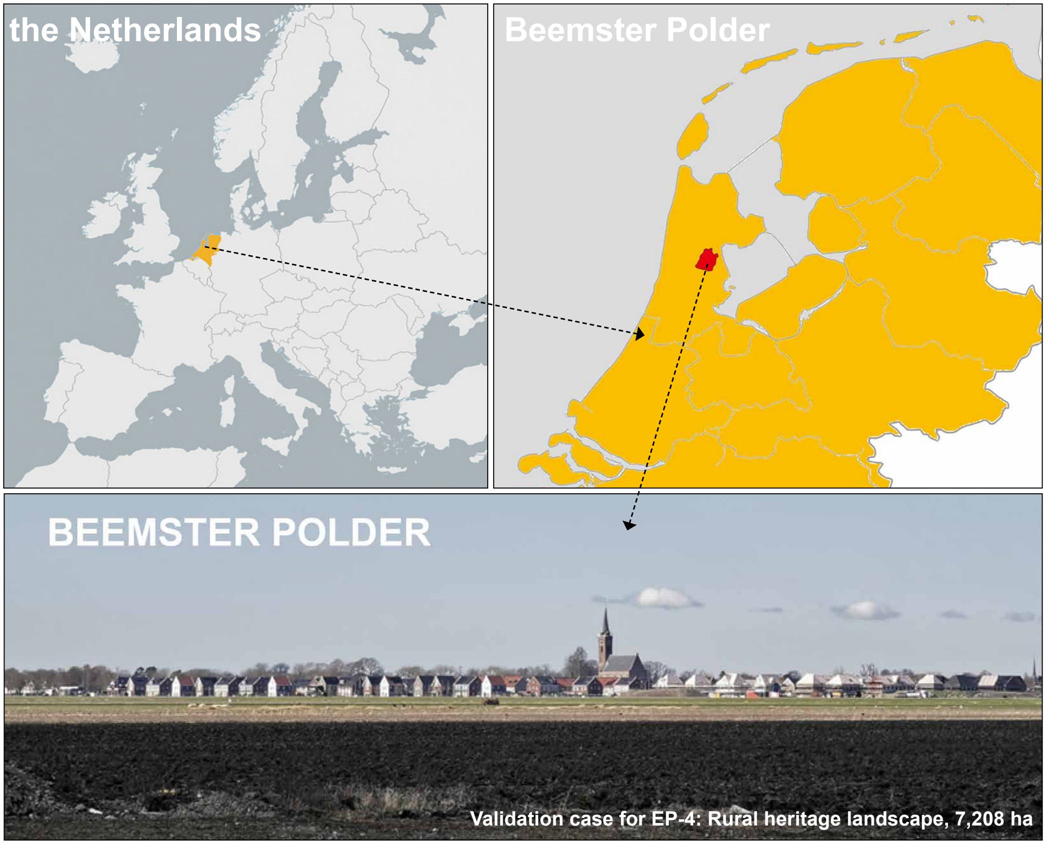
This West Lake case study was developed by the author in collaboration with the TU Delft promotors. The author was responsible for the research design and methodological framework, the writing and revision of the case-study text, the development of the analytical methods, data analysis, and part of the visualization of the results. The co-author contributed by collecting and preprocessing part of the streetscape imagery, carrying out part of the GIS computations, and producing some of the visualizations. The topographic survey data used in this case were provided by a research team from the author’s master’s studies; these mapping data had been de-identified before being made available for this research.

7 EP-4: Case study of rural heritage landscape

When to Stop? A Visual Impact Assessment Framework for Incremental Urban and Community Expansion in Rural Heritage Landscapes

This chapter is based on a published paper.
Peng, Y., Nijhuis, S., Wang, Z., Yu, Y.*, Verbree, E., & van Oosterom, P. (2026). "When to Stop? A Visual Impact Assessment Framework for Incremental Urban and Community Expansion in Rural Heritage Landscapes". *Sustainable Cities and Society.*

This chapter aims to develop a perception-informed visual impact assessment pathway that supports decision-making under incremental change in open rural heritage landscapes. Using Beemster Polder as a UNESCO rural heritage context, it integrates point-cloud-based visibility modeling with scenario-based assessment and immersive key observation point evaluation. The chapter compares multiple development stages and future expansion scenarios, demonstrating that traditional visibility methods can underestimate visual impacts in certain morphologies, while immersive evaluation aligns more closely with human perceptual responses. By linking spatial exposure indicators to perception-based metrics, the chapter makes the "when to stop" decision explicit through stage-comparable thresholds and stop rules. The resulting framework produces decision-grade evidence that can guide mitigation, scenario ranking, and adaptive governance, and it is designed to be transferable to other heritage-sensitive rural-urban fringes facing gradual development pressure.



Contents	Methods	Data
A. Object: rural heritage landscape, regional scale; B. Theme: Trade-off between local exploitation and heritage protection via visual impact assessment.	A. GIS-based spatial and visibility analysis B. Semantic segmentation C. 3D Guassian Splatting rendering (representation) D. VR head-/eye-tracking tools	A. Dense point cloud (ANH-5) B. Street view imagery (Google) C. UAV imagery D. Multi-view imagery by X-gride L1 scanner E. Hman Perception/behavior data

FIG. 7.1 Summaries of the case study

Abbreviations used in Chapter 7

Abbreviation	Full term	Notes (Chapter 7 context)
EP-4	Expanded Pathway 4	Pathway type used for the rural heritage landscape case study (Chapter 7).
VIA	Visual Impact Assessment	Core evaluation framework to assess visual impacts and define a stop-line for incremental development.
SDG	Sustainable Development Goal	United Nations Sustainable Development Goals referenced for policy relevance.
GIS	Geographic Information System	Spatial analysis environment used for visibility and landscape-structure metrics.
SVI	Street View Imagery	Multi-temporal street-level imagery used for panoramic segmentation and time-series change tracking.
KOP	Key Observation Point	Selected viewpoints for consistent, eye-level visual assessment across phases and scenarios.
3DGS	3D Gaussian Splatting	Reality-capture rendering method used to reconstruct present scenes and simulate future scenarios.
VR	Virtual Reality	Immersive environment used to present stimuli and collect eye- and head-movement responses.
LMM	Linear Mixed-effects Model	Statistical model used to estimate stage-/scenario-comparable contrasts while accounting for participant/viewpoint variability.
AOI	Area of Interest	Semantic regions (e.g., buildings, sky, vegetation) used for fixation/dwell aggregation.
FOV	Field of View	Visual field used for image segmentation and eye-level indicator computation (e.g., building share).
LiDAR	Light Detection and Ranging	Source of 3D point cloud data for terrain/vegetation/building geometry.
AHN-5	Actueel Hoogtebestand Nederland (version 5)	Dutch national LiDAR point-cloud dataset used to build the baseline 3D model.
DEM	Digital Elevation Model	Terrain model; discussed as a potential source of ‘bare-earth’ bias in viewshed analysis.
DSM	Digital Surface Model	Surface model including objects; referenced in comparison with point-cloud-based visibility analysis.
CI	Confidence Interval	95% confidence intervals reported for model estimates and contrasts.
GOR	Ground Occupation Ratio	Spatial indicator used to quantify land-domain occupation change across phases and scenarios.
ΔGOR	Change in Ground Occupation Ratio	Difference in GOR (often expressed in pp) relative to a baseline phase.
SBE	Scenic Beauty Evaluation	Referenced as an optional evaluation method in the decision layer of VIA.
OUV	Outstanding Universal Value	UNESCO concept used when discussing World Heritage decision strictness.
std	Standard deviation	Used for head-movement dispersion indicators (yaw, roll, pitch).

TOC

7.1 Introduction

In recent decades, global urbanization and the outward expansion of settlements have accelerated; by 2050, nearly 70% of the world's population will live in urban areas (Desa, 2006). Urban expansion in peri-urban and suburban areas has emerged as a dominant spatial process (Xue et al., 2025), reshaping the visual environment and the sense of place in suburban and rural landscapes (La Rosa et al., 2018; Tan et al., 2024). Many of these landscapes embody cultural and heritage values: they archive agrarian spatial patterns, production systems, and historic hydraulic networks, and they deliver cultural ecosystem services such as place attachment, aesthetic experience, and recreation (Aimar, 2024; Assessment, 2005; Zhang & Stewart, 2017). Professional practice and international guidelines, such as *Sustainable Development Goal 11* (SDG 11; Sustainable Cities and Communities) (Falah et al., 2025), particularly Target 11.3 on participatory and sustainable urbanization and Target 11.4 on safeguarding cultural and natural heritage, emphasize the importance of setting and authenticity for safeguarding such heritage landscapes and call for systematic impact identification and assessment during planning and design (Bond & Worthing, 2016; Pereira Roders & van Oers, 2012).

In practice, however, low-intensity, incremental urban expansion, such as the gradual spread of small clusters of low-rise, community-oriented housing at the urban fringe, is the most common form of edge growth yet is often overlooked (Echenique et al., 2012; Soltani et al., 2025). These changes are less conspicuous than landmark buildings or wind turbines and therefore tend to escape early scrutiny (Ravetz et al., 2013). Their cumulative effects produce visible degradation that is difficult to define and manage (Gazzola et al., 2018). Systematic assessment of these impacts on peri-urban rural heritage landscapes is both an academic concern and a pressing planning need, and it should also establish evidence-based "when to stop" limits for such development to prevent further impact (Bailoni et al., 2012).

Visual Impact Assessment (VIA) is the internationally adopted tool for addressing this problem (Fisher, 1993; Oxman, 1997). It typically combines GIS-based viewshed analysis (Wróżyński et al., 2024), photomontage (Zube et al., 1987), and 3D simulation to model change (Ervin, 2001), then compares existing, proposed, and future scenarios from key observation points (KOPs) and along moving viewpoints (Jin, 2023). Public perception and expert judgment are integrated into an overall appraisal (Han et al., 2025). Although the workflow is relatively mature, most practice and scholarship still concentrate on three object types:

a) **Linear transport infrastructure**, emphasizing the new geometric rhythms introduced by alignments, the cutting of landform lines, the legibility of bridge components in distant compositions, and the fragmentation of the night sky by vehicle headlights (Jaeger et al., 2011; Sangiorgi & Irali, 2012).

b) **Energy facilities** (wind/solar/transmission), focusing on turbine height and motion, the conspicuity of aviation obstruction lights, array-terrain fit, photovoltaic glint and glare, and edge-softening strategies (Apostol et al., 2016; Dower, 2020; Florio et al., 2021);

c) **High-rise or modern insertions**, centering on background–landmark–foreground relations and the preservation of historic skylines, typically using long-distance viewpoints and traditional viewing routes to compare skyline profile differences and corridor continuity, which in turn underpin guidance on height zoning, color-material control, and viewshed protection buffers (Yuan et al., 2024; M. Zhao et al., 2020).

Despite growing experience, four gaps remain central to the study and practice of VIA for low-intensity, incremental urban expansion in peri-urban rural heritage landscapes, specifically, the gradual spread of small clusters of low-rise, community-oriented housing at the urban fringe:

a) **Limited sensitivity to low-heterogeneity elements:** Common, unobtrusive developments (e.g., clusters of low-rise buildings and slow outward growth at community edges) often produce only subtle visual effects, near-absent skyline intrusions, minor color/texture mismatches, and incremental shifts in visual corridors, that standard DEM-based viewshed analyses or snapshot KOP methods struggle to detect (Penko Seidl & Golobič, 2020; Zeng et al., 2023).

b) **Weak characterization of cumulative and prospective change:** Many impacts unfold in multiple phases and at slow rates; current frameworks rarely track cumulative visual impact or anticipate how accretive change shifts perception over time, risking gradual and potentially irreversible degradation of cultural landscapes (Proverbs et al., 2020).

c) **Absence of an operational end-point ("when to stop"):** For incremental, nibbling encroachment typical of peri-urban growth, VIA seldom specifies decision-ready stop-rules or red-line thresholds that trigger a pause, mitigation, or redesign once cumulative change exceeds an acceptable envelope (Johnson & Ray, 2021; Llausàs et al., 2016).

d) **Insufficient integration across new technologies:** Despite advances (e.g., immersive technologies, point cloud, and new rendering technologies), many VIA applications still rely on DEM-based GIS or static KOP imagery, limiting evaluative granularity and depth (Habib et al., 2024; Lu et al., 2023).

Therefore, this chapter proposes and validates a comprehensive VIA framework that addresses these gaps. The framework spans historical change through future proposals, identifies cumulative impacts across incremental stages, and determines an evidence-based upper limit of tolerable visual impact. It integrates recent techniques that enhance conventional VIA by combining eye-level perception studies with point cloud-supported GIS analysis, and it links public evaluation with expert synthesis to establish decision-ready stop rules for incremental development. **Section 7.2** reviews existing VIA frameworks and emerging tools and presents the integrated framework. **Sections 7.3–7.5** apply and test the framework in the context of community expansion at the Beemster Polder, a typical rural heritage landscape in the Netherlands. **Section 6** sets out strategies to mitigate or reduce visual impacts and discusses implications for VIA practice. This chapter makes two substantive contributions: methodologically, it extends the scope and temporal dimension of VIA; practically, it introduces operational tools and evaluative criteria that support the day-to-day management of rural heritage landscapes and inform decision-making in peri-urban expansion.

7.2 Towards an integrated VIA framework for urban expansion

7.2.1 Conceptual foundations

Wide-applied VIA frameworks **(TABLE 7.1)** comprise two methodological clusters and one decision layer. The two clusters correspond to the principal ways visibility and perception are analyzed, while the decision layer links those forms of evidence to planning and management policy (Cilliers et al., 2023):

a) **Viewpoint-based assessment:** Typically conducted through KOP analysis. It examines how a landscape is perceived from representative viewpoints or routes, using photo-montages, 3D visualizations, or rendered interventions, followed by expert appraisal or public preference testing (Lange, 2011; Paar, 2006). Its strength lies in communicability and intuitive evidence. Its limits are equally clear: evaluations are often snapshot-based, lack immersion, and over-rely on subjective judgement, leaving insufficient objective, empirical support—especially for subtle, incremental change (Bishop & Rohrmann, 2003).

b) **GIS-based visibility and spatial analysis:** Landscapes are represented as terrain/land-cover models; the Zone of theoretical visibility (ZTV) and viewshed computations map potential exposure at the area scale; and advanced index models integrate coefficients such as visible-object counts, affected-settlement shares, observer distance/orientation, and exposed population (Cimburova & Blumentrath, 2022; Domingo-Santos et al., 2011). These methods are powerful for diagnosing spatial distribution and cumulative impact, particularly for large footprints (e.g., wind farms). Nevertheless, capturing inconspicuous, low-height, gradually expanding impacts remains difficult, even though this pattern is typical of suburban and settlement growth (Palmer, 2022; Wróżyński et al., 2016).

c) **Decision layer:** This interprets and integrates evidence into policy-legible conclusions through public evaluation and value-/expert-based judgement (Daniel, 1976). Public evaluation anchors judgements in social acceptability via preference models, intercept surveys, and structured questionnaires at representative viewpoints. Expert and value-based judgements interpret technical results concerning landscape sensitivity, statutory objectives, or landscape/heritage attributes (Berry et al., 2010).

TABLE 7.1 The summary of the widely applied VIA or VIA-related frameworks

Framework / Guidance	Primary focus	Core method features
BLM Visual Resource Management (contrast rating)	Viewpoint (KOP)	Elemental contrast judgment (form, line, color, texture) at representative viewpoints; standardized field sheets
Berkeley contrast rating (Palmer, 2022)	Viewpoint (KOP)	Numeric scaling of elemental contrasts; composite indices across views/options
GLVIA (LVIA)	Viewpoint (KOP) + GIS	Photomontage/visualization at KOPs; sensitivity (susceptibility + value) × magnitude → significance; ZTV screening
SP2 (wind-farm visibility index) (Palmer, 2022)	GIS	Multi-coefficient spatial model (visibility count, affected buildings, distance, orientation, population)
SAM (AUS)	Public metrics at viewpoints (KOP)	Large-sample preference model; significance tests for preference drops at representative views
Maine Wind Energy Act (WEA) guidelines	Mixed (GIS + KOP + public)	Statutory multi-criterion test (resource value, project scale, extent/duration, user expectations, continued enjoyment)
HIA for World Heritage	Value–expert judgement	Identifies effects on OUV attributes and setting; uses KOPs/corridors; may include GIS

7.2.2 Technical underpinnings

VIA is implemented through concrete data and tools. Several long-standing limitations can be mitigated by integrating newer techniques coherently across streams. In this study, we introduce four complementary technologies to overcome these limitations:

a) **Point cloud-based GIS visibility and spatial analysis:** We can work with both semantically enriched and raw point clouds. For our purposes, only a minimal set of semantics is required, limited to evaluation relevant classes such as ground, building mass or roofs and facades, above ground vegetation, and, where applicable, water and engineered structures (Bai et al., 2021; Y. Zhao et al., 2020). These labels may be provided at source or derived through a systematic preprocessing workflow; the absence of full semantics does not preclude analysis. At minimum, a georeferenced point cloud with sufficient density supports line of sight analysis that captures canopy and facade occlusion and retains contextual clutter, thereby reducing the background stripping bias of bare DEM DTM viewsheds (Bai et al., 2021; Marešová et al., 2024).

TOC

b) **Street View Imagery (SVI) with semantic segmentation:** SVI provides multi-temporal, geo-referenced panoramas at eye level and is well-suited to track incremental change. Semantic segmentation of façades, paved surfaces, vegetation, and sky produces indicators such as building or paving share, Green View Index, and sky ratio (Biljecki & Ito, 2021; Middel et al., 2018). These can be combined into construction-intensity indicators and compared across periods to monitor the urban expansions (Stalder et al., 2024). High-resolution panoramas can also be used as stimuli in perception experiments, allowing the effects of these visual changes on human perception to be quantified (Xu et al., 2024).

c) **3D Gaussian Splatting (3DGS) for scene rendering:** Traditional photomontage fixes the views, and large mesh renders are heavy and artefact-prone (Kerbl et al., 2023). 3DGS converts dense imagery and point clouds into anisotropic Gaussian primitives that render in real-time from arbitrary viewpoints, preserving material, color, and texture cues while enabling interactive exploration (Wang et al., 2025; Wen et al., 2025). The Gaussian splats are editable, the rendering cost is low, and the visual result remains close to reality. This makes 3DGS a practical bridge between past cumulative impacts, current conditions, and future proposals, supporting eye-level assessments of different development patterns and their likely visual impacts on rural landscapes.

d) **Immersive VR with eye/head-tracking:** Visual impact ultimately concerns human perception (Moreno-Arjonilla et al., 2024). Immersive VR affords free-view, embodied exploration, and records physiological signals such as fixation heatmaps, dwell time, saccade amplitude, and head-turn speed (Stein et al., 2024). These measures quantify attentional salience and cognitive effort, adding an objective and quantitative layer beyond subjective KOP preference ratings based on 2D stills. The immersive experience also better reflects how change is encountered in situ, improving the credibility of evidence about real-world impact. Thus, Immersive VR augments traditional preference ratings with objective attentional and exploratory markers, yielding human-centered and decision-grade evidence (Stalder et al., 2024).

In summary, point cloud analysis improves spatial precision; SVI time series capture incremental and cumulative change; 3DGS provides high-fidelity, free-view rendering for both present conditions and future scenarios; and VR with eye-/head-tracking strengthens human-level evidence. Together, these technologies address methodological and accuracy limits of traditional evaluation tools while remaining compatible with the prevailing VIA framework.

7.2.3 Proposed VIA framework

Following the prevailing VIA framework, the proposed framework is organized into three components that correspond directly to the two evidence streams and the decision layer, while also embedding a temporal perspective **(TABLE 7.2)**. Assessment, therefore, considers the past (incremental impact already accumulated), the present (current impact levels), and future scenarios (plausible development options). This sequencing enhances complementarity across perspectives, methods, and analytical dimensions.

a) **GIS analysis enhanced by point clouds:** Its objective is to identify where the project is visible, how strongly, and for whom, while also detecting how new interventions affect spatial composition and structural indicators (Bai et al., 2021). The analysis, therefore, addresses three layers: the direct impact of new elements on the landscape, their cumulative overlay with existing elements, and their influence on human activity spaces such as roads, open fields, or settlement edges (Peng et al., 2024).

b) **Enhanced KOP analysis:** This component is jointly supported by multi-date SVI, panoramic and 3DGS rendering, and immersive VR. First, multi-date SVI panoramas are semantically segmented to compute a construction-intensity index (for example, building or paving share) and its annualized change, revealing gradual and incremental shifts in the visual environment (Xia et al., 2021). Second, the current scene is reconstructed with 3DGS to produce consistent, eye-level visualizations; future development patterns are modeled with the same 3DGS workflow so that present and proposed constructions are comparable in fidelity and viewpoint control. All scenes are then presented in a VR environment for perception experiments. In parallel, the VR sessions record eye- and head-movement metrics such as fixation maps, dwell time, saccade amplitude, and head-turn dynamics (Moreno Arjonilla et al., 2024). These physiological signals provide an objective layer of evidence that complements subjective ratings and interviews and helps detect impacts that participants may find hard to verbalize. By combining two current-scene data sources (panorama and 3DGS) with the historical SVI time series and the hypothetical 3DGS scenarios, the enhanced KOP analysis bridges past, present, and future, enabling a cross-temporal assessment from cumulative past impacts to potential future impacts.

c) **Public evaluation and expert synthesis:** Public perception was elicited through preference scales, brief retrospective interviews, and small-group discussions after the perceptual experiments. Where feasible, collaborative formats—such as participatory workshops in heritage-sensitive settings—can convene experts and diverse stakeholders to co-evaluate potential visual impacts at early planning stages.

TOC

Expert assessment then integrates these findings with statutory frameworks and site attributes to produce the final evaluation. This requires comparing impact evidence across phases (past, present, prospective) to identify the point at which change becomes unacceptable, and then back-calculating a set of limiting indicators as decision rules and compliance thresholds for management (Gravagnuolo et al., 2024).

TABLE 7.2 The main compositions of the newly proposed VIA framework

Main	Analytical method	Description	Data and tools
GIS-based visibility and visual analysis	GIS-1: Theoretical visibility	Preliminary delineation of potential visibility	Standard visibility analysis; LiDAR-derived terrain/vegetation/building heights
	GIS-2: Contextual overlay visibility	Refines visibility by overlaying similar elements of the existing landscape	
	GIS-3: Activity-oriented visibility	Assesses visibility along major public routes and activity spaces	
	GIS-4: Spatial analysis	Computes landscape density, structural metrics, and spatial mechanisms relevant to heritage fabric	Historic maps; LiDAR-based layers; general GIS
Enhanced KOP analysis	KOP-1: Present-state	Evaluates current eye-level perception and impact; aligns with past cumulative evidence (SVI) and with scenario assessment (3DGS)	VR eye-/head-tracking; panoramas/3DGS/SVI
	KOP-2: Future-development	Uses 3DGS to simulate alternative build-out patterns and their perceptual effects.	
	KOP-3: Cumulative visual impact	Compares SVI/panoramas across periods to quantify cumulative change and its perceptual influence.	
Decision layer	Public evaluation	Summarizes preferences and perceived impacts across general public groups; identifies drivers (e.g., color-contrast, use patterns, salience cues)	Participatory perception sessions, short interviews, or workshops
	Expert synthesis and “when to end”	Integrates all indicators with public input to define a defensible stop-line and the corresponding compliance thresholds; also, the Scenic Beauty Evaluation/Heritage OUV evaluation methods are encouraged here.	Heritage attributes and setting; integrity/authenticity considerations; expert panel review

TOC

7.3 Case study: Middenbeemster Expansion Plan (2020-2040) for Beemster Polder

7.3.1 Background of the case study

Framed as a long-range response to housing pressure and service deficits in the Beemster municipality, the Middenbeemster Expansion Plan (2020–2040) sets out a phased program of urban growth in and around De Keyser II **(FIG. 7.2)**. It combines new housing, schools, and multi-use community facilities with selective redevelopment and the reuse of green parcels. Conceived to accommodate rising residential demand, the plan's interventions are intentionally incremental, gradually transforming existing farmland into low-rise but more concentrated residential communities. At the same time, the plan unfolds within the Beemster Polder, a canonical Dutch polder landscape created in 1612 through lake drainage and organized as a strict geometric grid of canals, dikes, roads, and agricultural plots. This rational agrarian order is highly sensitive to spatial and visual disturbance. The area is also inscribed on the UNESCO World Heritage List, underscoring its international recognition (RENES, 2019).

These circumstances highlight a core tension between protecting a rural heritage landscape and the pressures of local community expansion. The key question is how to assess the visual impacts of the current expansion plan on the surrounding polder landscape, especially given that such impacts do not occur abruptly but emerge gradually over time. Against this background, the Middenbeemster case provides an appropriate testbed for applying and validating an integrated VIA framework that explicitly tracks past cumulative change, present conditions, and prospective scenarios across the plan's phased implementation.

TOC

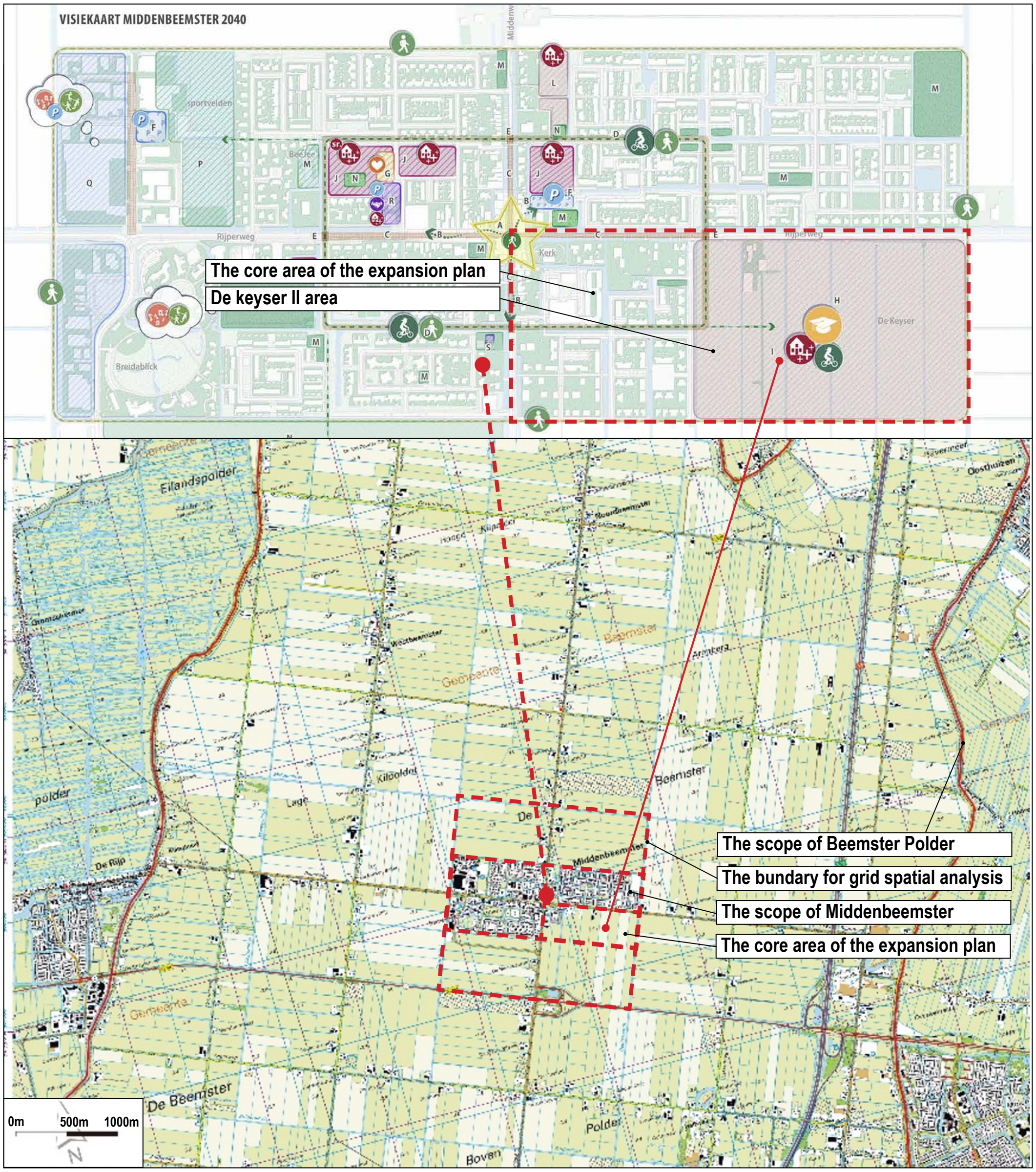


FIG. 7.2 Middenbeemster expansion plan and Beemster Polder: the location of the targeted study area.

7.3.2 Data collection

This study relies on three primary categories of data **(TABLE 7.3)**: (a) point-cloud data for visibility analysis, (b) multi-view imagery and scan data for 3DGS rendering, and (c) SVI and panoramic photos for temporal analysis. These datasets enable a cross-temporal assessment of past, present, and prospective impacts. The AHN-5 and Google SVI datasets are publicly available, ensuring transparency and reproducibility. In contrast, drone imagery was collected using consumer-grade UAVs under controlled conditions. X-Grid L1 multi-angle imagery and sparse point clouds were obtained with specialized, higher-cost equipment to ensure sufficient fidelity for 3DGS rendering. In addition, multi-angle imagery and point-cloud data for three proposed construction models were collected: the imagery served to create 3DGS virtual environments, while the point clouds enabled visibility analysis under different development scenarios.

TABLE 7.3 Summary of the research data

Data	Data type	Source/acquisition	Description and use
AHN 5 (Actueel Hoogtebestand Nederland)	Point-cloud data	Open-access	Dutch national elevation database containing high-precision LiDAR point clouds. Includes four variants (raw and edited) for visibility and spatial metrics analysis.
Drone aerial images	Image data	DJI Mini 2	Collected to generate 3D Gaussian Splatting (3DGS) renderings, construct scenario scenes, and provide inputs for VR perception experiments.
Multi-angle images and sparse point clouds	Image and point-cloud data	X-Grid L1	Acquired to create high-fidelity 3DGS visualizations, support hypothetical scenario construction, and complement VR experiments.
Google SVIs	Image data with geolocation	Open-access	High-resolution panoramas are used for temporal analysis of cumulative changes. Multi-date images were selected from comparable seasons to minimize confounding due to vegetation cycles.

7.4 Methods and data

FIG. 7.3 Case study sites and prototype references in/around Beemster Polder.

Building on the Chapter 2 framework, we assess the *Middenbeemster Expansion Plan (2020–2040,* **FIG. 7.3a***)* using a design that couples three development scenarios with three temporal stages, conducted through the framework's three analytical components (GIS visibility and spatial metrics; enhanced KOP analysis; public evaluation and expert synthesis).

a) **Temporal staging:** To capture incremental change, we adopt a phase-aware timeline comprising past, present, and future. "Past" is further resolved into "*2020-phase*" (earlier than 2020) / "*2023-phase*" (from 2022-2024) / "*2025-phase*" (after 2024) to detect gradual drift prior to the plan. "*Present-phase*" (June 2025) is the baseline against which past increments and future scenarios are compared. "Future development" comprises three hypothetical build-out patterns reflecting local form controls.

b) **Development scenarios:** Three plausible patterns are modeled in addition to the present-phase as baseline M-0. M-1, dispersed low-rise residences, derived from existing dispersed housing clusters **(FIG. 7.3b)**; M-2, centralized linear buildings, inspired by local flat, elongated industrial sheds (a cheese factory, **FIG. 7.3c**); and M-3, centralized community-center buildings, echoing nearby town/community centers (approximately four stories, **FIG. 7.3d**).

7.4.1 GIS visibility and spatial metrics (point-cloud enhanced)

The first analytical component applies a point cloud-enhanced GIS workflow to quantify the visual impacts from the present-phase and proposed constructions (M-0 – M-3). The approach combines a structured four-step method following the new VIA framework: (GIS-1) Theoretical visibility, (GIS-2) Contextual overlay visibility, overlaying the theoretical envelope with existing buildings to diagnose cumulative exposure relative to the current built fabric; (GIS-3) Activity-oriented visibility, projecting exposure values onto major outdoor activity spaces, particularly the roads surrounding the De Keyser II expansion site, to reflect realistic everyday encounters; (GIS-4) Spatial analysis, deriving compositional and structural measures for deviations from the historic dike-canal-parcel grid, which is a defining feature of the Beemster Polder landscape. To fulfill the four evaluation processes, the following steps have been taken:

a) **Model construction:** The workflow commenced with creating a baseline model (M-0) that integrates the AHN-5 national LiDAR point-cloud dataset with supplementary site-specific scans. This combined dataset represents terrain morphology, vegetation volumes, and existing built mass in explicit 3D geometry, thus avoiding the "bare-earth" bias of DEM/DSM-based viewsheds. On this baseline, three hypothetical development scenarios were generated. Each scenario was constructed by replicating and spatially positioning building segments extracted from representative local structures to ensure morphological plausibility.

b) **Visibility computation:** Visibility calculations were carried out in ArcGIS Pro using cumulative raster-based viewshed analysis. The integrated terrain-building models were rasterized into 1-m grid cells, balancing computational efficiency with the resolution required for fine-scale heritage landscape analysis. For cumulative visibility, dense observer points were distributed across building façades and roof surfaces. In parallel, pedestrian-level visibility was assessed by placing observer points every 5 m along road centerlines around De Keyser II, with an eye height of 1.7 m to simulate human viewpoints. This dual configuration captures both theoretical exposure at area scale and practical exposure along everyday activity routes.

c) **Spatial analysis-1:** To capture how the new construction "fills in" the Beemster's rectangular dike-canal-parcel grid, we classify scenes into buildings (usually built along dikes), polder, and water, and measure infill magnitude with a land-domain grid-occupation ratio (GOR), the share of buildings over land (buildings + polder). Because water is structurally stable and not the infill target, we assess it only against the original water surface: a baseline water mask (from the earliest intact map) is fixed, and each period/scene reports a water-retention value as the proportion of the baseline water that remains. This baseline-anchored check focuses interpretation on whether the historic canal geometry and open corridors stay legible.

d) **Spatial analysis-2:** To capture distributional mechanism beyond pixel overlap, we compute mechanism-aware similarity for buildings: (i) axis-profile correlations along the grid's two principal directions by dividing each scene into 16 bands per axis and using a shift-tolerant Pearson correlation (±1 band), indicating whether infill follows the same strip rhythm; and (ii) an edge-orientation spectrum correlation (0–180°, 18 bins) that reflects directional regularity. A mechanism composite (mean of the two axis correlations and the orientation correlation, 0–1) summarizes distributional similarity. For completeness we also report strict Jaccard and a shape-tolerant Jaccard (after small dilation) for buildings. All metrics are computed on the same canvas without geometric warping; only color segmentation and per-class masking are applied.

7.4.2 Enhanced KOP analysis

We conduct the eye-level (KOP) module by building a single, comparable pipeline across past → present → proposed and by measuring perception in immersive VR. Multi-date SVI panoramas (past) are aligned to matched on-site panoramas/3DGS baseline; the same KOPs are then reused in three proposed 3DGS scenarios so that viewpoint control and visual metrics are consistent. The present stage acts as the bridge that links incremental SVI change to current perception and to controlled scenario visuals.

7.4.2.1 Gaussian splats construction for VR

To stay consistent with the GIS massing used in **Section 7.4.1**, scenes M-1–M-3 were reconstructed as different Gaussian splats based on M-0 (present-stage). We implemented two data-acquisition routes to test feasibility under different constraints. (a) UAV + ground multi-view: UAV and ground photos were processed with Structure-from-Motion (SfM) to recover camera poses and a sparse cloud, then converted to splats by software jawset Postshot; denoising and density/contrast tuning improved real-time fidelity. This low-cost route was applied to M-1–M-3. (b)

Multi-angle camera + sparse cloud: an X-Grid L1 device with LCC studio produced a professional 3DGS of M-0 for cross-checking. All proposed scenes preserve the spatial composition used in the GIS analysis so that spatial/visibility analysis and eye-level visualization stay comparable. From M-0 to M-3, we exported ten scenes per condition from Unity for the subsequent eye-tracking experiments. The same interactive Unity environment was also used to facilitate the post-experiment public preference interviews, ensuring stimulus consistency across methods.

7.4.2.2 Panorama and SVI segmentation

Multi-date SVI panoramas and matched on-site panoramas at selected KOPs were segmented into six classes: *buildings*, *vegetation, paved ground*, *water/canals*, *sky*, and *polder/groundcover*. In simulated environments for the present and scenarios we additionally retain an explicit *new constructions* class to distinguish added buildings. The primary indicator is *buildings* share in the field of view (FOV) and its phase-to-phase change; we note potential confounds (e.g., seasonal canopy, temporary works) at the image level. Because scene editing in scenario 3DGS can introduce pixel-level alignment noise, only the present 3DGS baseline is used for quantitative comparison with SVI/panoramas; scenario 3DGS (M-1–M-3) serve as controlled stimuli in perception tests.

To reflect spatial exposure, KOPs are split into near and far views. *Far views* lie along the southern road (≥500 m from the main construction area) and monitor skyline/edge expansion; *near views* lie along the northern road adjacent to the site and capture internal or near-edge impacts. This split is kept throughout segmentation, stimulus building, and analysis.

7.4.2.3 Perception experiment

We ran an immersive VR study (HTC VIVE Pro Eye, integrated Tobii Pro Lab, 120 Hz, ~0.5°–1.1° accuracy) with 30 participants (public; demographics in **Appendix D1**). Stimuli comprised: (a) SVI time-series panoramas (2020/2023/2025), (b) *present-phase* panoramas/3DGS (M-0), and (c) scenario 3DGS (M-1–M-3). All scenes were presented in Unity with identical FOV and horizon alignment. Each scene was viewed for 30 s with free head/eye movement; blocks were counter-balanced, and participants were not informed about the temporal stage or whether a scene was proposed. Three practice scenes preceded the formal trials.

We recorded (a) AOI-level fixation dwell (*buildings, sky, polder, vegetation*, and—where applicable—*new constructions*), (b) head-movement dispersion in yaw (horizontal turning range), roll (lateral tilt range), and pitch (vertical scanning range). Fixation duration quantifies what attracts attention; head-movement captures how people explore: contraction in yaw/roll implies tighter focus, while higher pitch indicates stronger building–sky vertical engagement. Because of 3DGS coverage limits, present and proposed scenes are primarily near views (present: 11 scenes; each proposal: 10 scenes). In SVI, we use 7 near and 5 far views. The study comprises a "3DGS group" and a "panorama group," each internally randomized.

7.4.2.4 Data analysis

SVI segmentation outputs, especially *buildings share* as a proxy for construction intensity, were summarized by viewpoint and phase to track past changes (color/contrast features are out of scope). Eye and head data were cleaned and aggregated by scene and AOI to ensure stable sample sizes across past phases and future proposals before modeling. To separate the effects of stage (2020/2023/2025/Present), scenario (M-1/M-2/M-3), distance band (near/far), and AOI, while accounting for participant and viewpoint variability, we fitted linear mixed-effects models (LMMs). We applied log (x+1) and back-transformed estimates to geometric means for eye-dwell. We report backtransformed means, ratios vs. the 2020phase for eyetracking metrics and differences vs. the 2020phase for headtracking metrics (SVI), and contrasts vs. the Present phase for scenario comparisons, all with 95% confidence intervals.

7.4.3 Public evaluation

Because the participant pool was small, we did not employ standardized rating scales. Instead, we designed a brief oral questionnaire to capture participants' spontaneous evaluations of the visual scenes immediately after each VR/SVI session. The aim was to probe three aspects of perception: *(a) attention*, what elements of the scene initially drew their focus and why; *(b) preference,* which scenes they liked or disliked and the reasons for those judgments; *(c) recognition,* whether and how they detected newly introduced construction; and *(d) debriefing*, open comments on the experimental environment, equipment, and procedure (e.g., comfort, clarity, potential distractions). To aid recall during interviews, participants were reintroduced to an interactive Unity-based VR environment identical to the eye-tracking setup, while the interviewer referenced synchronized fixation heatmaps and gaze-trajectory overlays for targeted probing.

Responses were noted in real time and organized by scene and question type. Analysis relied on simple frequency counts of recurrent answers (e.g., the counts of participants mentioning "new buildings appeared brighter"), supplemented by selected short quotations to illustrate typical reasoning. This descriptive but systematic approach provides a clear overview of participants' scene preferences and recognition patterns, offering a qualitative complement to the quantitative eye- and head-tracking indicators. Together, the two strands of evidence enrich the interpretation of perceptual outcomes and support expert synthesis in the decision layer.

7.4.4 Expert synthesis and "when to stop"

Our objective is to answer a practical VIA question for low-rise, low-intensity yet cumulative expansion: when does additional construction exceed the acceptance capacity of a heritage-sensitive landscape? Rather than prescribing thresholds a priori or relying solely on expert intuition, we derive a site-specific upper bound by synthesizing spatial metrics, eye-level evidence, and public/expert judgements across past → present → prospective conditions. An expert panel consolidates these strands into operational rules for planning and management, thereby extending established VIA practice toward transparent, data-grounded, and temporally explicit decision-making.

In detail, spatial indicators include the three visibility-based indicators, GOR, mechanism-aware similarity, and baseline water retention. Eye-level evidence is summarized as skyline-band exposure at sentinel KOPs (far views), and VR-based perception indicators completed by public acceptability from interviews. Three steps are included in the assessment procedure: *(a) Historical back-casting:* We reconstruct 2015–2020–2025 on a common canvas to establish the historically tolerated range—i.e., across all indicator dimensions, we identify what visual impacts have already occurred on site and to what cumulative degree. *(b) Scenario stress-testing:* We evaluate M-1 / M-2 / M-3 using the same indicator set on the same canvas, and record PSI and public evaluation for each pattern. *(c) Threshold identification and rules:* We locate the highest pattern jointly acceptable across spatial/visibility, perception, and social layers; this pattern defines the upper bound. We then adopt operational rules: proposals at or below that bound are *compatible* *under controls*; proposals above it require *detailed justification and mitigation* (and may be refused). Accordingly, the thresholds and stop rules are presented as SDG-11 aligned management controls that support inclusive planning (Target 11.3) and the protection of cultural heritage (Target 11.4).

7.5 Results

7.5.1 GIS-based visibility analysis

The GIS-based visibility analysis comprises three interrelated components (detailed results see **Appendix D2**): pedestrian-level visibility along surrounding roads, theoretical visibility of proposed constructions, and cumulative visibility integrating proposed and existing structures.

a) **GIS-1, Theoretical visibility (ZTV, FIG. 7.4):** As a standalone potential envelope of new massing, M-3 attains the widest visible reach (≈8.05M rasters), slightly exceeding M-2 and M-1, with M-0 being the smallest. High-intensity peaks are anchored by M-0 (≈176k) and M-3 (≈162k), indicating that while M-3 maximizes spatial extent, the existing baseline still forms pronounced focal nodes. Overall, the theoretical field suggests M-3 ≥ M-2 > M-1 > M-0 in potential impact.

b) **GIS-2, Contextual overlay visibility (FIG. 7.5):** When the new schemes are inserted into the existing fabric, overall visible coverage remains highest in M-3 (≈2.06M, cells) (≈M-1 and M-0), whereas M-2 is smaller. However, mid/high-intensity areas appear relatively limited across schemes (e.g., the sharpest high-intensity spike occurs in M-2 ≈62k, with M-3 ≈50k), which is likely a counting/occlusion effect: small, intricate building pieces are visually subsumed by larger, contiguous masses, thereby compressing mid/high intensity counts even when the total footprint is broad. Interpreted accordingly, M-3 exhibits the most pervasive perceptual presence, while M-2 concentrates disturbance into localized peaks over a smaller range.

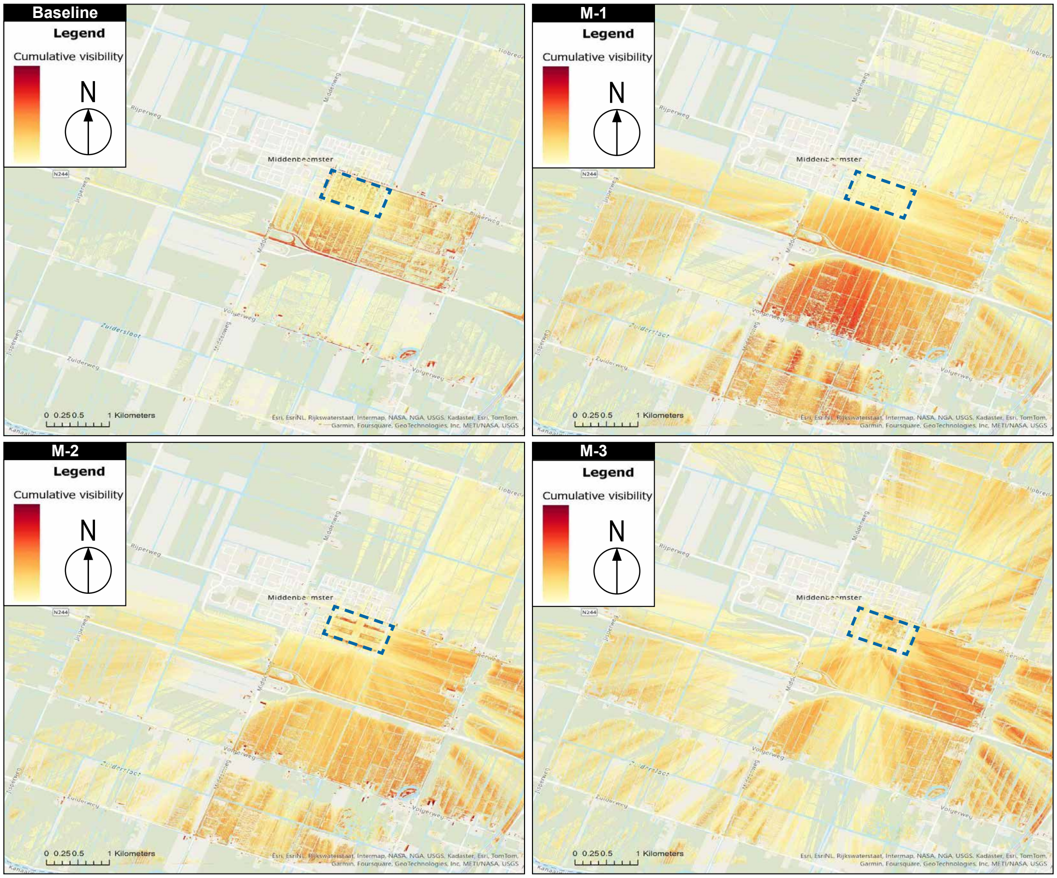


FIG. 7.4 Theoretical visibility maps (ZTV) for M0/M1/M2/M3.

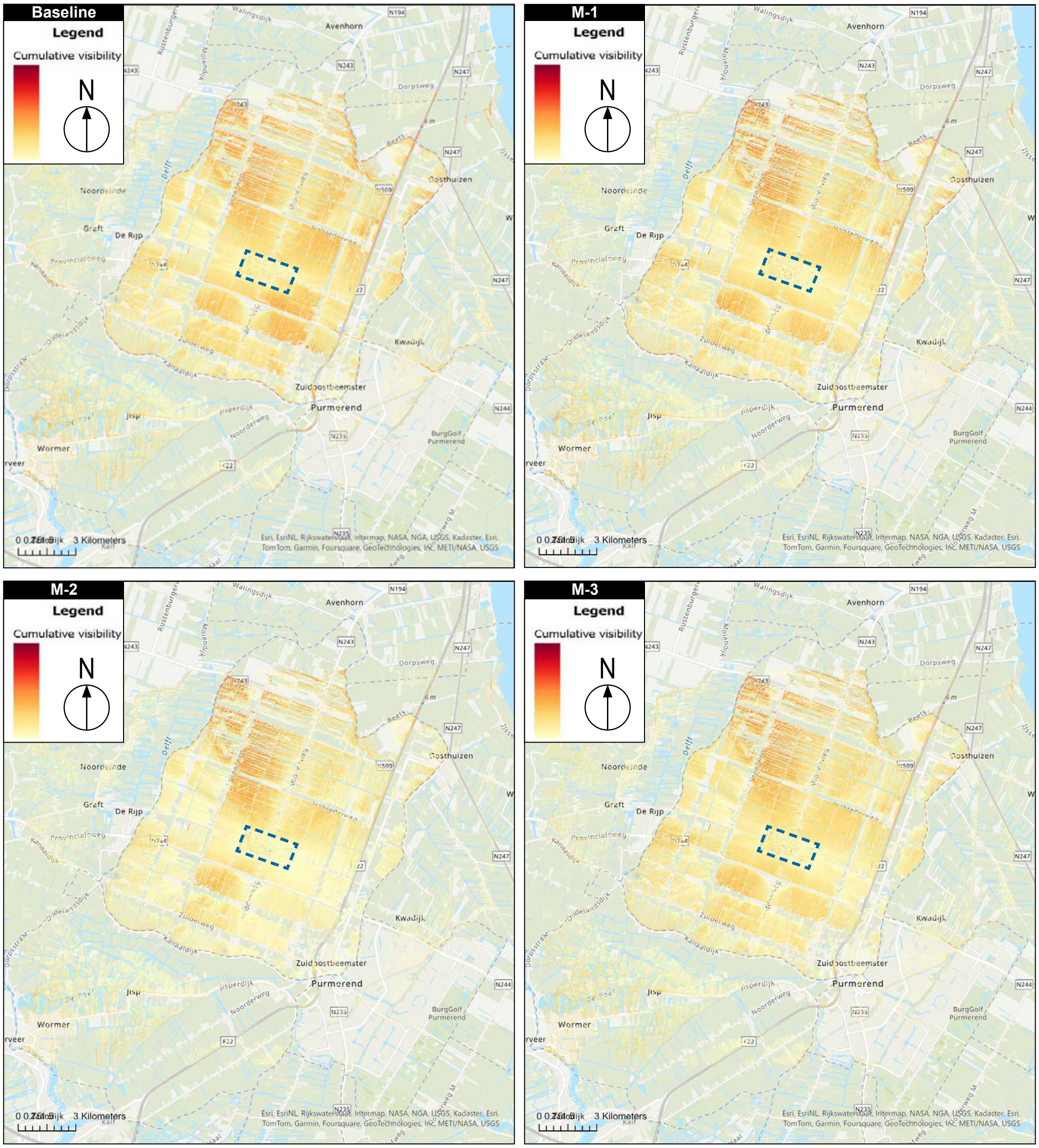


FIG. 7.5 Contextual overlay maps for M0/M1/M2/M3.

c) **GIS-3, Activity-based visibility (FIG. 7.6)**: From publicly accessible routes, larger values indicate more space remains visible (less obstruction). M-3 offers the most open network (Total ≈408,865; High ≈120k; Medium ≈125k), implying the least obstruction and the most frequent long-range encounters along streets. M-1 follows with extensive but more fragmented corridors (High ≈83k). M-0 is the most constrained overall (Total ≈104k) yet retains clear hotspots (High ≈30k). M-2 shows minimal road-legible openness (High <1k), suggesting that its concentrated massing, while producing localized peaks in the combined view, reduces visibility along movement corridors.

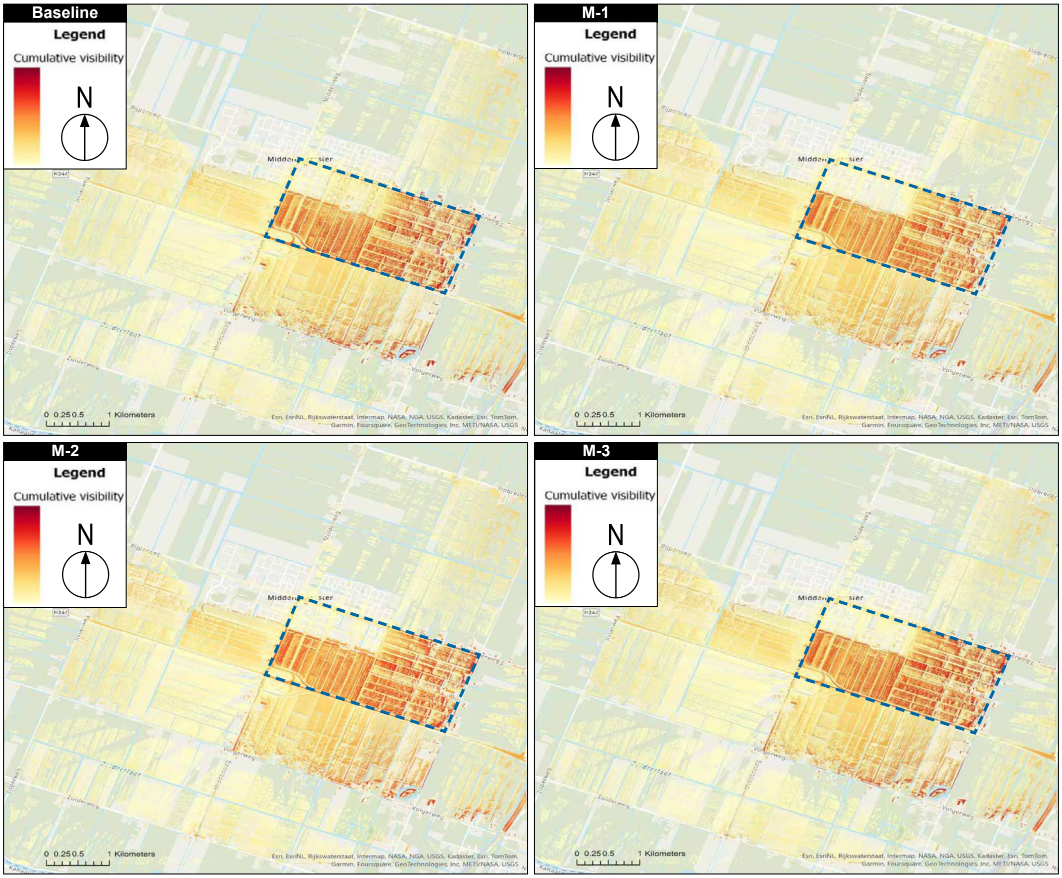


FIG. 7.6 Activity-based visibility maps for M0/M1/M2/M3.

Across analyses, M-3 consistently delivers the largest spatial reach and strongest road-legible openness, making it the most dominant in everyday perception. M-2 is defined by localized, high-intensity spikes in the integrated context but a limited footprint and weak openness from roads, consistent with occlusion/aggregation effects in counting. M-1 trades intensity for distributed, softer corridors, and M-0 preserves an open baseline punctuated by a few strong focal nodes. In short: M-3 = network-wide dominance with high openness; M-2 = concentrated disturbance, low road openness; M-1 = dispersed softness; M-0 = open baseline with anchors.

7.5.2 GIS-based spatial analysis

Over the past decade, the polder grid experienced gradual yet cumulative infill **(FIG. 7.7a-c, TABLE 7.4)**. The land-domain GOR increased from 9.13% (2015) to 10.93% (2020) and 11.90% (2025), while baseline water retention relative to 2015 remained essentially complete (100.0%, 99.98%, 99.95%), indicating preservation of the canal "blue skeleton." Mechanism-aware metrics confirm that the historic strip logic was largely maintained. Strict Jaccard overlaps equaled 0.867 (2015–2020), 0.943 (2020–2025), and 0.820 (2015–2025), reflecting additive infill. At the same time, similarity indexed by axis-profile correlations and edge-orientation spectra remained very high (0.983, 0.993, and 0.970), with both column and row correlations exceeding 0.95 and orientation spectra approaching 1.0. Taken together, changes from 2015 to 2025 amount to slow intensification without structural disruption.

Against the 2025 baseline, three prospective build-out patterns diverge in magnitude and mechanism **(FIG. 7.7d-f)**. M-1 (dispersed, low-rise) adds +0.72 pp to GOR (final 12.62%) and retains 99.96% of baseline water; its mechanism composite is 0.987 (axis profiles: col 0.970, row 0.990; orientation 0.999). M-3 (centralized, mid-rise community blocks) introduces a larger increment (+1.80 pp, final 13.69%) and lowers water retention to 98.53%; the mechanism composite declines to 0.954 (col 0.912, row 0.950; orientation 0.999). M-2 (centralized, elongated sheds) exerts the greatest effect (+2.82 pp, final 14.72%) and reduces water retention to 96.48%; its mechanism composite is 0.924 (col 0.842, the lowest, row 0.936; orientation 0.995).

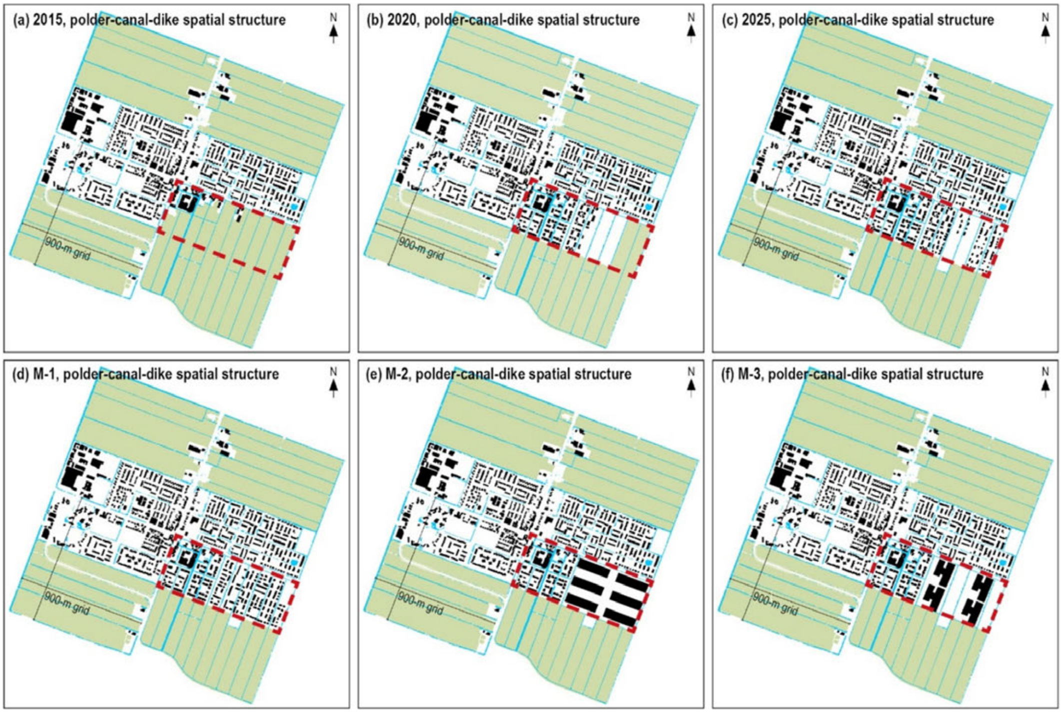


FIG. 7.7 GIS-based spatial analysis of the three historical period and three proposed constructions.

TABLE 7.4 Results of the evaluation with spatial indicators

Stage	GOR (%)	Water retention vs 2015 (%)	ΔGOR vs 2025 (pp)	Jaccard	Jaccard (dilated)	Axis cols	Axis rows	Orient corr	Mech-anism compos-ite
2015	9.13	100.00	-2.77	-	-	-	-	-	-
2020	10.93	99.98	-0.97	-	-	-	-	-	-
2025	11.9	99.95	0.00	-	-	-	-	-	-
M-1	12.62	99.96	0.72	-	-	-	-	-	-
M-3	13.69	98.53	1.80	-	-	-	-	-	-
M-2	14.72	96.48	2.82	-	-	-	-	-	-
2015 vs 2020	-	-	-	0.867	0.872	0.974	0.975	1.000	0.983
2020 vs 2025	-	-	-	0.943	0.928	0.984	0.994	0.999	0.993
2015 vs 2025	-	-	-	0.820	0.813	0.959	0.951	1.000	0.970
2025 vs M-1	-	-	-	0.825	0.865	0.970	0.990	0.999	0.987
2025 vs M-3	-	-	-	0.770	0.879	0.912	0.950	0.999	0.954
2025 vs M-2	-	-	-	0.723	0.860	0.842	0.936	0.995	0.924

Since 2015, intensification has increased land occupation without compromising the strip-based grid mechanism or canal integrity. However, the proposed expansion patterns separate clearly: M-1 maintains the historic two-axis rhythm with minimal additional land take; M-3 begins to erode water retention and departs moderately from the strip logic; M-2 produces the largest land-take and the strongest deviation from the grid mechanism. These results indicate that spatial compatibility declines from M-1→M-3→M-2, with corresponding escalation in pressure on the historic fabric.

7.5.3 Enhanced KOP analysis

7.5.3.1 Eye-level construction intensity analysis results

We report findings in two sets: far views farther from the proposed construction, and near views adjacent to the new parcels.

a) **Far views (FIG. 7.8a-c):** Across the perimeter roads, the *buildings* fraction in the field of view (FOV) remains very low, with most links consistently in the 0–0.5% range. From 2018 to 2022, the pattern is basically unchanged; the small fluctuations observed are attributable to vegetation occlusion (seasonality and pruning) rather than to new mass. By 2025, a localized increase emerges around the Volgerweg–N244 junction, where the *buildings* share rises to ≥ 4–5%, making this node the only area of notable change. Elsewhere, differences remain minor and patchy, lacking a coherent spatial trend. Taken at face value, these SVI-based metrics indicate that the Middenbeemster expansion does not materially alter eye-level visibility at peripheral viewpoints; the impact of the new construction on the outer road network is subtle in numerical terms.

b) **Near views (FIG. 7.8d-f):** In contrast, roads abutting the development show marked shifts. The *buildings* share increases sharply. These results confirm that the measurable, construction-driven change is concentrated within the project parcels, whereas far-view effects (≈ > 500 m) are difficult to capture with image-based methods relying on semantic segmentation because of occlusion, perspective compression, and viewangle limitations. Therefore, whether such subtle outerring changes are perceptible to observers is a question for the VR-based perception tests reported in the next section.

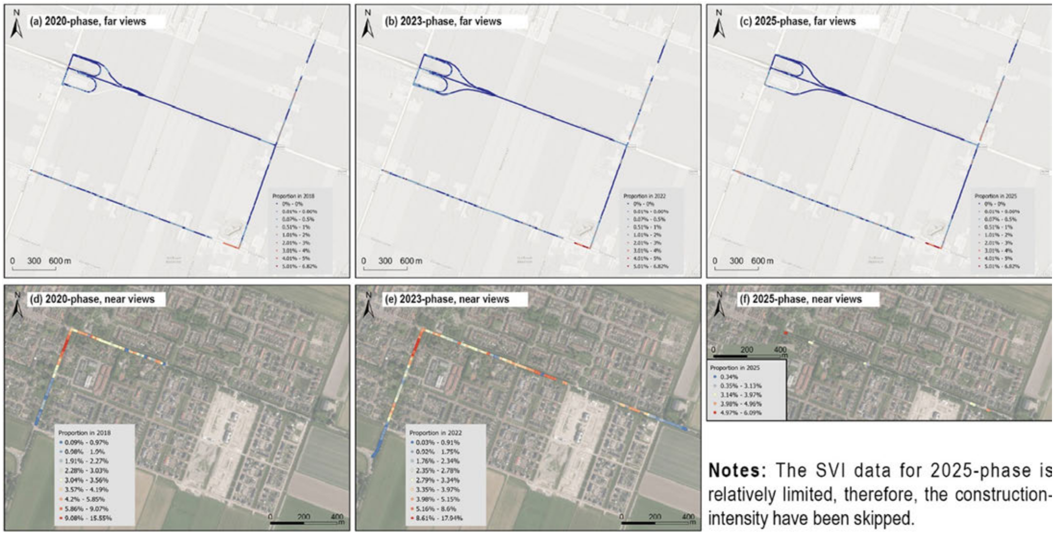


FIG. 7.8 The visualization of construction-intensity from the SVI.

7.5.3.2 Perception-based analysis results

The VR-based eye-tracking results for different phases (from past to present) are shown below **(FIG. 7.9)**. Meanwhile, the LMM results show that in the near views **(FIG. 7.9a-b)**, total fixation duration rose from the *2020-phase* to the *2022-phase*, but fell slightly in the *2025-phase*, while attention to *buildings* peaked in the *2023-phase*. In fact, from *2020-phase* to *2023-phase*, the values change little; however, from *2023-phase* to *2025-phase*, *sky* dwell increases while *polder* decreases (because the land is being leveled and prepared for construction). When the sequence reaches the *present-phase* scene, *sky* and *polder* both drop, while *buildings* and *new constructions* rise sharply, indicating construction is completed or ongoing and drawing strong attention. At the same time, roll decreases and yaw increases, suggesting larger exploration movements as participants are eager to look around and see what has been built. Importantly, in the *present-phase*, *buildings* fixation surges again (around 1.3 seconds, more than five times higher than *2020-phase* and twelve times higher than *2025-phase*), and new constructions suddenly appear as a strong new attractor (around 2.7 seconds, about one quarter of all dwells). By contrast, *polder* collapses from roughly 3 seconds in SVI to just 0.35 seconds in *present-phase* (new constructions block the views to polder). The pattern is steadier in the far views (Fig. 10c-d): total fixation duration rises gradually across phases, with *polder* decreasing and *sky* increasing, and *buildings* slowly gaining share; here, the upward trend in *building* share is evident.

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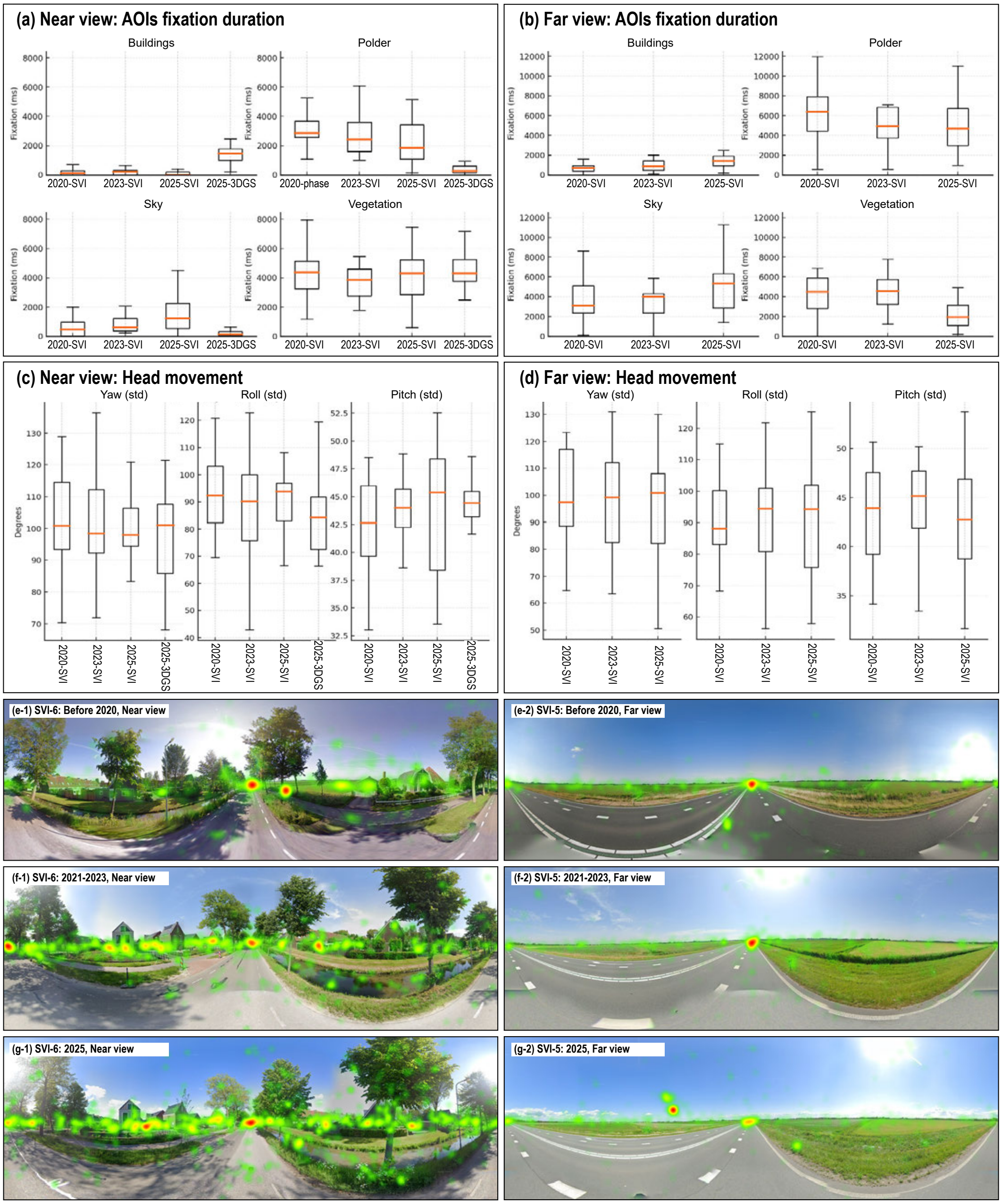

FIG. 7.9 Results of past to present-phase eye- and head-tracking (detailed results in Appendix D3).

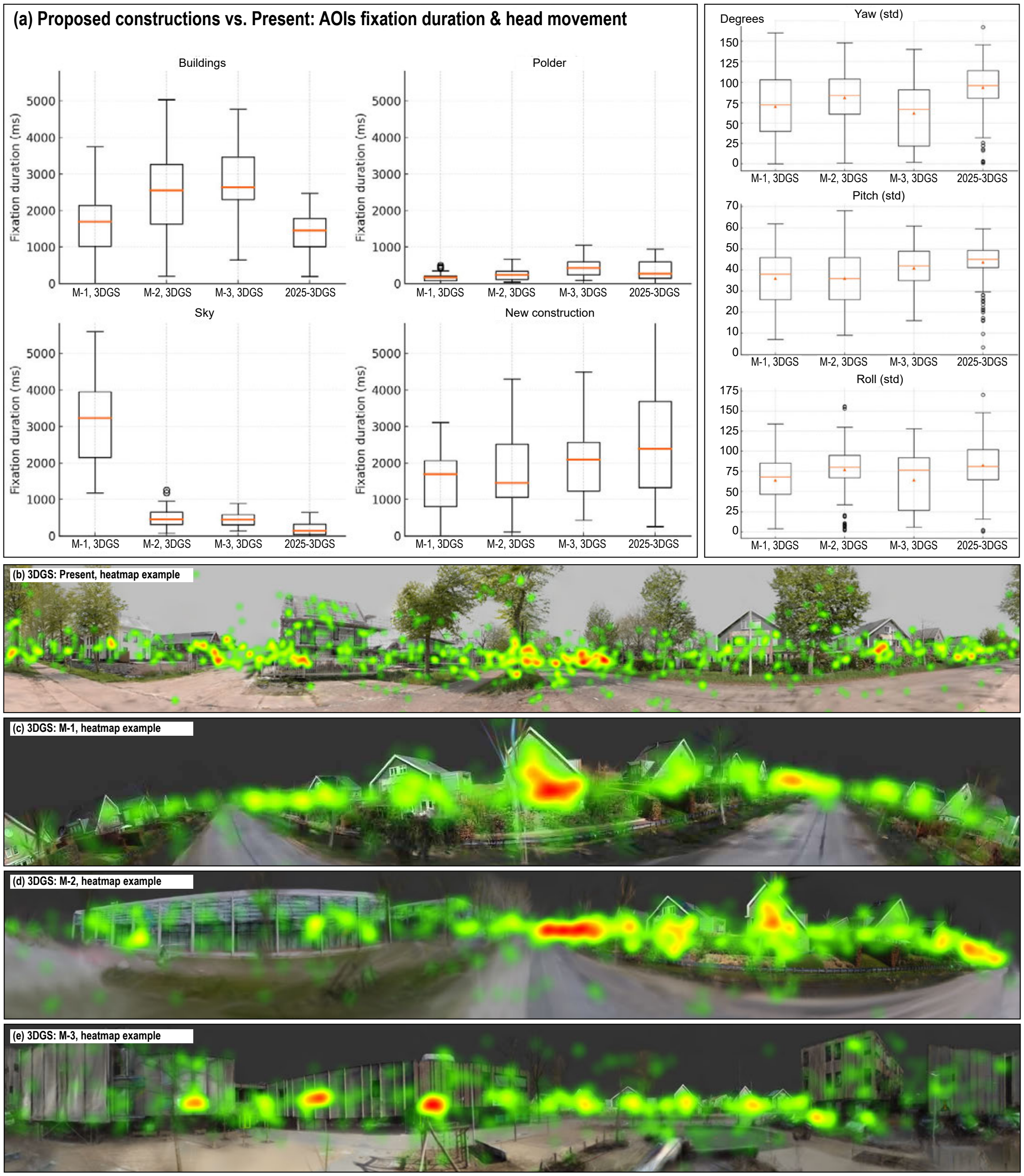

FIG. 7.10 Results of present-phase to proposed constructions' eye- and head-tracking (detailed results in Appendix D3).

In addition, the eye-/head-tracking results for three proposed construction patterns are also showcased **(FIG. 7.10)**. From the present to the three proposals, all three head-motion metrics decline; part of this drop stems from lower scene fidelity in the proposals. Even after using the LMM to filter out a portion of this performance-related difference, overall head-movement amplitude remains reduced, which makes between-group (between-proposal) contrasts more reliable **(FIG. 7.11e-f)**. M-1 represents the lowest-impact option: *building' dwell times remain* minimal (≈170 ms) and *new constructions* attract only modest attention. M-2 elevates the impact substantially: total dwell is about 45% higher than M-1 (5.5 vs. 3.8 seconds), *buildings* dwell rises more than threefold (to ≈570 ms), and *new constructions* attract significantly more attention (≈240 ms, more than twice M-1). M-3 pushes the effect to an extreme: *buildings* fixation jumps to ≈1.8 seconds (more than ten times M-1 and clearly above M-2), but M-3 does not create a stable advantage in *new constructions*, its modeled mean is only ≈110 ms with considerable variability, and the differences from M-1 and M-2 are not statistically significant. Compared with the earlier near-view results, M-3 drives *buildings* higher and makes the *sky* far more salient, showing that the design scenarios can produce even stronger impacts than the real present.

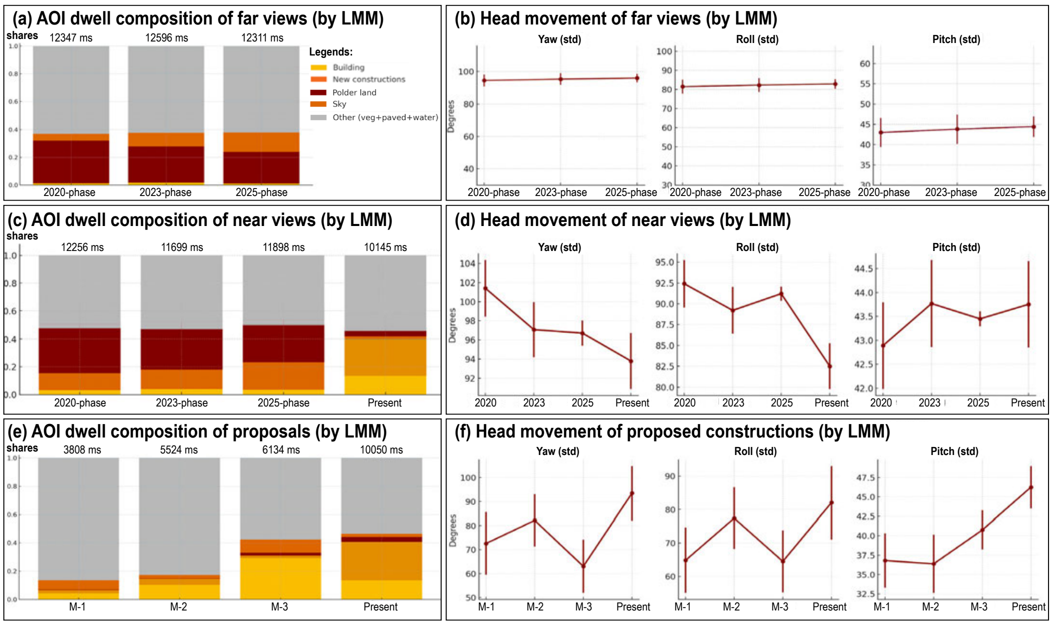

FIG. 7.11 Results of the LMMs for eye- and head-tracking.
Note: Values are estimated marginal means (LMM, participant random intercept). Error bars show 95% CIs. Because M-1/M-2/M-3 scenarios were generated with a low-cost 3DGS model that introduces systematic deviations from present-3DGS (by L1) baselines, results are interpreted primarily regarding relative group differences. Full model statistics and pairwise comparisons are provided in Appendix D4.

TOC

Across both SVI and modeled scenarios, the clues of visual impacts are consistent. *Buildings* and *new constructions* are the primary visual impact sources, while *polder* and *vegetation* retreat, and *sky* rises in some conditions to reinforce contrast. The integrated LMM results demonstrate a coherent trajectory: from gradual cumulative impact on human perception in SVI, through a breakpoint in *Present-phase*, to amplified impacts in M-2/M-3.

7.5.4 Public evaluation results

Interviews revealed a clear normative stance at the outset. Within a World Heritage setting such as the Beemster Polder, participants generally opposed further urban or community expansion in principle (27 participants opposed, 3 not sure). For the eye-level stimuli, near views were evaluated in the following order: the *2020-phase* scenes received the most favorable judgments, the *2025-phase* scenes were rated slightly lower, and the *2023-phase* scenes were rated lowest (24/30 agreed on the ranking). Notably, without prompting, two present-stage views were not identified as “new” (12/30 mismatch the scene present-5, 14/30 the present-8), and these scenes attracted relatively positive comments, suggesting low visual salience when massing and façade tone blend with the context. In far-view scenes, respondents reported that differences were detectable mainly because new buildings appeared brighter (19/30) and higher-contrast than the old ones (25/30), which drew attention and lowered preference (21/30); however, participants consistently characterized these changes as minor rather than severe (24/30). In the scenario comparison, the present condition (M-0) and the dispersed, low-rise option (M-1) were most acceptable, whereas the centralized forms (M-2 and M-3) were least preferred (26/30). Participants repeatedly valued morphological continuity with the existing settlement logic (block size, spacing, and strip-based rhythm) and expressed negative views toward non-local, highly heterogeneous insertions.

Overall, consistent with the quantitative analyses, perceived impact is concentrated near the new parcels, while effects at far-distance KOPs are subtle and mainly mediated by luminance/color contrast and morphological coherence. Given the small, non-local sample and the interview-based design, these findings are descriptive rather than inferential, but they triangulate with the perception metrics and the GIS spatial analysis: continuity with the grid-aligned development pattern and restrained tonal contrast underpin higher public acceptability.

7.5.5 Integrated assessment and definition of thresholds

By synthesizing spatial metrics, KOP/SVI assessments, VR-based perception, and public/expert interviews, we find the acceptable upper bound for further expansion between the *2025-phase* and a trimmed version of M-1. The *2025-phase* is spatially compatible; however, the *present-phase* perceptual metrics already show threshold exceedances in near views. M-1, as specified, pushes the envelope in another way: it preserves most of the grid and canal skeleton but increases near-view attentional load and modestly elevates skyline exposure. Therefore, public preferences and expert synthesis delimit acceptable infill to a narrow band between the *2025-phase*, M-0, and M-1.

Given the site's World Heritage status, we adopt stricter decision criteria (**TABLE 7.5** standards may be relaxed in ordinary contexts). The trigger rules and final thresholds are as follows: **Rule 1** for spatial and visibility metrics and KOP construction-intensity: any single exceedance triggers immediate review of the plan or of works in progress; **Rule 2** for perception-based indicators (eye and head metrics): if, in a spot-check, >50% of tested KOP scenes exceed the cap, the condition is notable and must be tracked; if ≥75% exceed, a formal evaluation is required; if ≥90% exceed, construction should be stopped pending mitigation.

The visibility metrics (GIS1 to GIS3) are calibrated to the Middenbeemster context and should be treated as case-specific. By contrast, spatialcharacter indicators (ΔGOR, baseline water retention, mechanism composite) apply more broadly to lowland countries and polder-type landscapes elsewhere, provided analyses adopt comparable spatial canvases and sampling ratios. The KOP/VR conclusions are still more general: in flat rural landscapes facing slow, low-intensity development, the same perceptual patterns and thresholds offer helpful guidance. Using these rules and assessment thresholds, M2 and M3 fall outside the acceptable range of visual impact. M1 exceeds mainly on perception measures; with edge planting, tonal softening, height and setback discipline, and a period of weathering, it may be brought to a marginally acceptable level under continued monitoring.

TABLE 7.5 The final thresholds for Middenbeemster expansion's "when to end"

Main	Indicator	Threshold	Description
GIS visibility	Theoretical visibility	<= 36,000	Within the limited envelope of M-1. Exceedance indicates unrealistic expansion.
	Route-based visibility	>= 75,000	Must not exceed the activity-space envelope of M-0 (considering vegetation masking)
	Contextual overlay visibility	<= 205,000	Four models tested; exceedance indicates horizontal or vertical over-expansion of new massing.
Spatial characters (within 4 grids)	ΔGOR vs 2025 (pp)	<= 0.60	Slightly stricter than M-1; exceedance signals over-densification
	Mechanism composite (vs 2025)	>= 0.98	
	Water retention vs 2015 (pp)	>= 0.95	
	Jaccard (vs 2025)	>= 0.83	
KOP (Near views)	Construction-intensity (Near KOPs)	<= 18%	Remain below the *2025-phase* peak
	Buildings' dwell (ms, p75)	<= 1500	Remain below the present-phase level
	New construction dwell (ms, p75)	<= 2000	Remain below 2000 ms to avoid strong salience
	Over-exploration (p75)	Yaw(std) >108° and Roll(std) >96°	Indicates a high horizontal search load typical of the *present phase*
	Horizontal lock-in (p75)	Yaw(std) <75° and Roll(std) <70°	Strong attraction of nearby masses with little further exploration (M-1–M-3)
	Vertical lock-in (p75)	Pitch(std) >49° and Yaw(std) <80°	Indicates vertical dominance of new massing
KOP (Far views)	Construction-intensity	<= 0.8%	Remain below the *2025-phase* peak
	Building dwell (ms, p90)	<= 1600	
	Lock-in (p75)	Yaw(std) <80° and Roll(std) <80°	Projected from near-view patterns indicates fixation on the new construction.

Note: In this case, there are no conventional SBEs or visual scene compositions, and the analysis of the visual corridor (where such impacts are not obvious) is therefore omitted. However, in other cases, this can be added as appropriate.

7.6 Discussions

7.6.1 Core findings

This chapter develops an integrated, enhanced VIA framework that consolidates established and emerging techniques into a coherent workflow. The framework provides objective, quantitative evidence for decision-making on incremental, low-intensity urban and community expansion at the edges of rural and heritage landscapes, and it supplies analytic procedures for determining when construction should stop. Conventional VIA often captures snapshot conditions or focuses on heterogeneous projects, and it relies on subjective judgment for low-heterogeneity cases (Dronova, 2017). Our framework systematically incorporates multi-temporal evidence (SVI time series and proposed scenarios), multi-angle analysis (eye-level FOV and bird's-eye view GIS analysis), mechanism-aware distribution metrics, and human-centered perception tools (VR with eye- and head-tracking complemented by validation interviews). These layers yield a granular, reproducible, and decision-ready understanding of how slow growth accumulates and how it is perceived.

In the application for the evaluation of Middenbeemster's expansion plan in Beemster Polder, three core findings are highlighted:

a) **Quantification of incremental impacts:** By comparing 2015/2020/2025/present, and three proposed scenarios, we show that gradual expansion can be measured objectively using spatial change rates and similarity indices, changes in construction intensity in panoramic imagery, and VR-based perceptual indicators. Together, these measures reveal how incremental impacts arise and how they progressively reshape human perception and the visual environment.

b) **Operational visual stop rules:** A stepwise analysis across past, present, and future conditions identifies calibrated visual thresholds that define an upper bound for additional expansion and provide decision-ready criteria for halting or moderating projects.

c) **Evidence for mitigation through design and management:** We observe several additional findings about visual impact mitigation strategies. Pattern-conforming, low-rise development that follows surrounding grain, materials, and textures reduces visual impact. Vegetation buffers shorten gaze dwell on new construction in VR tests, thereby attenuating perceived disturbance. Managing temporarily exposed facades during construction also limits peak impacts. These points are elaborated in **Section 6.4**.

The chapter offers both methodological advances, namely a multi-temporal, multi-method, mechanism-aware VIA framework, and substantive insights, namely that incremental expansion is measurable and that its strongest effects concentrate at the parcel scale. That pattern-conforming, low-rise development is less intrusive than heterogeneous or centralized forms.

7.6.2 Incremental visual impact

The findings suggest that the low-density, incremental encroachment poses the greater long-term threat to rural and peri-urban cultural landscapes (Palmer, 2019). Many landscapes of heritage value are not lost in a single disruptive project, but are gradually eroded by accumulating small, seemingly innocuous additions (Dentoni et al., 2023; Gobster et al., 2019). By reconstructing visual characteristics across multiple time steps, this study provides an empirical sample of such slow attrition of the visual environment.

Two perspectives are particularly revealing. First, from the standpoint of land-use proportions and environmental texture, similarity of parcels with the original grid has declined since the mid-2010s, as new construction fills previously open landscape (Niesterowicz & Stepinski, 2016; Sertel et al., 2018). Second, from the standpoint of perception experiments, far-field horizons illustrate a paradox: participants seldom fixated on the gradual advance of building clusters toward the skyline, yet if left unchecked, such progression will eventually distort the proportional balance between horizon, polder, and sky (Cheng et al., 2019). Incremental impacts may therefore be imperceptible in the short term but decisive in the long run.

This leads to the case for defining a clear “red line”, understood as a threshold of expansion beyond which a rural heritage landscape’s visual and spatial character is compromised. In the Dutch context, the Randstad Green Heart offers a precedent (Kühn, 2003). Although its edges have experienced gradual encroachment, respect for an ultimate boundary has preserved the rural landscape structure and allowed surrounding cities to continue benefiting from the rural landscape's cultural ecosystem service (Romanazzi et al., 2023). For the Beemster Polder, we propose that once expansion completes the town's current rectangular outline, while maintaining proportional similarity to the historic grid, this should be treated as the maximum tolerable extent. Additional centralized or mid-rise insertions within that frame are not advisable because they would cross the heritage threshold.

A further insight is that impact intensity is not linear over time. Our evidence suggests a temporal curve: strongest during construction, lower once completed, and gradually diminishing as façades' weather and visual contrast decrease. This dynamic should inform management strategies in heritage-sensitive areas: while ultimate limits must be clearly defined, the construction phase itself is often the most visually disruptive period, and expediting completion can significantly reduce perceived impact (Wang et al., 2024).

7.6.3 Extensions and methodological implications of the VIA framework

In designing the proposed VIA framework, we deliberately incorporated a set of recently emerging techniques that extend the methodological horizon of VIA and provide new pathways for studying perception and visual-spatial features in cities and landscapes.

7.6.3.1 KOP workflow integrating 3DGS and VR

This study is among the first to deploy an integrated 3DGS-VR workflow in visual landscape research. Cross-checks against panoramic photography (e.g., SVI) and retrospective interviews indicate that the pipeline is reliable for both analytic assessment and participant communication. Relative to imagery- or photomontage-based tools, 3DGS offers clear advantages for perception experiments: it renders immersive scenes in interactive VR (Yu et al., 2025), yielding stronger realism and engagement than still 2D images. High-precision captures (e.g., X-Grid or UAV-based 3DGS) approach panoramic fidelity and, as the literature notes, often exceed mesh-based models in perceived realism. At the same time, low-cost 3DGS proved adequate for identifying visual foci and activity patterns; despite lower geometric accuracy, participants adapted quickly and reported perceptions consistent with quantitative metrics. This suggests the 3DGS-VR workflow is well-suited for scaling perception-oriented VIA in contexts with limited access to high-end hardware (Yu et al., 2025).

Beyond VIA, the workflow shows broad application potential, for participatory design, built-environment analysis and perception studies, and even online communication of heritage/urban identity. A key limitation, however, is infrastructural: our evaluation ran inside Unity with VR headsets, and perceptual data (eye/head metrics) were exported as panoramas for analysis on separate specialist platforms. The ecosystem still lacks seamless bridges between interactive VR engines and professional eye-tracking/analytics toolchains, underscoring the need for more integrated end-to-end platforms or shared information infrastructure.

7.6.3.2 GIS analysis workflow enhanced by point cloud

Long-standing critiques note that GIS-based visibility analysis can be imprecise and, on its own, is not a sufficient basis for VIA conclusions (Cimburova & Blumentrath, 2022). In particular, DEM/DSM viewsheds tend to ignore micro-relief and canopy/ façade occlusion, inflating theoretical exposure (Zong et al., 2021). Point-cloud integration addresses these weaknesses directly: by representing terrain, vegetation volumes, and built mass as explicit 3D geometry, it improves the computation accuracy and reduces the “bare-earth” bias of conventional viewsheds.

Even with these gains, the explanatory power of visibility metrics is context-dependent. In our low-rise, slow community expansion case, GIS visibility counts changed little and were difficult to translate into clear conclusions at eye-level (Mikita et al., 2023). By contrast, GIS visibility results are usually clearer and easier to interpret for high-salience, tall, or clustered projects such as high-rises and wind turbines. For such projects, contextual-overlay visibility (new constructions layered onto the existing skyline fabric) is often more decision-useful because it shows when a proposed tower is visually absorbed within an existing high-rise field and when it breaches the skyline envelope (Cimburova & Blumentrath, 2022). Two visibility products are more informative for low-rise schemes, although they can be harder to interpret. First, activity-space viewsheds along public routes identify where people encounter change. Second, the zone of theoretical visibility around the new construction shows where material or tonal mismatches cannot be visually masked—the first product links directly to perception indicators such as route-level salience and search effort. The second product quantifies where and how often the new construction is seen when contextual blending is weak, bringing the analysis closer to experienced impact rather than abstract exposure counts (Kissling et al., 2023).

Looking forward, the feasibility of point cloud-enhanced workflows is improving rapidly. Urban- and national-scale open point-cloud datasets are now available in several jurisdictions, lowering data-acquisition barriers and standardizing inputs for visual-spatial analysis. As such datasets become more widely available, point-cloud support will likely become a baseline requirement for credible GIS visibility analysis within VIA, particularly in cases where new construction occurs in heritage-sensitive settings.

7.6.3.3 Perception experiments as support for decision-making

Even though our validation interviews were modest in scale, they exposed clear divergences in value orientations. While non-local participants opposed expansion within a World Heritage site on principle, local stakeholders often expressed pragmatic support, reflecting divergent benefit positions even within "the public." This underscores that attitudinal preferences alone are insufficient for robust VIA. Objective perception experiments with eye/head-tracking or controlled VR stimuli are needed to anchor judgements in measurable responses rather than subjective statements of liking. Moreover, traditional expert-based VIA has historically downplayed perception because it was difficult to quantify, instead favoring technical indicators. The framework demonstrates that perceptual data can be quantifiable and reproducible, offering complementary evidence-based alongside expert value judgment and conventional preference scores.

7.6.3.4 Evaluation delivery: "When to end"

Rather than relying primarily on expert intuition or normative assertions, our procedure defines the stop-line through converging evidence across multiple modalities: spatial metrics, visibility diagnostics, perception experiments, and public preference. By calibrating thresholds jointly, the framework identifies the highest condition acceptable across all layers, offering a transparent and reproducible way to decide "*when enough is enough*". This approach is also transferable. Although developed in the context of peri-urban growth at a World Heritage landscape, the logic of cross-modal calibration and threshold identification can be adapted to other settings where change is gradual and heterogeneous impacts are weak. In such cases, the framework can function as a final evaluative deliverable: a decision-ready instrument that provides planners and managers with a defensible upper bound, and a clear rationale for mitigation or refusal. In this sense, the "when to end" procedure is not site-specific but constitutes a generalizable VIA component for managing low-intensity, incremental change.

7.6.4 Visual impact mitigation strategies in design and planning

The case study reveals several observations that can inform the mitigation of visual impacts where new construction is unavoidable. First, respect for local morphology is fundamental. Our results suggest that the relatively modest impact scores for the Middenbeemster expansion are partly explained by the decision to follow the historic parcel texture and strip-based rhythm. Even though the new buildings are not identical in form to older ones, adherence to similar materials and proportions preserved a sense of coherence (Antrop, 2005). This highlights the importance of design guidelines that prioritize continuity of scale, texture, and alignment with the underlying grid. Second, community involvement in design control is effective. In the Dutch planning context, local residents and committees (e.g., Welstandscommissie) retain the right to review and advise on façade styles, reducing the likelihood of highly discordant insertions (De Somer, 2018). This form of participatory governance emerges as a key institutional safeguard against random or opportunistic building forms. Third, construction phasing can strongly influence impact perception. Both the quantitative results and perception experiments indicate that the construction phase is the most disruptive period, while completed buildings gradually weather into their context. Mitigation, therefore, includes shortening construction timelines and adopting phasing strategies that reduce visual impacts, building peripheral parcels first, or applying pre-weathered materials that immediately reduce color/brightness contrast with the surroundings. Fourth, vegetation can be strategically employed. Eye-level perception tests confirmed that trees exceeding building height attenuate the visibility of new blocks and soften skyline discontinuities. Therefore, landscape design can serve as a proactive tool for restoring visual balance, for example, by planting tall hedgerows or aligning tree belts along parcel edges, which help mediate between new constructions, the polder landscape, and far-view skylines.

Overall, these strategies suggest that impact mitigation is not only a matter of limiting volumes, but also of sensitive design, controlled phasing, material treatment, and context-sensitive planning. Together, they provide a practicable pathway for reconciling expansion needs with protecting heritage landscapes.

TOC

7.6.5 Limitations

Several limitations of this chapter should be acknowledged. First, the sample size for perception experiments and validation interviews was modest, and participants were non-local; consequently, the public and expert assessments reported here are indicative rather than representative. We deliberately simplified this component, as the primary contribution of the chapter lies in the development of an objective, evidence-based analytical VIA framework, but the minor local stakeholder voices limit the social depth of evaluation (Karatas & El-Rayes, 2015). Second, although low-cost 3DGS capture shows strong potential for scaling perception-oriented VIA, its geometric and radiometric accuracy remains lower than that of professional multi-sensor systems. In addition, practical integration between VR environments and 3DGS pipelines is imperfect. In this study, repeated trials and participant acclimation mitigated these issues and supported consistent perception findings; nevertheless, fine-grained fidelity remains a constraint for rigorous heritage assessments. Third, the temporal coverage of SVI is sparse and highly sensitive to seasonal conditions (leaf-on/leaf-off and pruning cycles) (Sánchez & Labib, 2024), which introduces noise into measurements of incremental change. The 2025 street-view record is limited near the site, further constraining phase-to-phase comparisons at near views. Fourth, despite the precision gains of point cloud-based GIS visibility analysis, fundamental challenges of visibility methods remain (Palmer, 2022). Object masking, occlusion, and the paradox of cumulative counts under low-rise accretion mean that visibility rasters cannot, on their own, capture perceptual dominance or salience. These issues highlight the necessity of combining ZTV with contextual overlays and perceptual experiments.

Taken together, these limitations suggest caution in interpreting the results' perceptual generalizability and fine-scale numerical precision. Future research should enlarge local participant pools, incorporate denser temporal imagery, and further refine low-cost 3DGS methods. Nonetheless, by foregrounding an objective and replicable analytical framework, the study provides a methodological advance even as its evaluative components remain deliberately light.

7.7 Conclusions

This chapter presents an integrated VIA framework that tracks incremental urban and community expansion, assesses the visual impact on rural heritage and cultural landscapes, and determines the operational endpoint at which further construction should stop. The “when to stop” decision is made explicit by linking spatial indicators and visibility with perceptual salience and by reporting comparable indicator thresholds across development stages, with evidence drawn from experts and the public.

In the Middenbeemster expansion case, multi-stage comparisons from past phases to future proposed scenarios quantitatively confirm gradual visual impacts and show how these impacts accumulate to affect human perception. Aligning changes in exposure and visibility with perception-based metrics identifies that the acceptable range lies between the trimmed Present phase and M1 (both acceptable only in part and subject to controls), while M2/M3 exceed thresholds. This implies that further expansion would no longer be acceptable in this setting. Methodologically, the framework integrates GIS-based spatial and visibility analysis with SVI and KOP-based perception-enhanced assessment, supported by 3DGS eye-level rendering and VR eye and head tracking. The synthesis produces decision-grade evidence for the management of rural heritage landscapes.

Beyond this case, the approach is transferable to heritage-sensitive ruralurban fringes and points to practical mitigation strategies such as morphological continuity, targeted vegetation, and constructionphase controls. By coupling spatial exposure with human perception in a single, stagecomparable system and translating this evidence into indicator-based stop rules, the framework provides a predictive, threshold-based tool for day-to-day planning and heritage management consistent with SDG 11.

Author’s contribution in this case study

This Beemster Polder case study was conducted by the author under the supervision of promotor Steffen Nijhuis and in collaboration with the Digital Technology group at TU Delft. The author was responsible for the experimental and research design, the development of the methodological framework, data processing, logical and analytical argumentation, and the writing and revision of the case-study text. The author also carried out part of the spatial analysis, perception experiments and participant recruitment, performed the analysis of the perception data and the streetscape analysis, and produced a substantial part of the visualizations. The co-authors contributed by processing the AHN point cloud data and conducting part of the spatial and visibility analyses, as well as part of the perception experiments and participant recruitment.

PART III

Synthesis, Navigation, and Outlook

This part focuses on consolidating cross-case insights into a navigable framework that helps researchers and practitioners make context-sensitive choices when multiple data sources and methods are available. Chapter 8 conducts cross-case comparison across content, data, and method layers, distilling transferable patterns, key divergences, and practical selection-and-combination logic for constructing research pathways under real constraints. Building on this synthesis, it articulates a structured navigation framework to support goal-oriented pathway design and clearer methodological transparency. Chapter 9 concludes the thesis by answering the research questions, summarizing theoretical and methodological contributions, reflecting on limitations, and outlining directions for future work in integrated visual heritage landscape research and practice.

8 Synthesizing the insights and structuring the pathways of the study cases

From Case Evidence to Navigable Model for Selecting and Integrating Data-Method-Content Pathways

This chapter aims to generalize beyond individual cases by synthesizing how pathway configurations perform across different heritage types, scales, and research intents. Drawing on the four case studies, it compares EP1-EP4 across content, data, and methods, identifying what travels reliably across contexts and what must remain case-sensitive. The chapter then organizes recurring approaches into families based on functional roles and thematic relevance, helping clarify how spatial analysis, perception evidence, expert interpretation, and digital visualization can be combined strategically rather than opportunistically. Building on these abstractions, it proposes navigation models and decision logic for pathway selection and combination, supporting goal-oriented methodological design under varying constraints of data availability, resources, and stakeholder needs. The outcome is a structured, adaptable framework that helps researchers and practitioners navigate complexity while maintaining transparency, transferability, and contextual fit.

List of abbreviations for chapter 8

Abbreviation	Full term	Meaning in Chapter 8
EP-1	Expanded Pathway 1	Integrated spatial–perceptual analysis pathway (case-based evidence synthesis).
EP-2	Expanded Pathway 2	Digitally supported, multi-perspective perception evaluation pathway.
EP-3	Expanded Pathway 3	Multi-source visual–spatial analysis pathway for cross-scale interpretation.
EP-4	Expanded Pathway 4	Perception–visibility pathway for decision-making and threshold setting.
GIS	Geographic Information System	Core platform for spatial analysis, visibility modeling, and map-based synthesis.
VAM	Visual Analysis Method	A family of methods for modeling and measuring visibility/visual structure.
VIA	Visual Impact Assessment	Decision-oriented assessment logic referenced for governance and planning control.
KOP	Key Observation Point	Representative viewpoints used for consistent eye-level assessment and comparison.
CV	Cumulative Viewshed	Visibility summed across multiple viewpoints to express collective exposure.
VM	Visual Magnitude	A measure of visual prominence/intensity derived from visibility geometry.
FOV	Field of View	Eye-level viewing range used to define viewpoint-based visual measurement.
SVI	Street View Imagery	Street-level panoramas used for large-scale, viewpoint-rich visual evaluation.
UAV	Unmanned Aerial Vehicle	Aerial imaging platform supporting rapid scene capture and reconstruction.
LiDAR	Light Detection and Ranging	3D sensing technology producing point clouds for terrain/vegetation/buildings.
TLS	Terrestrial Laser Scanning	Ground-based LiDAR acquisition for high-detail local 3D capture.
UGC	User-Generated Content	Geo-tagged photos/images used to infer visual attention, hotspots, or landscape popularity.
3DGS	3D Gaussian Splatting	Rendering/reconstruction technique referenced for immersive, cost-efficient 3D visualization.
LIM	Landscape Information Model	Modeling concept referenced for structured landscape-scale digital representations.
BIM	Building Information Model	Digital building model referenced (including heritage variants) for integrated datasets.
H-BIM	(Heritage) Building Information Model	Heritage-oriented BIM referenced in relation to modeling and conservation workflows.
BGI	Blue-Green Infrastructure	Combined blue (water) and green (vegetation) elements in visual-perceptual evaluation.
BI	Blue Infrastructure	Water-related component of BGI referenced in exposure/composition logic.
GI	Green Infrastructure	Vegetation-related component of BGI referenced in exposure/composition logic.

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List of abbreviations for chapter 8

Abbreviation	Full term	Meaning in Chapter 8
DEM	Digital Elevation Model	Terrain model referenced when discussing visibility modeling inputs.
DSM	Digital Surface Model	Surface model including objects; contrasted with point-cloud-based modeling.
DTM	Digital Terrain Model	Bare-earth terrain model referenced alongside DEM/DSM terminology.
AR/VR	Augmented Reality / Virtual Reality	Immersive/interactive visualization strategies referenced for public engagement.
AI/ML/DL	Artificial Intelligence / Machine Learning / Deep Learning	Computational approaches referenced for classification, clustering, and automated interpretation.
LLM	Large Language Model	Referenced as a support for clustering, tagging, and scene interpretation in synthesis stages.
LMM	Linear Mixed-effects Model	Referenced for handling participant/viewpoint variability in perception experiments.

8.1 Introduction

Visual research on heritage landscapes has expanded rapidly, with methods ranging from spatial modeling and empirical perception analysis to immersive visualization and AI-supported tools (Harvey & Waterton, 2015; Inglis et al., 2022; Jamil & Brennan, 2025a; Sarihan, 2021; Zhou et al., 2023). At the same time, diverse evidence sources, including high-resolution point clouds, eye-tracking records, and large-scale digital imagery such as street-view data, are increasingly integrated into analytical workflows (Richter & Döllner, 2014; Zhang & Yu, 2021). These developments signal a shift toward multi-source integration, cross-disciplinary convergence, and more context-sensitive applications in visual-heritage studies (Wang & Zakaria, 2025). Despite this methodological richness, a structural challenge remains: researchers and practitioners often lack a coherent framework to navigate the expanding set of themes, tools, and datasets, and to align data types, analytical methods, and research goals in a systematic and scalable way (Münster, 2017). As a result, method selection can remain case-specific, and research outcomes are less transferable across heritage contexts.

Responding to **Research Question 3**, this chapter synthesizes the four case studies and translates their findings into a structured framework for navigating research pathway choices. The framework is intended to support informed selection and integration of data, methods, and research content. Drawing on Chapters 4 to 7, the chapter identifies cross-case performance patterns and context dependencies, organizes recurring data and method families by functional roles, and refines pathway models and selection logic to support more transferable pathway navigation across heritage landscape studies **(FIG. 8.1)**.

This chapter is organized as follows: **Section 8.2** summarizes the four case studies in terms of objectives, data, methods, and outputs. **Section 8.3** compares the expanded pathways across cases and formalizes a compact indicator family set for transparent cross-case comparison. **Section 8.4** generalizes the pathway models and provides a decision logic for pathway selection and adaptation. **Section 8.5** concludes with implications and recommendations for future work.

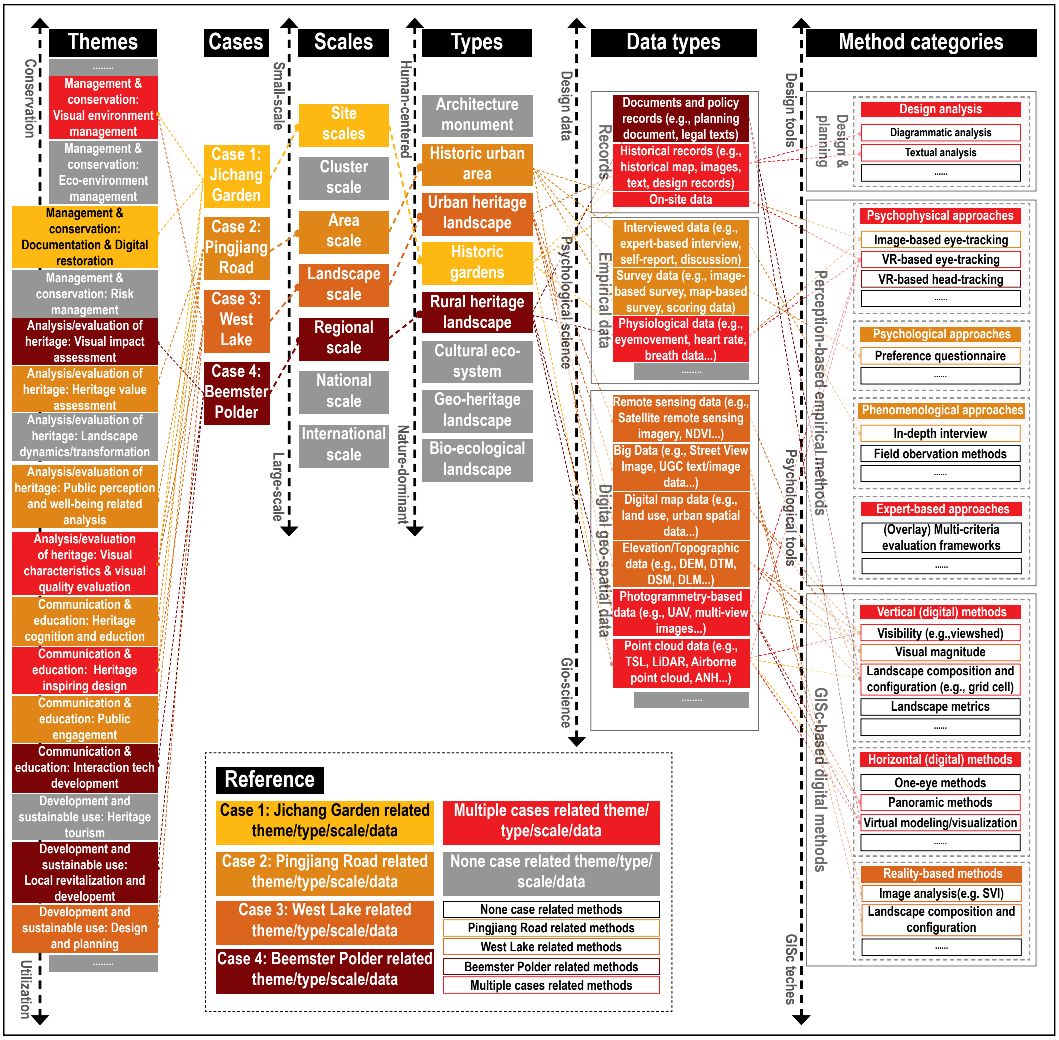

FIG. 8.1 The integrated data-method-content map of the four case studies: The diversity and complexity already evident in these four representative cases highlight the need for a more abstracted and navigable framework for selecting research pathways.

8.2 Summaries of the case studies

This section summarizes the four case studies (Chapters 4 to 7) as implemented tests of the pathway framework across contrasting heritage landscape conditions. Each case corresponds to one expanded and integrative pathway type, EP1 to EP4, and operationalizes a distinct configuration of data, methods, and research tasks. The summaries highlight the evidence package and the type of output each pathway can reliably support, without repeating case-level procedural detail, so that the following synthesis can abstract transferable patterns.

8.2.1 Jichang Garden: EP-1 Integrated visual-spatial and visual-perceptual landscape analysis pathway

The Jichang Garden case implements the EP1 integrated visual-spatial and visual-perceptual landscape analysis pathway in an enclosed, sequential classical garden where viewpoint orchestration and layered vegetation make spatial experience highly structured (Peng et al., 2023). The pathway combines high-resolution point clouds and panoramic imagery with VR-based eye-tracking, enabling human-level 3D viewshed analysis together with bird's-eye visibility modeling. This configuration links measurable spatial features, such as openness, sequence, and vegetation layers, to empirical gaze behavior, supported by ML-based gaze classification and correlation tests (Peng et al., 2023; Yuan, 2024). The case demonstrates how EP1 strengthens explanation by coupling perception evidence with multi-view spatial analysis, producing design-relevant insights for conservation and landscape practice, while also depending on high-fidelity 3D data and controlled perception sampling.

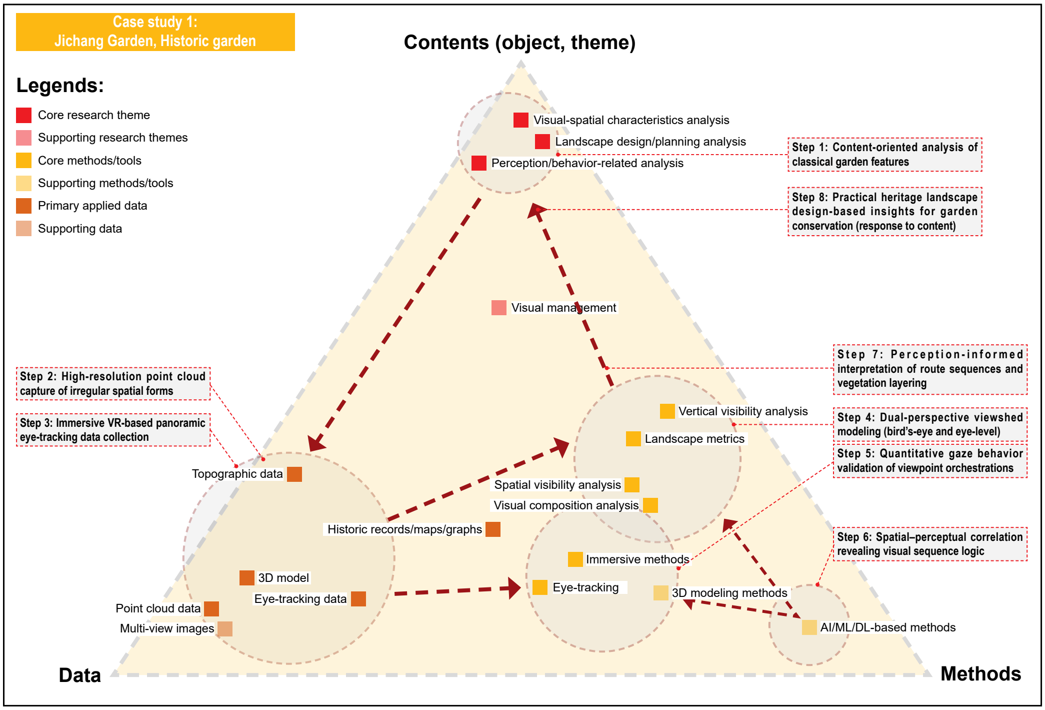

FIG. 8.2 Steps for constructing the pathway for case study of Jichang Garden.

8.2.2 Pingjiang Road: EP-2 digital-supported perceptual evaluation for multi-audience pathway

The Pingjiang Road case exemplifies the EP2 digitally supported perceptual evaluation for multi-audience pathway by examining how blue-green infrastructure influences attention, preference, and interpretation in historic urban environments. The pathway integrates UAV-derived 3D semantic mesh modeling and exposure quantification with a layered perception structure supported by eye-tracking, structured questionnaires, and semi-structured interviews, enabling systematic comparison between expert and public groups (Hu & Minner, 2023). Spatially derived typologies guide stimulus selection, while the multi-channel perception evidence differentiates physiological attention from affective preference and cognitive meaning-making. Findings indicate that green infrastructure consistently attracts attention and improves perceived quality without displacing heritage focal points, while blue infrastructure effects vary with context, providing an evidence base that can inform heritage-sensitive planning and visual management. The case shows how EP2 supports scalability across audiences, while making explicit the tradeoffs between participation load, experimental control, and interpretability across perception channels.

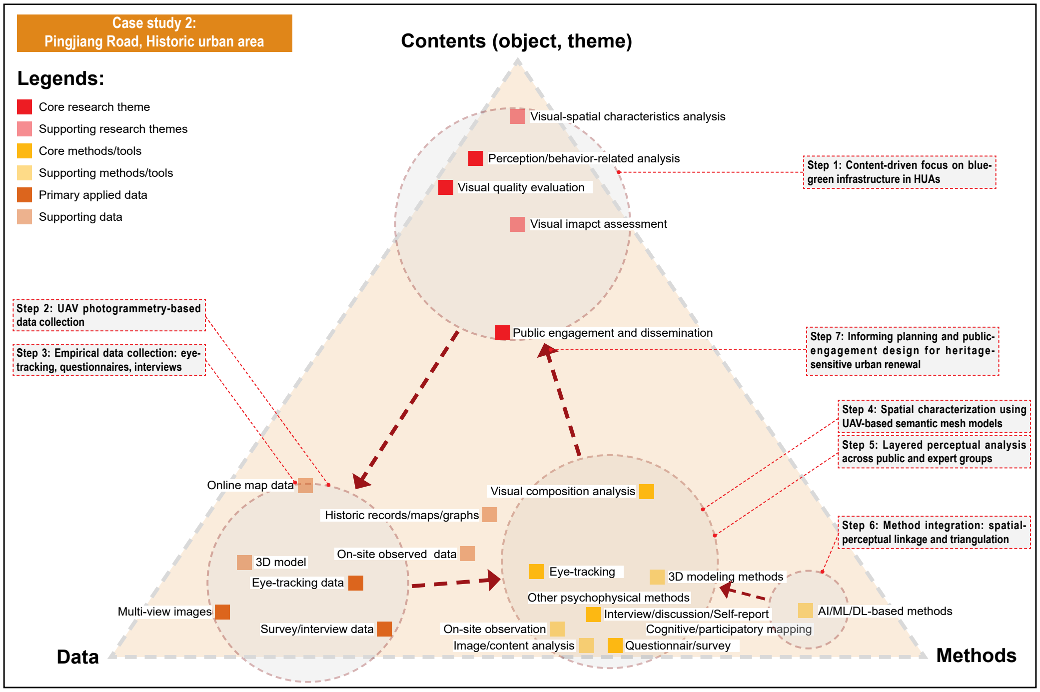

FIG. 8.3 Steps for constructing the pathway for case study of Pingjiang Road.

TOC

8.2.3 West Lake: EP-3 multi-source geo-data visual analysis pathway

The West Lake case constructs the EP3 multi-source geo-data visual analysis pathway to interpret layered visual-spatial logic at a large urban heritage scale, emphasizing structural visibility and composition rather than direct perception testing (Peng & Nijhuis, 2021). The pathway assembles multi-scale evidence, including terrain and built-form data, panoramic street-view imagery, and historical photographs, and integrates complementary GIS-based methods to capture different dimensions of visibility and scene structure. By combining cumulative viewshed, visual magnitude, and field-of-view metrics with street-view composition evidence, the pathway reveals view corridors, skyline values, and obstruction patterns that cannot be resolved through any single method alone (Peng & Nijhuis, 2021). The case demonstrates how EP3 can translate multi-source spatial evidence into typology-informed insights for visual management and design coherence, supporting both site-level decisions and city-scale planning.

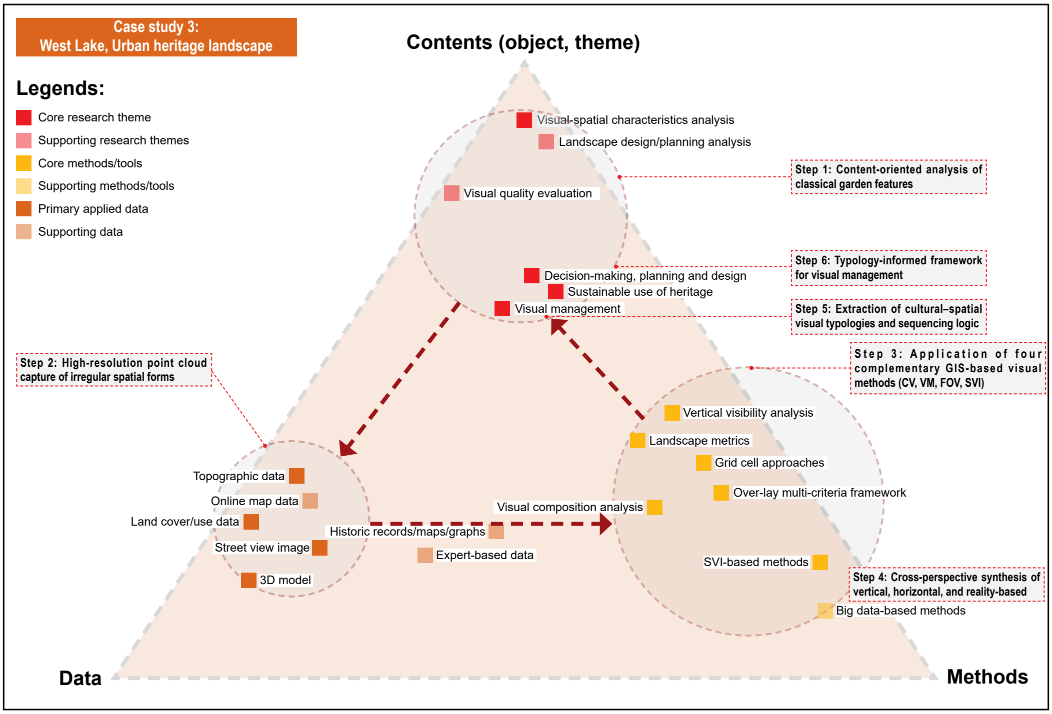

FIG. 8.4 Steps for constructing the pathway for case study of West Lake.

8.2.4 Beemster Polder: EP-4 visual management enhanced by perceptual information pathway

The Beemster Polder case implements the EP4 visual management enhanced by perceptual information pathway in a UNESCO-listed rural grid landscape facing incremental town-edge expansion. The pathway is designed as a cross-temporal evidence configuration that aligns spatial visibility and structural metrics with perception evidence across past, present, and scenario-tested futures, so that visual impact assessment can move toward an operational stop-line rather than a purely descriptive statement. High-fidelity yet cost-efficient spatial baselines are supported by hybrid point clouds from AHN-5 LiDAR, UAV photogrammetry, and mobile imagery (Y. Yu et al., 2025), while immersive representations are enabled through 3DGS modeling for perception testing (Franke et al., 2025; Jamil & Brennan, 2025b). Spatial mechanism is tracked with visibility and structure indicators, including occupancy and strip-logic similarity (Yang et al., 2019), and perception evidence is captured through multi-temporal street-view series and VR eye-head tracking. The case shows how EP4 can translate integrated spatial and perceptual evidence into governance-ready guidance, while also requiring longitudinal evidence availability and careful scenario control.

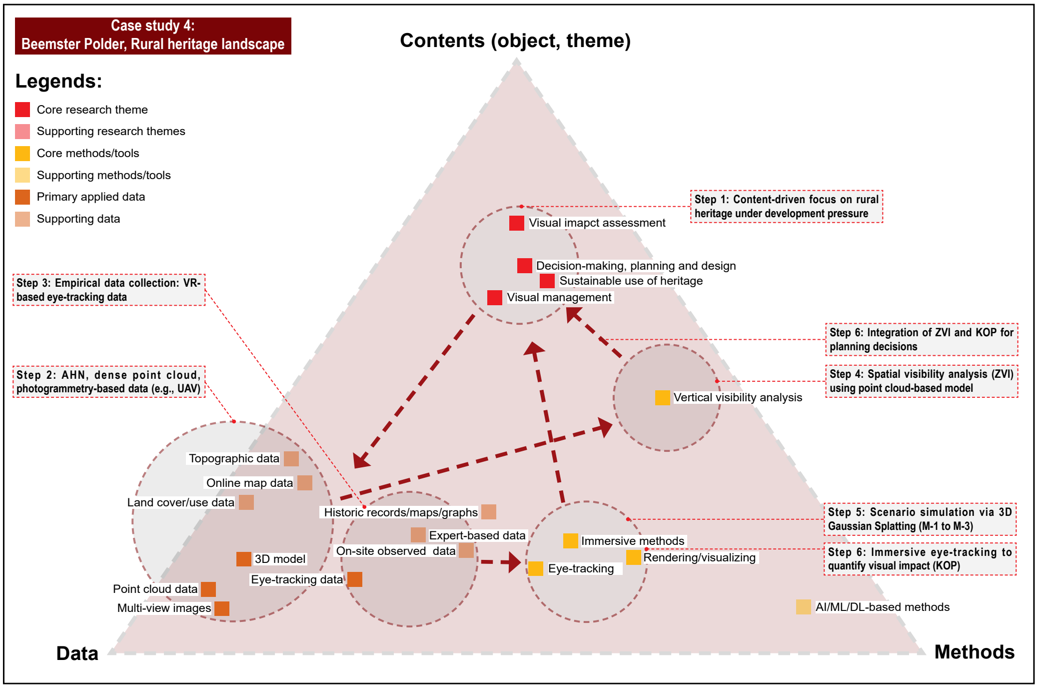

FIG. 8.5 Steps for constructing the pathway for case study of Beemster Polder.

TOC

8.2.5 Summary

The four case studies presented above demonstrate how pathway-oriented research can facilitate a more structured, adaptive, and context-sensitive approach to visual heritage landscape analysis. Despite their differences in landscape type, spatial scale, and research focus, each case reflects a deliberate configuration of data sources, analytical methods, and visual tasks that together form a coherent methodological pathway.

8.3 Cross-case comparison

This section prepares the ground for the generalization that follows. It compares the four extended pathways (EP-1 to EP-4) across the three layers of content, data, and methods, and distills a set of shared insights. The aim is to clarify what consistently travels across contexts and where choices should remain context sensitive, so that the next section can formalize a navigable, decision-ready model of pathway selection and combination. To strengthen empirical generalization, the section uses two complementary devices: pathway-level evidence constructs that remain stable across cases, and a compact indicator family set that enables transparent cross-case comparison without forcing raw numerical equivalence across scales.

8.3.1 Cross-pathway insights

This section compares the four pathways through two complementary lenses and one intent axis. The lenses pair structural analysis with perceptual evidence, while the intent axis spans problem-driven research and practice-oriented decision making **(TABLE 8.1)**. Positioned in this 2-by-2 frame, EP-1 balances structure and perception to build explanatory accounts of how heritage-landscape features affect people, making it suitable for design analysis and environmental-psychology questions. EP-2 is perception-led, typically layering attention, affect, and cognition, with spatial analysis supporting the generalization and localization of human-centered findings. EP-3 is structure-led and relies on multiple spatial methods and expert reading rather than perceptual data, excelling at rapid, cross-scale identification of spatial structures and types. EP-4 resembles EP-1 in balancing the two lenses but is practice-oriented: it turns spatial and perceptual evidence into thresholds, stopping lines, and scenario ranking for evaluation and governance. Building on this frame, the next section formalizes a navigable model for selecting and combining pathways.

To keep the comparison at the appropriate level of generality, the pathways are linked to a shared set of evidence constructs rather than tool-specific metrics. These constructs describe what each pathway aims to produce, in forms that remain comparable across heritage types, scales, and data conditions.

TABLE 8.1 Cross-case comparable evidence constructs across the four expanded pathways (EP-1 to EP-4).

Pathway	Primary purpose	Core evidence type	Comparable evidence constructs (cross-case)
EP-1	Explain mechanisms linking heritage structure to human experience	Coupled structure and attention evidence	a) Alignment between modeled structure and observed attention; b) sequence logic along routes and nodes; c) stability of salient anchors across viewpoints.
EP-2	Evaluate perceived quality across scenes and audiences	Perception distributions grounded in scene evidence	a) Composition of what is seen; diversity of viewpoints and scenes; b) preference and meaning distributions across groups; c) exposure-response sensitivity.
EP-3	Diagnose structural patterns rapidly across scales	Structural visibility and configuration evidence	a) Exposure structure; connectivity of corridors and nodes; b) complexity and hierarchy of visual fields; c) skyline and silhouette control.
EP-4	Translate evidence into thresholds, rankings, and governance rules	Change-based evidence under scenarios plus acceptability	a) Sensitivity to change; b) acceptability bands and stopping lines; c) robustness of rankings across methods and groups; d) risk concentration at key observation points.

8.3.2 Cross-method insights

Across the four cases, methodological variation reflects different evidence strategies rather than isolated tool choices. Some pathways integrate perception-based evidence to examine how people attend to and interpret heritage scenes, while others rely on multi-source spatial diagnostics and expert reading to identify structural patterns at scale. In this chapter, these differences are expressed through the relative emphasis placed on recurring analytical functions across the cases **(TABLE 8.2)**.

TABLE 8.2 Cross-case method profiles showing the evidence modules assembled in each case

Case	Spatial base modeling and reconstruction	Visibility and exposure modeling	Image and scene decomposition	Perception and behavior measurement	Cross-evidence synthesis and decision translation
Jichang Garden	High	High	Mid	High	Low
Pingjiang Road	Low	Low	Low	High	Low
West Lake	High	High	High	None	Mid
Beemster Polder	High	High	High	High	High

Note: High, Mid, and Low indicate the relative role of each method module within a case: High = primary evidence, Mid = supporting use, Low = contextual or occasional use.

Viewed through this lens, EP-1 and EP-4 represent high-integration configurations that couple detailed spatial reconstruction and visibility reasoning with perception measurement, enabling structural findings to be interpreted alongside behavioral evidence. EP-2 prioritizes perception-led evaluation and uses spatial inputs mainly to structure scene sampling and interpret results in context. EP-3 is structure-led and does not include perception testing; it instead strengthens interpretation by combining complementary geo-data sources and multiple visibility-oriented diagnostics across scales.

Two methodological implications remain consistent. First, the quality of the spatial substrate constrains downstream visibility modeling. DEM- or DSM-based models can under-represent understory and vertical occlusion and therefore overestimate theoretical visibility in vegetation-rich environments. Point clouds reduce this bias but introduce computational costs and require explicit resolution-efficiency decisions such as down-sampling, gridding, or tiered processing. Second, when perception evidence is used, triangulation across channels improves interpretability. Subjective reports capture meaning and trade-offs, while behavioral measures capture attention allocation and viewing strategies. Reporting perception results as distributions rather than single averages also improves robustness across contexts.

Because the cases differ in scale, viewpoint density, and sampling intensity, cross-case synthesis relies on normalized or ordinal reporting. Visibility outputs can be normalized per unit area, per route length, per viewpoint, or within standardized viewing distances. Perception outputs can be normalized per participant and per stimulus and summarized using medians and interquartile ranges. Where full metric re-computation is infeasible, within-case quantile bands provide a transparent comparison layer without overstating precision.

8.3.3 Cross-case insights

Direct numerical comparison across the four cases is difficult because the sites differ in scale, landscape type, viewpoint and route sampling, and the availability of perception evidence. To enable meaningful comparison across heterogeneous heritage contexts and methodological configurations, this study adopts a principle of relative and pathway-specific indicator normalization rather than absolute metric equivalence. Indicators are normalized within each case according to their analytical unit (e.g., per viewpoint, street segment, landscape unit, or scenario), observation scale (site, area, landscape, or regional), and data source (e.g., GIS-derived visibility metrics, eye-tracking measures, or perception-based evaluations). Where applicable, values are expressed as proportions, densities, standardized scores, or threshold classes (e.g., low-medium-high) to reduce scale effects and ensure internal consistency. Cross-case comparison therefore operates at the level of patterns, relative magnitudes, and indicator relationships rather than direct numerical matching. This approach avoids false comparability between fundamentally different datasets while allowing cumulative interpretation of how visual–perceptual mechanisms and visibility structures vary across heritage types, spatial scales, and pathway configurations.

Building on this normalization logic, this chapter first extracts five indicator families as a shared comparison spine **(TABLE 8.3)**. Within each family, a small number of comparable descriptors is then selected and reported using ordinal evidence bands, producing a concise cross-case comparison that remains explicit about what is and is not assessed in each pathway **(TABLE 8.4)**.

TABLE 8.3 Indicator families with scope, objects, and what each family captures.

Indicator family	Scope and object	What it captures (cross-case)
1) Visibility and exposure (heritage targets)	Predefined heritage targets and character-defining elements (landmarks, key nodes, water edges, skyline-defining features, historic interfaces, framing elements)	Where the heritage "object of concern" is presented clearly and repeatedly from relevant viewpoints/routes; whether exposure forms stable cores/belts that support heritage legibility
2) Spatial structure and morphology	Spatial skeleton (corridor–node–edge organization, hierarchy/rhythm, breakpoint locations, openness–enclosure morphology)	The intelligible structural organization that supports orientation, sequencing, and stable reading; where the skeleton is coherent vs fragmented
3) Scene physical visual attributes	Observer-height scene properties (composition shares, depth cues, framing/occlusion, apparent extent, viewpoint variability) plus appearance disturbances (glare, contrast conflicts, texture complexity, lighting/seasonal effects)	Why scenes are practically readable or noisy, even when the spatial skeleton exists; how stable/variable scene properties are across viewpoints
4) Heritage meaning and symbolic cues	Semantic and symbolic layer: historical sense, narrative continuity, authenticity signals (patina as meaning), identity cues, cultural-historical signifiers, place-specific codes	Why similar physical structure and appearance can still yield different heritage readings; where meaning resources are dense vs thin and coherent vs fragmented
5) Visual risk and impact intensity	Negative visual factors in existing states and under change: incompatible massing, infrastructure, clutter, reflective materials, skyline disruption, competing focal points; plus scenario/maintenance/season change impacts	Where risk concentrates, how strongly impacts intensify under change, and where governance tools (thresholds, stopping lines, zoning cues) are needed

TABLE 8.4 Cross-case comparative indicators.

Indicator family	Comparable descriptor	Jichang Garden (EP-1)	Pingjiang Road (EP-2)	West Lake (EP-3)	Beemster Polder (EP-4)
1 Visibility and exposure (targets)	Target category and exposure potential	Mid-high (water-based visibility for selected viewpoints)	Mid (BGI as exposure proxies)	Mid (Lake-surface visibility)	N-A (present but not evaluated)
2 Spatial structure and morphology	Legibility of axes / spatial-organization logic	Mid (lake-edge-oriented layout around the water surface)	N-A (present but not evaluated)	Mid (mountain-city-lake framework)	High (strong grid-route logic; breaks occur at town-edge changes)
	Skyline and horizon relationship type (typology)	N-A (present but not evaluated)	N-A (present but not evaluated)	Mountain-lake-city composite skyline type	Dyke and tree-line with low-rise built edge (rural horizon-dominant type)
	Scene-change rate along routes	High (rapid scene transitions by design)	Mid-high (frequent micro-variations along street segments)	Mid (changes across lakeside segments and vantage types)	Low (high homogeneity; small changes stand out when they occur)
	Openness-enclosure regime (overall)	Low (enclosed, layered occlusion)	Low-mid (street enclosure with local openings)	High (open interface with wide view fields)	High (very open polder; long sightlines)
3 Scene physical visual attributes	View composition profile	Vegetation-structure-water balance; framed compositions	Green share with heritage facades as focal layers; blue context-dependent	Mixed profile across types; lake-sky-vegetation-buildings vary by segment	Built fraction low; fields, sky, and roads dominate
	View complexity at viewpoints	High (large variability across sequential nodes)	Mid-high (variable scenes driven by BGI and street elements)	Mid (typology-driven variability across lakeside zones)	Low (stable baseline; scenario-driven spikes at specific KOPs)
	Attention or dwell concentration	High (eye-tracking gaze patterns concentrated at framed anchors)	Mid (fixation concentrated on GI, with context effects for BI)	N-A (not evaluated)	Low (generally dispersed, with occasional spikes at specific KOPs)
4 Heritage meaning and symbolic cues	Meaning cues and interpretation divergence	High (shapes perceptual and behavioral patterns)	High (BGI enhances perceived historic-heritage ambience)	Mid (mountain-city-lake structure with heritage traces)	Mid (polder-canal-dyke structure as meaning cue)
5 Visual risk and impact intensity	Risk or impact intensity (existing or under change)	Low (vegetation-management risks)	Mid-high (commercialization and renovations lacking local character)	High (corridor blockage and urbanization risks)	Mid-high (threats from expansion of central settlements)

Note: Bands are ordinal evidence bands, not raw-value comparisons. N-A indicates that the indicator was not assessed or not required by the pathway aim and is excluded from cross-case inference.

Read through this indicator spine, the cases differentiate into distinct morphological regimes. Openness–enclosure conditions and scene-change rates form clear contrasts that align with landscape type and spatial organization: enclosed, sequence-driven environments show rapid scene transitions by design, while open, grid-like rural settings exhibit lower variability, with change becoming salient at specific observation points. Where perception evidence is available, attention patterns also track these scene properties. Framed or anchor-driven compositions tend to produce more concentrated attention, while visually homogeneous and highly open settings tend to yield more dispersed viewing, consistent with the paired reading of viewpoint-level complexity and attention or dwell concentration in the comparative descriptors.

Beyond these direct contrasts, the comparison becomes more informative when indicator families are read together. Visual risk is context dependent and differs not only in intensity but also in form, ranging from corridor blockage and skyline disruption to commercialization pressures and town-edge expansion. Interpreting risk alongside exposure and structural descriptors helps clarify where impacts are likely to accumulate and where governance-oriented controls become necessary. At the same time, heritage meaning and symbolic cues modulate how similar physical conditions are interpreted. Comparable exposure or openness does not guarantee similar heritage readings; differences in narrative continuity, authenticity signals, and place-specific codes help explain why some contexts sustain coherent heritage interpretations while others fragment.

When the indicator comparison is placed back into the broader case evidence, a stable overarching pattern emerges. Across the four contexts, surface appearance shifts through seasons, maintenance, and incremental development, yet structural legibility, expressed through corridors, nodes and edges, landmark relations, and skyline logic, tends to persist over longer periods. Evaluation should therefore consider past, present, and proposed states, anchor interventions in persistent structural elements, and allow surface appearance to adapt where structural reading remains intact. The cases also show that visual effects are produced by interacting conditions rather than single variables: water, vegetation layers, landform, and built massing interact with lighting, material reflectance, and management regimes to shape recognizability and rhythm. As a result, isolated interventions can underperform or generate unintended trade-offs when they alter silhouettes, contrast relations, or corridor readability. Finally, the comparative value of the framework becomes most operational when evidence is translated into decision-ready formats. Across cases, the strongest governance-facing outcomes occur when structural evidence and, where available, perception evidence are turned into scenario ranking, stopping lines, or zoning cues that make trade-offs explicit and communicable to stakeholders.

8.4 Generalizing pathway models for visual heritage landscape research

This section consolidates the framework developed in the previous chapters into a practical structure for building and navigating visual-heritage research pathways. It proceeds in three steps. First, content themes, data types, and methods are organized into functional groups based on what they contribute to visual heritage analysis. The goal is not to force rigid categories but to provide a shared vocabulary that reduces duplication and clarifies roles across disciplines. Second, the section shows how these grouped elements can be combined into coherent pathways and how recurring combinations form a limited set of stable model types. Third, it provides a navigation logic via a decision tree to support transparent pathway selection under different project aims and evidence conditions. Together, these steps aim to improve clarity and adaptability.

8.4.1 Groups of methods, data and contents

Because content, data, and methods overlap in practice, this subsection groups them by function rather than by disciplinary ownership. The three group systems, content groups (CG), data groups (DG), and method groups (MG), provide the building blocks used later to describe pathway models and their variants. The groups are intentionally non-exclusive. A single technique or dataset may appear in different groupings when it serves different roles in a workflow. The following subsections introduce content groups **(8.4.1.1)**, data groups **(8.4.1.2)**, and method groups **(8.4.1.3)**.

8.4.1.1 Content groups

Building on the synthesis of visual-heritage landscape studies, five content groups are defined to clarify what pathways are designed to address **(TABLE 8.5)**. The groups are organized into research-oriented and practice-oriented orientations, reflecting whether the primary aim is explanation or delivery. The groups are not mutually exclusive, but most projects have one dominant content focus that shapes pathway design.

TABLE 8.5 Content groups for visual heritage landscape research: orientation, core focus, and typical subtopics

Content group	Orientation	Core focus	Typical subtopics
CG1 Perception- and behavior-led analysis	Research-oriented	How individuals and groups see, feel, and cognitively engage with heritage landscapes, including emotional response and meaning-making	CG1-1 Visual preference; CG1-2Physio-psychological response; CG1-3 Visual-spatial understanding; CG1-4 Cultural and heritage value construction
CG2 Spatial- and geo-structure-led analysis	Research-oriented	Material arrangement, spatial logic, and visibility dynamics of heritage landscapes and how structure supports or constrains experience	CG2-1Overall spatial characteristics; CG2-2 Viewpoint-specific visual features; CG2-3 Pathway and sequence structure; CG2-4Cross-dimensional constructs; CG2-5 Design principles extraction
CG3 Digital documentation and platform interoperability	Practice-oriented	Precise and shareable recording of heritage spaces in digital form for preservation, analysis, and access; reuse across technical ecosystems	CG3-1 Precision and technical fidelity; CG3-2 Platform compatibility and data reuse
CG4 Visual management, sustainable use, and planning	Practice-oriented	Governance tasks for protection and change management using visual-spatial evidence in planning and negotiation	CG4-1 Visual impact assessment; CG4-2 Protective visual governance; CG4-3 Conservation-development integration
CG5 Public engagement and dissemination	Practice-oriented	Communication, participation, and social uptake of heritage knowledge across audiences and media	CG5-1 Communication strategies; CG5-2 Co-evaluation and participatory governance; CG5-3 Assessment of digital dissemination

8.4.1.2 Data groups

To support method-data alignment in pathway construction, this subsection distinguishes four functional data groups. Together they span the key evidence needs of visual heritage landscape research, from large-scale spatial baselines to site-specific capture and human response data. While each group can support standalone analyses, most pathways integrate multiple groups to improve robustness and applicability **(TABLE 8.6)**.

TABLE 8.6 Data groups for visual heritage landscape research: what each group provides, typical subtypes, and roles in pathways.

Data group	What it provides	Typical subtypes	Typical roles in pathways
DG1 Open-source geo-data	Widely accessible standardized datasets for scalable baselines and macro context	DG1-1 Elevation and terrain; DG1-2 Land use and land cover; DG1-3 Online map platforms and vectors; DG1-4 Open point clouds; DG1-5 Open remote sensing	Baseline characterization; macro visibility and exposure screening; policy-driven comparisons
DG2 Contextual knowledge data	Historical, semantic, and expert framing that links measurable features with heritage values	DG2-1 Historical documentation; DG2-2 Expert-annotated materials; DG2-3 Observational and ethnographic notes	Diachronic comparison; interpretive framing; value narratives; decision framing support
DG3 Field-surveyed geo-data	Site-specific high-resolution geometry for detailed modeling, simulation, and immersion	DG3-1 Point clouds; DG3-2 Semantic mesh and digital models; DG3-3 SfM photogrammetry; DG3-4 Mobile and real-time surveys; DG3-5 Rendering outputs for immersion	Human-scale occlusion and visibility modeling; documentation; immersive scene construction
DG4 Perception-based data	Empirical datasets of attention, affect, meaning, and behavior in heritage settings	DG4-1 Eye-tracking; DG4-2 Physiology and affect; DG4-3 Surveys and interviews; DG4-4 User-generated content; DG4-5 Behavioral and participatory data	Perception-grounded evaluation; stakeholder legitimacy; participation and co-design evidence

TOC

8.4.1.3 Methods groups

This subsection groups the methods used in visual heritage landscape research into five method groups according to their functional role in a pathway workflow **(TABLE 8.7)**. The grouping follows three stages, preparation, core visual analysis, and synthesis, so that method choices can be aligned with data readiness and content focus. The five groups span from building analysis-ready or immersive-ready environments, to quantifying visual-spatial structure and measuring human perception, and finally to integrating results through data-driven inference and expert interpretation. The aim is not to prescribe a fixed sequence, but to provide modular method families that can be combined and reordered to form task-sensitive pathways.

TABLE 8.7 Method groups for visual heritage landscape research: main functions, typical techniques, and typical outputs.

Method group	Main function	Typical subgroups or techniques	Typical outputs
MG1 Spatial modeling and visualization	**Preparation:** Transform raw spatial data into analysis-ready or immersive-ready environments	MG1-1 Geometric modeling for analysis; MG1-2 Visualization and immersive rendering (3DGS, Blender, Unity, Unreal)	Analysis-ready models; VR-ready scenes; visualizations
MG2 GISc-based VAMs	**Visual analysis:** Quantify structural and formal visual attributes such as openness, rhythm, skyline continuity, exposure	MG2-1 Vertical VAMs (viewshed, cumulative visibility, isovists, visual magnitude, landscape metrics); MG2-2 Horizontal VAMs (3D isovists, field-of-view mapping, eye-level composition metrics); MG2-3 Reality-based VAMs (street view, UGC, clustering, tagging)	Visibility and exposure surfaces; corridor and skyline diagnostics; spatial typologies
MG3 Visual perception and behavioral analysis	**Visual analysis:** Measure attention, affect, meaning, and behavior responses to heritage scenes	MG3-1 Survey-based techniques; MG3-2 Interviews and self-reporting; MG3-3 Physiological and neurophysiological measures; MG3-4 Behavioral observation and participatory methods	Gaze patterns; preference distributions; meaning themes; behavior traces
MG4 Data-driven analysis and interpretation	**Synthesis:** Pattern extraction and relationship testing from complex datasets	MG4-1 AI-ML-DL techniques; MG4-2 Statistical and structural analysis (regression, PCA, SEM, LMM)	Comparable indicators; models of association; cross-group contrasts
MG5 Expert-based interpretation and synthesis	**Synthesis:** Interpret and translate findings within cultural and policy contexts	MG5-1 Content analysis; MG5-2 Visual media analysis; MG5-3 Multi-criteria overlay and scoring; MG5-4 Planning and design diagramming	Narratives; composite scores; planning diagrams; decision framing

8.4.2 Generalizing the pathways

With the content, data, and method groups clarified in Section 8.4.1, the framework now has a modular vocabulary for assembling pathways. These groups provide the building blocks for constructing application-oriented models, because they make explicit what can be combined, what tends to be paired, and what roles each module plays in visual heritage landscape research.

The next step is therefore to summarize and abstract the space of possible pathways implied by the CG-DG-MG grouping scheme. **FIG. 8.6** offers a structured overview of these potential combinations and highlights recurring configurations. Based on this abstraction, the following subsection condenses the recurring configurations into a small set of major pathway models that can be selected and adapted in practice.

CG1: Perception- and behavior-led analysis CG1-1: Visual preference CG1-2: Physio-psychological response CG1-3 Visual-spatial understanding CG1-4 Cultural and heritage value construction	**CG2: Spatial- and geo-structure-led analysis** CG2-1 Overall spatial characteristics CG2-2 Viewpoint-specific visual features CG2-3 Pathway and sequence structure CG2-4 Cross-dimensional visual analysis CG2-5 Design principles extraction	**CG3: Digital documentation and interoperability** CG3-1 Precision and technical fidelity CG3-2 Platform compatibility and data reuse **CG4: Visual management, sustainable planning** CG4-1 Visual impact assessment CG4-2 Protective visual governance CG4-3 Conservation-development integration	**CG5: Public engagement and dissemination** CG5-1 Communication strategies CG5-2 Co-evaluation/participatory governance CG5-3 Assessment of digital dissemination
DG1: Open-source geo-data DG1-1: Elevation and terrain data DG1-2: Land use and land cover data DG1-3: Online map platforms and vector data DG1-4: Open-source point cloud datasets DG1-5: High-resolution remote sensing data	**DG2: Contextual knowledge data** DG2-1: Historical documentation DG2-2: Expert-annotated materials DG2-3: Observational and ethnographic notes	**DG3: Field-collected geo-data** DG3-1: Remote sensing and point cloud data DG3-2: Semantic mesh and other digital models DG3-3: Image-based data for modeling DG3-4: Real-time/mobile remote sensing data DG3-5: 3D rendering outputs	**DG4: Perception-based data** DG4-1: Eye-tracking and visual attention data DG4-2: Other physiological data DG4-3: Survey and interview data DG4-4: User-generated content, social data DG4-5: Behavioral and participatory data
MG1: Spatial modeling and visualization MG1-1 Geometric modeling for analysis MG1-2: Visualization and immersive rendering **MG4: Data-driven analysis and interpretation** MG4-1: AI/ML/DL-enabled techniques MG4-2: Statistical and structural analysis	**MG2: GISc-based VAMs** MG2-1: Vertical VAMs MG2-2: Horizontal VAMs MG2-3: Reality-based VAMs	**MG3: Visual perception and behavioral analysis** MG3-1: Survey-based techniques MG3-2: Interview and self-reporting methods MG3-3: Physiological measures MG3-4: Behavior observation/participation	**MG5: Expert interpretation and synthesis** MG5-1: Content analysis MG5-2: Graphical or visual media analysis MG5-3: Multi-criteria/overlay frameworks MG5-4: Planning and design diagramming

FIG. 8.6 Summary of the groups and sub-groups of data, methods, and contents.

8.4.2.1 Major pathway navigation models

This subsection presents five models for visual heritage landscape research **(FIG. 8.6)**. The models are formulated after the preceding synthesis of content, data, and method layers: they translate that three-layer reading into application-oriented configurations that can be selected and reused across projects. In other words, the models do not add a new conceptual layer; they summarize recurring ways in which specific research aims are paired with typical evidence types and analytical workflows. Each model therefore clarifies (i) what kinds of heritage questions it is suited to address, (ii) what forms of data are minimally needed to make the approach defensible, and (iii) what methodological stance is emphasized (structure-led, perception-led, or decision-led). The five models are derived from the four emerging empirical pathways (EP-1 to EP-4) together with the documentation pathway in the traditional set (P1–P6), and they provide a practical bridge from the framework developed above to the selection logic introduced in the next subsection **(FIG. 8.7)**.

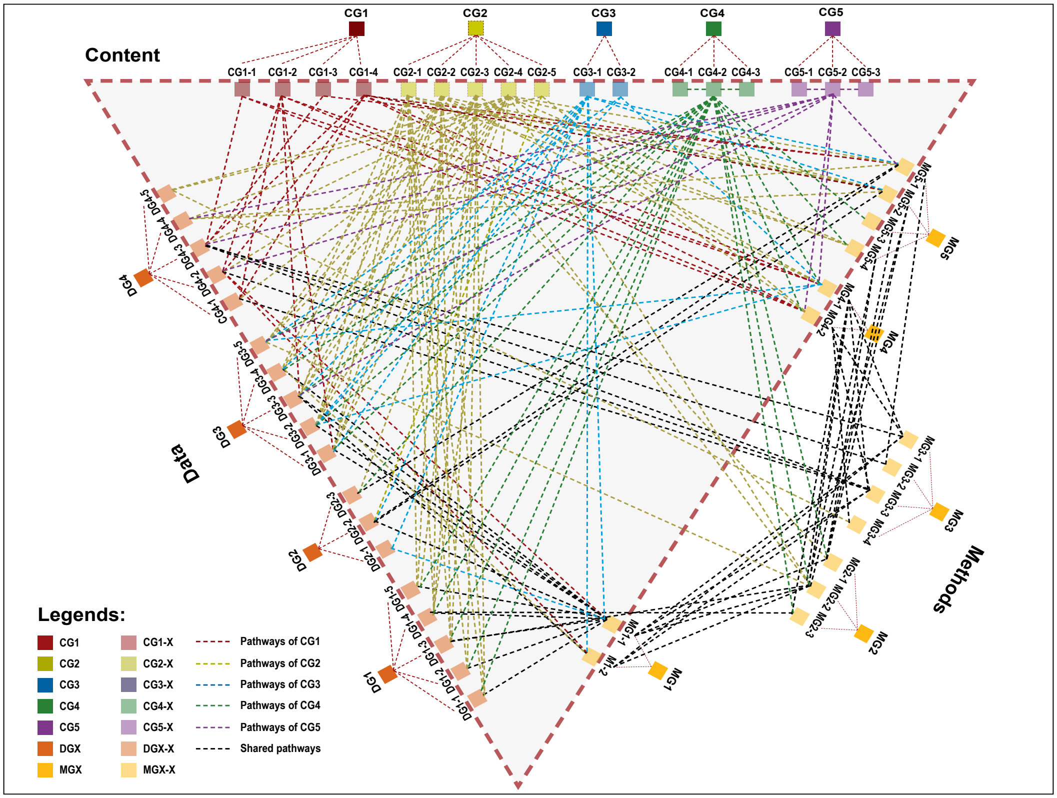

FIG. 8.7 Visualization observed or possible research pathways between content, data, and method subgroups: Users

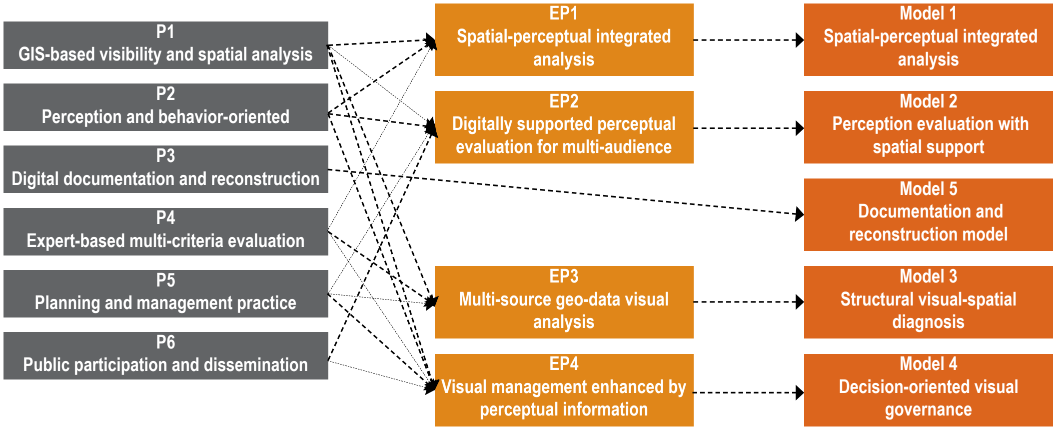

FIG. 8.8 The relationship among traditional pathways, emerging pathways and generalized models.

a) **Model 1 Spatial-perceptual integrated analysis (from EP-1):** This model aims to explain heritage landscapes through their visual–spatial structure, including openness, rhythm, depth, and focality. It combines GISc-based spatial/visibility analysis with empirical perception evidence, linking bird's-eye structure with eye-level experience. High-resolution representations (e.g., point clouds or 3D models) support human-scale visibility reasoning, while lower-resolution geospatial data support broader pattern reading. Perception evidence such as eye-tracking or surveys helps calibrate interpretations and reveal user-specific experience patterns (Tekin et al., 2025). The model is useful for diagnosing perceptual gaps and informing evidence-based redesign or interpretation.

b) **Model 2 Perception evaluation with spatial support (from EP-2):** This model places affective and cognitive perception at the center of the research design. Spatial analysis is used to contextualize, localize, and structure perceptual findings rather than to be "validated" by them. It relies on empirical evidence from surveys, interviews, eye-tracking, or behavioral observation, and may incorporate expert insight to interpret symbolic content (Ren, 2024). Supporting spatial techniques, such as view composition modeling or field-of-view mapping, help connect audience evidence to spatial settings. This model is effective for studying affective responses, cultural memory, and differences among user groups, especially for co-design, interpretation, and inclusive evaluation (Rusnak & Majczyk, 2025). This model also supports multi-audience interpretation by using perception-oriented evidence to examine how different groups understand and value heritage landscapes (Li et al., 2024).

c) **Model 3 Structural visual-spatial diagnosis (from EP-3):** This model is structure-led and is selected when the main need is to identify and compare stable visual–spatial structures across a site, corridor, or wider landscape. It focuses on extracting corridor–node–edge organization, openness-enclosure regimes, skyline and horizon relations, and patterns of continuity or fragmentation using multi-source geo-data and visibility-oriented analysis. The outcome is a defensible diagnostic account—where the visual-spatial skeleton holds, where it breaks, and which locations are structurally critical—supporting rapid screening and cross-scale interpretation when perception evidence is limited.

d) **Model 4 Decision-oriented visual governance (from EP-4):** This model is chosen when the study must support management and planning decisions, such as evaluating change, comparing options, and formulating controls for visual impact mitigation and sustainable use (Aimar, 2024). Unlike Model 3, which stops at diagnosis, Model 4 is organized around decision framing: it evaluates scenarios and supports rule setting and prioritization. Typical applications include view corridor delineation, skyline integrity evaluation, and tourism capacity modeling (Gu et al., 2022). Where feasible, empirical perception evidence and expert interpretation complement geospatial simulation to strengthen decision legitimacy under contested trade-offs.

When governance requires broader uptake, Model 4 can be implemented with participatory components, not as a separate research aim but as part of decision framing and implementation. Stakeholder dialogue, participatory mapping, and co-design processes can be used to surface disagreements, calibrate priorities, and support negotiated guidance that remains actionable (Li et al., 2024). Expert-based knowledge may still be necessary to maintain comparability and to structure trade-offs across scenarios (Antonio et al., 2020), while participatory evidence helps ensure that management responses address social meaning and public concern in a transparent way. In this sense, Model 4 supports inclusive heritage management by linking analysis to implementable controls and shared decisions under real-world constraints (Borseková et al., 2023).

e) **Model 5 Documentation and reconstruction (from the documentation pathway, P3):** This model is selected when producing a high-fidelity record is the primary deliverable, supporting preservation, visualization, or simulation (Baik, 2024). It relies on digital recording techniques to produce detailed 3D representations, typically using field-collected datasets such as point clouds, mesh models, and textured reconstructions (Albourae, 2024). While perception evidence is not required for the model to be valid, the outputs often provide a foundation for later analysis and dissemination. It is fundamental for digital archiving, restoration planning, and structural monitoring.

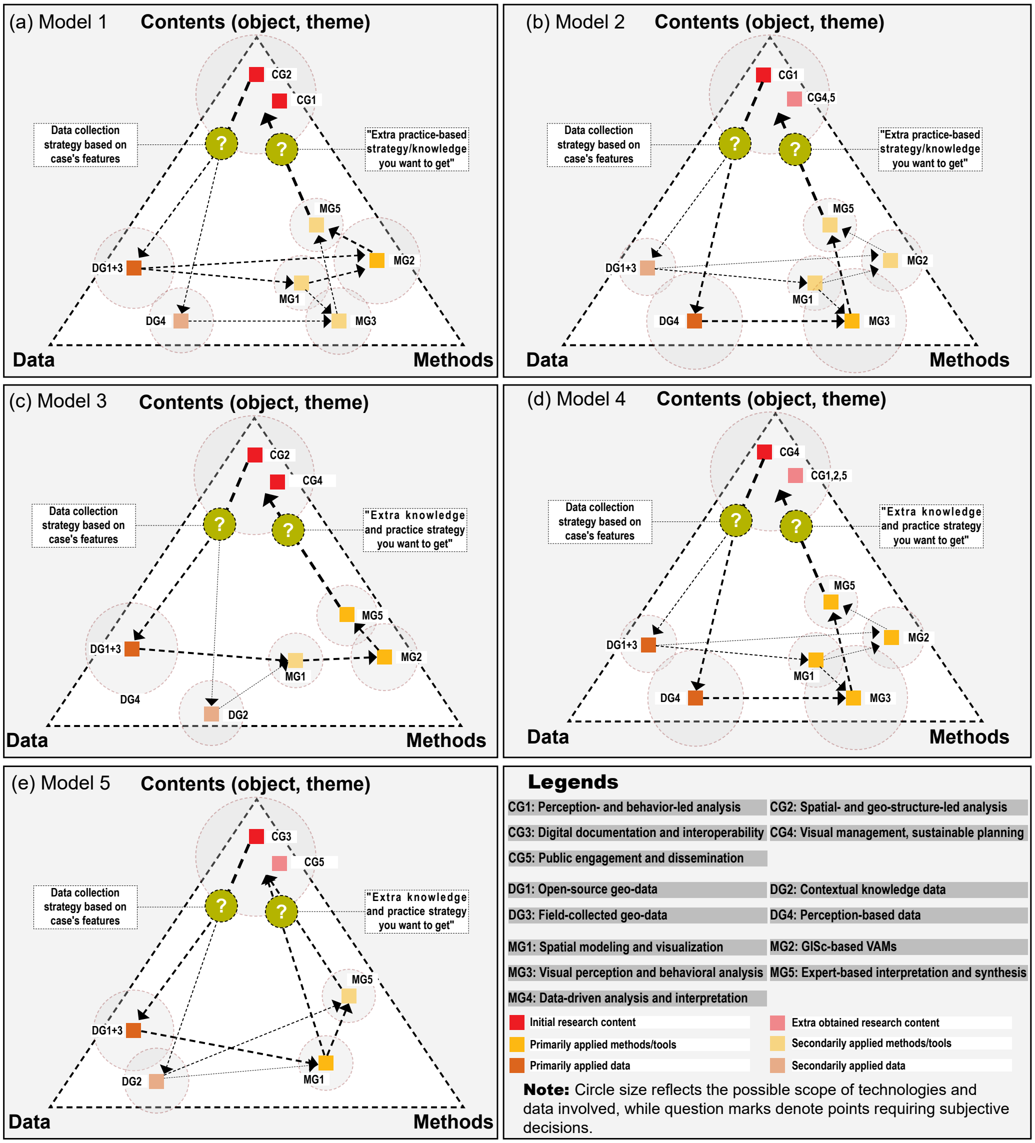

FIG. 8.9 Core navigation models illustrating the major pathway types: Serving as prototypes for various derivative configurations. Although these pathways are typically structured around content themes, alternative entry points, such as data availability or methodological innovation, are equally valid starting positions.

8.4.2.2 Pathway selection principles

This subsection explains how to select among Model 1 to Model 5 and how to use the decision tree **(FIG. 8.9)** as a practical selection tool. Model choice is guided by two hard gates, content motivation and minimum evidence readiness, because together they define what the project must deliver and what kinds of claims can be defended. **TABLE 8.8** provides a compact checklist of selection conditions across the five models. **FIG. 8.10** then operationalizes the same logic as a step-by-step route so that users can move from project aims and constraints to an implementable pathway choice.

TABLE 8.8 Research pathway model selection conditions.

Model	Content motivation	Minimum data readiness	Type and scale notes
Model 1	Coupling structure and experience, diagnosing alignment and mismatch	DG4 plus geo-data adequate for human-scale structure DG3 or high-quality DG1	Works best where structure and perception can be measured at compatible resolution
Model 2	Experience, affect, meaning, group differences, inclusive evaluation	DG4 plus at least basic geo referencing DG1	Type influences audience framing, scale influences sampling strategy and group stratification
Model 3	Structure-led screening and diagnosis when perception evidence is not feasible	Geo-data readiness DG1 and or DG3	Scale affects whether DG1 baselines suffice or DG3 is needed for occlusion and vertical layering
Model 4	Decision-ready outputs under change, scenarios, rules, prioritization	Geo-data readiness DG1 and or DG3 plus explicit decision context and scenarios	Larger extents need careful viewpoint and route sampling, contested contexts benefit from DG4 and DG2
Model 5	High-fidelity record as primary deliverable	DG3 plus georeferencing and site extent	Type and scale mainly affect capture design and cost, not model logic

TOC

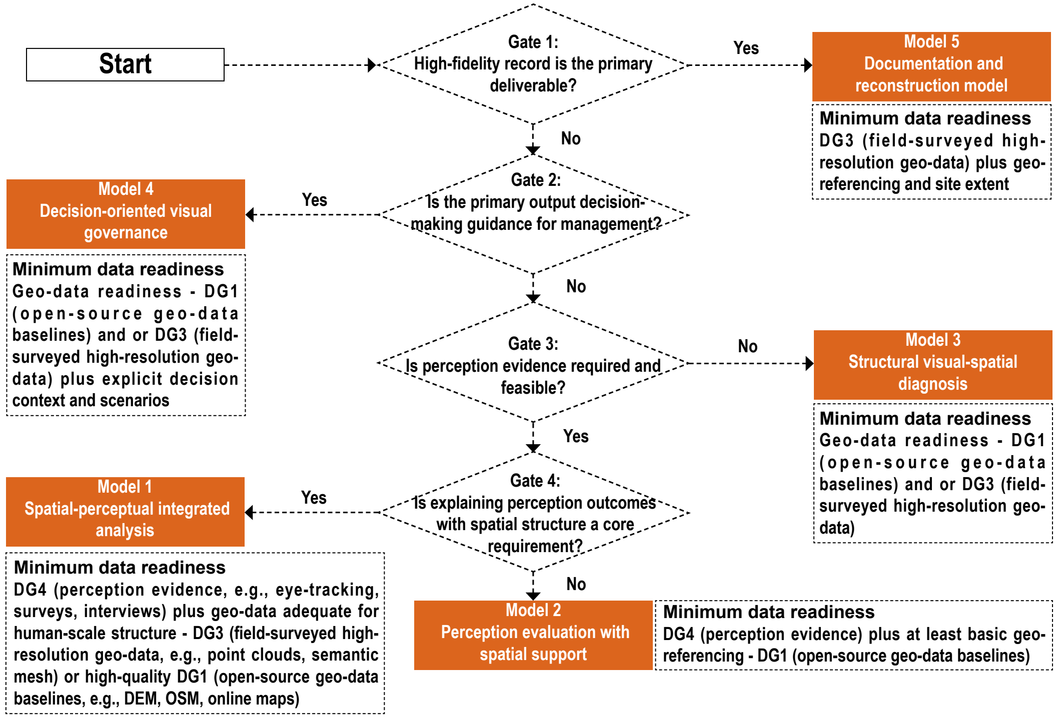

FIG. 8.10 The way to select your visual heritage research model and pathway.

The decision tree translates the checklist into sequential gates by asking what the primary deliverable is and whether the minimum evidence required to support it is available. **Gate 1** asks whether documentation and reconstruction is the dominant motivation. This gate should be answered “Yes” when success is evaluated mainly by capture completeness, geometric and visual fidelity, and interoperability for preservation, monitoring, restoration support, and visualization or simulation. Under this condition, **Model 5** is selected (Baik, 2024; Albourae, 2024). The minimum requirement is a field-surveyed, high-resolution spatial baseline with georeferencing and a defined site extent. Outcomes improve when contextual documentation is also assembled, because it supports heritage framing, metadata clarity, and later reuse in analysis or dissemination.

If documentation is not the main aim, **Gate 2** asks whether the project must deliver governance-facing outputs under change. This gate should be answered “Yes” when the intended output includes scenario comparison, prioritization, and recommendations that can function as operational controls, such as stopping lines, corridor controls, or threshold-like guidance. Under this condition, **Model 4** is selected (Aimar, 2024; Gu et al., 2022). The minimum requirement is a defensible geo-data baseline together with explicit scenarios and criteria, because decision-oriented outputs depend on consistent comparison across alternatives rather than on a single descriptive account. Results become more robust and more legitimate when perception evidence and participatory input are feasible, especially in contested contexts where trade-offs must be communicated and negotiated (Li et al., 2024; Antonio et al., 2020; Borseková et al., 2023). Contextual framing also strengthens defensibility by linking measured change to heritage values and governance language.

If governance support is not required, **Gate 3** asks whether perception evidence is required and feasible. This gate should be answered “No” when the study can be judged through structural legibility, visibility configuration, or typological diagnosis without making claims about human response, or when perception sampling is impractical under resource or access constraints. Under this condition, **Model 3** is selected to produce a structure-led diagnosis from geo-data readiness. The minimum requirement is basic georeferencing, an analysis-ready surface representation, and a defined set of relevant viewpoints and or routes. Where vertical occlusion, layered vegetation, or fine-grained enclosure effects are critical, higher-resolution spatial data improve validity. Where interpretation depends on value narratives or protective intent, contextual documentation improves defensibility and interpretability.

If perception evidence is required and feasible, **Gate 4** distinguishes why perception is being used. When the non-negotiable requirement is to explain perception outcomes through spatial structure, **Model 1** is selected because it depends on coupling and mechanism-oriented claims (Tekin et al., 2025). The minimum requirement is therefore a defensible perception channel together with geo-data adequate for human-scale structural reasoning, so that occlusion, framing, and viewpoint relationships are represented at the relevant viewing scale. Outcomes improve when perception evidence is triangulated across channels and when contextual framing supports interpretation and translation. When the dominant aim is perception-led evaluation of experience, affect, meaning, or group differences, with spatial analysis mainly supporting scene structuring and contextual interpretation, **Model 2** is selected. The minimum requirement is a defensible perception channel and basic geo-referencing so that scenes and results can be anchored in place. Outcomes improve with richer spatial baselines that support stronger scene typologies and exposure interpretation, and with contextual documentation when meaning-making is central (Ren, 2024; Rusnak and Majczyk, 2025; Li et al., 2024).

In summary, **TABLE 8.8** functions as a quick checklist for matching project motivation with minimum evidence readiness, while **FIG. 8.10** provides the operational route for making the selection step by step. Heritage type and scale act as feasibility modifiers rather than primary selectors: they influence sampling density, representation fidelity, and the balance between open-source baselines and field-surveyed high-resolution data, but rarely change the underlying model logic. In practice, projects may begin with the lowest-burden model that satisfies the primary deliverable and minimum evidence requirements, and then upgrade toward higher-fidelity spatial representations, additional perception channels, and stronger decision translation as access and resources improve, which is addressed through derivative and adaptive pathways in the next subsection.

8.4.2.3 Derivative and adaptive pathways

In practice, each major model is better understood as a family of variants rather than a fixed recipe. Derivative pathways therefore describe how the major types are reconfigured under evidence constraints or when more uptake-oriented outputs are needed, while preserving the underlying pathway logic. Three adaptations recur most often: (a) substituting field-surveyed high-resolution geo-data with open-source or platform-derived baselines (e.g., street-view or online maps) to improve feasibility and coverage (Szekely et al., 2023); (b) replacing intensive perception experiments with lighter channels such as structured surveys, interviews, or observational feedback when recruitment or experimental control is infeasible (Yu et al., 2025); and (c) strengthening translation through contextual framing and synthesis so results can be compared across scenarios and carried into planning and governance discussions. When direct perception sampling is difficult, user-generated content and social media imagery can provide supplementary perception signals via content recognition or semantic tagging (Blanco, 2024). Derivative applications also commonly extend documentation outputs toward monitoring, appraisal, and risk-oriented tasks (Cook et al., 2021; Ravankhah et al., 2021) and support management-oriented evaluations using mid-resolution spatial metrics and planning evidence for validation (You et al., 2017; van Lanen et al., 2022). Pathway design is iterative: projects can start with the most feasible variant that satisfies the hard gates in **Section 8.4.2.2** and upgrade evidence packages over time as access, data quality, or participation capacity improves.

8.5 Conclusions

This chapter addresses **Research Question 3** by proposing a structured approach for navigating the complexity of visual heritage research design. By classifying content themes, data types, and method groups, it established a foundation for assembling flexible and scalable research pathways. Through cross-case comparison, five major pathway models and their derivative variants were identified, showing how evidence packages can be configured and adjusted according to site conditions, resource constraints, and analytical priorities. Pathway navigation is therefore not the selection of a fixed template, but the intentional alignment of available data and methods with the intended focus, whether perceptual, spatial, managerial, or participatory, so that workflows remain feasible while preserving conceptual coherence.

Across the five models, a shared structural logic can be observed. Most pathways connect perception-oriented evidence with spatial-analytic explanation, enabling experiential responses to be interpreted against the visual and spatial structure of heritage environments and vice versa. This dual core is typically embedded in a full-cycle workflow that moves from environment or model construction, to analysis and perception integration, and finally to synthesis and translation into communicable outputs. In practice, each major model is better understood as a family of variants rather than a fixed recipe, because derivative pathways usually adjust evidence intensity while keeping the same internal logic.

A further strength of the framework is its modularity in pathway construction. Projects may begin from a content question, an available dataset, or a methodological innovation, and then iteratively assemble the remaining components across the content-data-methods axes. This design supports collaboration across different fields by making pathway choices explicit, comparable, and adaptable to different technical capacities and project demands.

9 Conclusion and outlook

This chapter concludes the thesis by synthesizing its main contributions, answering the research questions, and outlining future directions. It consolidates how the systematic review and pathway modeling clarify the field's structural fragmentation, how the four empirical cases demonstrate the feasibility and value of integrative pathway types, and how the synthesis chapter turns case-based insights into a navigable framework for method and data choice. The chapter also reflects on limitations related to case representativeness, data constraints, and the balance between ecological validity and experimental control in perception-oriented components. Finally, it proposes an outlook for future research, including expanding pathway testbeds to additional heritage types and governance contexts, improving cross-case comparability through shared indicators, and strengthening practical uptake through decision-support integration and stakeholder-facing visualization.

9.1 Introduction

This chapter closes the thesis by summarizing what it contributes, answering the three research questions, and outlining limitations and future directions. It draws together three parts of the study: the literature review that maps how visual-heritage research currently connects aims, evidence, and analysis; the four case studies that test pathway designs in different landscape settings; and the synthesis chapter that turns case results into practical rules for choosing pathways under real constraints. The chapter ends by identifying what must be tested next to strengthen comparison across cases and support use in planning and management settings.

9.2 Answers to the research questions

— **RQ1: What types of visual research methods, data sources, thematic focuses, and case types currently exist in heritage landscape studies, and how are they interrelated?**

— **Chapters 2 and 3** show that visual research on heritage landscapes uses a wide range of methods and data sources, but these are often developed in separate strands. The systematic review identifies six common pathway configurations, covering GISc-based modeling, perception-focused studies, digital recording, expert-led evaluation, planning-oriented applications, and public communication, distributed across four thematic content clusters. These strands have produced valuable insights, yet links among them are often implicit, which makes it difficult to compare findings or transfer workflows across contexts. By grouping studies by function and mapping how research aims, evidence types, and analysis choices tend to co-occur, the thesis provides a clearer picture of how the field is organized and where the main gaps in linkage and comparability remain.

— **RQ2: How can new data sources and research methods be expanded or introduced, and how can they be effectively matched to support diverse visual research tasks related to heritage landscapes?**

— **Chapters 4 to 7** test four pathway types (EP-1 to EP-4) that assemble multi-source spatial evidence and, where relevant, perception evidence to address different visual tasks. Across the cases, point clouds, platform-based imagery, VR-based eye tracking, and other perception instruments are treated as evidence components that must match site scale, visual task, and heritage setting. The cases show that new tools become useful when they are placed within a workflow with defined inputs, outputs, and claim boundaries, rather than being added as standalone techniques. This task-driven matching clarifies what each evidence component contributes, what it cannot support, and how choices shift when resources, access, or data quality change.

— RQ3: **When multiple data sources and methodological options are available, how can one navigate this complexity and make appropriate, case-sensitive choices for visual research design?**

The thesis responds to this challenge by proposing a pathway framework for research design and navigation. It organizes content aims, evidence packages, and analysis workflows into five model types and derivative variants, and provides a step-by-step selection logic that starts from the required deliverable and checks whether the minimum evidence needed to support it is available. The framework also proposes a shared comparison spine, structured as indicator families and comparable descriptors reported in normalized or ordinal forms, so that cross-case comparison can remain transparent without forcing raw metric equivalence. Together, these elements support case-sensitive pathway choice while keeping evidence requirements, trade-offs, and limitations explicit.

9.3 Limitations and outlook

This thesis proposes a pathway framework and tests it through four cases, but several limitations define a clear agenda beyond the present work.

First, coverage remains incomplete. The literature review is constrained by language and database scope and may miss non-English studies and practice reports outside academic outlets. The pathway framework is also grounded in a limited set of cases selected to cover contrasts in type, scale, and data conditions. This supports comparison, but it cannot represent the full range of heritage contexts, especially low-resource settings and politically complex governance situations. Future work should extend the testbed to additional heritage types and planning contexts, including ordinary landscapes and constrained settings, to evaluate how well the selection rules hold under different institutional and regulatory conditions.

Second, perception-related evidence is limited by sampling and setting. Several case components rely on relatively small participant numbers, uneven stakeholder coverage, and recruitment constraints that affect representativeness. Most perception and behavioral evidence also comes from device-mediated or workshop settings rather than in-situ protocols. These settings are useful for controlled testing, but they simplify the embodied, sensory, and social conditions of real visits and real decision processes. Future work should prioritize field-capable protocols and scalable low-cost instruments, such as mobile interfaces, web-based surveys, and rapid feedback tools deployed around site visits, together with improved recruitment strategies for time-constrained residents and underrepresented groups.

Third, external testing in practice remains limited. The framework has not yet been evaluated systematically by practitioners who were not involved in its development. The thesis proposes cross-case comparison through relative and pathway-specific normalization and ordinal reporting, which improves transparency across heterogeneous datasets but also constrains inference: cross-case synthesis is primarily pattern- and relationship-based, rather than a test of absolute metric equivalence, and results can be sensitive to choices of analytical unit, observation scale, and thresholding strategy. Full cross-case recalculation using shared metrics, structured sensitivity testing, and longitudinal studies that track decision trajectories over time are therefore still needed. Future work should combine replication using shared indicators with practitioner-facing trials, such as structured interviews, workshops, and embedded pilot projects with planning authorities and consultants. These engagements can test usability under operational constraints, refine guidance (including normalization rules and reporting conventions), and strengthen credibility for real-world use.

9.4 Conclusions

This thesis contributes a pathway framework for visual heritage landscape research that links content aims, evidence packages, and analysis workflows.

a) **Field mapping and problem definition:** By reviewing the literature and reorganizing studies into functional pathway configurations and content clusters, the thesis clarifies how methods and data types are currently distributed and why research outputs often remain difficult to compare across cases.

b) **Case-based testing of pathway designs:** Four case studies implement EP-1 to EP-4 across contrasting landscape settings, showing how multi-source spatial evidence and, where relevant, perception evidence can be assembled into workflows with defined outputs and clear claim boundaries.

c) **Selection rules for research design:** Building on cross-case synthesis, the thesis proposes five model types and derivative variants and provides a step-by-step selection logic that uses the required deliverable and minimum evidence readiness as primary gates. This makes pathway choice more transparent under real constraints.

d) **A comparison spine for cross-case learning:** The thesis proposes indicator families and comparable descriptors that can be reported in normalized or ordinal forms. This supports transparent cross-case comparison while acknowledging differences in scale, sampling, and evidence availability, and it provides a practical basis for future cumulative testing.

Overall, the pathway framework supports clearer research design in heritage landscape studies by specifying what evidence is required for a given claim, enabling comparison across cases through a shared indicator spine, and supporting the development of workflows that can be tested, reused, and adapted in future research and, where relevant, planning and management contexts.

Appendices

APPENDIX A

For Chapter 2

TABLE A1 Coding results of research themes (Cohen's κ = 0.78).

Category of themes	Sub-category of themes	Count	Percentage	Literature
Analysis/ evaluation of heritage (106 publications, 52.22%)	Visual characterization and visual quality evaluation	48	23.65%	3, 4, 5, 6, 12, 23, 24, 26, 28, 39, 41, 51, 52, 54, 56, 59, 71, 75, 76, 80, 84, 94, 103, 105, 107, 114, 115, 128, 129, 130, 131, 134, 136, 139, 140, 142, 144, 148, 154, 158, 163, 169, 171, 177, 181, 196, 197, 201
	Public perception and well-being related analysis	24	11.82%	8, 27, 35, 65, 68, 81, 98, 104, 112, 125, 126, 127, 135, 166, 167, 168, 173, 179, 182, 185, 188, 195, 198, 203
	Environmental impact assessment	13	6.4%	31, 66, 86, 88, 89, 90, 100, 133, 143, 160, 183, 191, 202
	Landscape dynamics/transformation	5	2.46%	46, 93, 174, 175, 184
	Heritage value assessment	16	7.88%%	16, 17, 21, 32, 32, 33, 40, 79, 82, 91, 117, 150, 153, 156, 161, 161, 164, 165
Management and conservation of heritage (47 publications, 25.15%)	(Digital) Documentation and restoration	33	16.26%	1, 18, 19, 20, 29, 30, 36, 37, 38, 43, 47, 49, 55, 57, 58, 69, 74, 77, 78, 95, 108, 109, 113, 116, 122, 132, 137, 145, 147, 152, 155, 159, 178
	Visual environment management (e.g., buffer zone/ visibility)	8	3.94%	10, 15, 85, 110, 180, 192, 193, 194
	Eco-environment conservation and management	2	0.99%	101, 170
	Risk management	3	1.48%	45, 99, 187
	Visualization + Monitoring/Risk management	1	0.49%	124

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TABLE A1 Coding results of research themes (Cohen's κ = 0.78).

Category of themes	Sub-category of themes	Count	Percentage	Literature
Development and sustainable use of heritage (24 publications, 11.82%)	Heritage tourism	9	4.43%	9, 14, 25, 44, 60, 64, 72, 73, 151
	Local revitalization and development	7	3.45%	61, 83, 96, 111, 189, 190, 200
	Design and planning of heritage landscape	6	2.96%	22, 118, 119, 120, 138, 157
	Using heritage as design inspiration	2	0.99%	70, 146
Heritage promotion and public engagement (17 publications, 8.37%)	(Digital) Public engagement of heritage	7	3.45%	50, 63, 67, 87, 141, 172, 186
	Heritage cognition and education	6	2.96%	42, 53, 62, 97, 102, 162
	Visualization and interaction methods development	4	1.97%	48, 106, 121, 199
Research trend analysis (9 publications, 4.43%)	Literature analysis	9	4.43%	2, 7, 11, 13, 34, 92, 123, 149, 176

TABLE A2a Coding results of research objects (Cohen's κ = 0.85 for types, 0.81 for scales).

Landscape type	Count	Percentage	Scale	Count	Literature
Archaeological site/Heritage remains (In the landscape context)	13	6.4%	Site	6	30, 145, 155, 159, 186, 187
			Cluster	6	20, 42, 49, 160, 163, 178
			Landscape	1	82
Bio-ecological heritage	2	0.99%	Regional	2	35, 67
Bio-ecological + Geo-heritage	5	2.46%	Cluster	1	133
			Landscape	1	142
			Regional	3	44, 88, 151
Cultural ecosystem services	7	3.45%	Landscape	1	17
			Regional	6	3, 60, 76, 86, 96, 101
Geo-heritage landscape	18	8.87%	Cluster	1	56
			Landscape	1	85
			Regional	14	25, 39, 59, 62, 64, 72, 73, 79, 89, 103, 129, 148, 149, 170
			Global	2(Review)	11, 13
Integrated heritage/ cultural landscape (including heritage complex, no specific type)	18	8.87%	Cluster	1	121
			Landscape	1	127
			Regional	11	15, 37, 68, 93, 98, 99, 131, 157, 167, 184, 198
			National	2	92, 174
			Global	3(Review)	2, 50, 115
Historic urban area/Urban heritage landscape	39	19.21%	Site	1	106
			Cluster	1	126
			Area	22	5, 8, 9, 19, 23, 41, 52, 58, 61, 63, 65, 100, 105, 122, 128, 130, 134, 135, 139, 182, 188, 202
			Landscape	13	6, 22, 28, 31, 117, 125, 154, 158, 179, 180, 181, 194, 196
			Regional	1	66
			National	1(Review)	123

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TOC

TABLE A2a Coding results of research objects (Cohen's κ = 0.85 for types, 0.81 for scales).

Landscape type	Count	Percentage	Scale	Count	Literature
Historic/ Heritage garden (including historic instate, palace landscape)	22	10.84%	Site	10	71, 75, 95, 141, 147, 153, 168, 171, 193, 201
			Cluster	8	10, 51, 70, 78, 120, 137, 146, 169
			Area	3	45, 152, 164
			Global	1(Review)	34
Monuments/ Architectural heritage (In the landscape context)	26	12.81%	Site	14	1, 4, 18, 43, 47, 53, 54, 57, 69, 77, 162, 172, 185, 195
			Cluster	10	36, 48, 55, 74, 107, 108, 109, 110, 116, 124
			Area	1	38
			Landscape	1	94
Rural heritage landscape + Monument	1	0.49%	Cluster	1	156
Rural/ Agricultural/ Rural settlement heritage landscape	40	19.7%	Site	1	112
			Cluster	1	40
			Area	4	29, 144, 175, 190
			Landscape	4	26, 84, 102, 114
			Regional	28	12, 14, 16, 27, 32, 80, 81, 83, 91, 97, 104, 111, 132, 140, 143, 150, 161, 165, 166, 173, 183, 189, 191, 192, 197, 199, 200, 203
			Global	2(Review)	7, 176
Transportation/ Industrial heritage	9	4.43%	Site	2	33, 136
			Cluster	1	113
			Landscape	2	46, 118
			Regional	3	21, 87, 138
			National	1	177
Urban heritage landscape + Rural heritage landscape	3	1.48%	Regional	3	24, 90, 119

TABLE A2b Definitions and references for these heritage landscape types.

Landscape type	Definition	Official basis
Archaeological site / Heritage remains (in the landscape context)	Material evidence of past human activity, including structures, deposits, features, and movable objects, together with the stratigraphic and environmental context.	**Council of Europe**, European Convention on the Protection of the Archaeological Heritage (Revised) (1992), https://www.coe.int/en/web/culture-and-heritage/valletta-convention; **ICOMOS**, Charter for the Protection and Management of the Archaeological Heritage (1990), https://www.icomos.org/charters-and-doctrinal-texts/
Bio-ecological heritage	Natural heritage whose value is primarily biological and ecological in character, encompassing biota, ecological processes, and delineated natural areas.	**UNESCO**, Convention concerning the Protection of the World Cultural and Natural Heritage (1972), https://whc.unesco.org/en/conventiontext/;
Cultural ecosystem services	The nonmaterial contributions of ecosystems to people include spiritual and religious values, aesthetic and inspirational experience, knowledge and education, and recreation and tourism.	**Millennium Ecosystem Assessment**, Ecosystems and Human Well-being: Synthesis (2005), https://www.millenniumassessment.org/
Geo-heritage landscape	A landscape whose significance derives from the geological heritage of international value within a single, clearly defined area, managed as an integrated whole for protection, education, and sustainable development.	**UNESCO**, International Geoscience and Geoparks Programme, https://www.unesco.org/en/iggp/geoparks
Integrated heritage / Cultural landscape (including heritage complex, no specific type)	The combined works of nature and humankind, classified as designed, organically evolved (relict or continuing), or associative, and managed through an integrated approach to nature and culture.	**UNESCO**, Operational Guidelines for the Implementation of the World Heritage Convention (2008), https://whc.unesco.org/en/guidelines/; **UNESCO**, Cultural Landscape, https://whc.unesco.org/en/culturallandscape/
Historic urban area / Urban heritage landscape	Historic areas are understood within their wider urban context; under the Historic Urban Landscape approach, conservation addresses layered natural and cultural values across the broader urban setting.	**UNESCO**, Recommendation on the Historic Urban Landscape (2011), https://whc.unesco.org/en/hul/;
Historic / Heritage garden (incl. historic estate, palace landscape)	An architectural and horticultural composition in which living plants are the principal material, recognized for historical or artistic value and conserved as a monument with due regard to authenticity and integrity.	**ICOMOS–IFLA**, The Florence Charter on Historic Gardens (1981), https://www.icomos.org/charters-and-doctrinal-texts/
Monuments / Architectural heritage (in the landscape context)	monuments, groups of buildings, and sites, together with the urban or rural setting that provides context, scale, and meaning.	**UNESCO**, Convention concerning the Protection of the World Cultural and Natural Heritage (1972), https://whc.unesco.org/en/conventiontext/; **ICOMOS**, International Charter for the Conservation and Restoration of Monuments and Sites (The Venice Charter) (1964), https://www.icomos.org/charters-and-doctrinal-texts/

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TOC

TABLE A2b Definitions and references for these heritage landscape types.

Landscape type	Definition	Official basis
Rural / Agricultural / Rural settlement heritage landscape	Cultural landscapes that embody traditional land-use systems and rural settlement patterns often represent relict or continuing organically evolved landscapes.	**UNESCO**, Cultural Landscape, https://whc.unesco.org/en/culturallandscape/ **FAO**, Globally Important Agricultural Heritage Systems (GIAHS), https://www.fao.org/giahs/en
Transportation / Industrial heritage	The physical remains of industrial culture possessing historical, technological, social, architectural, or scientific value, including transport systems and associated infrastructure.	ICOMOS–TICCIH, Principles for the Conservation of Industrial Heritage Sites, Structures, Areas and Landscapes (The Dublin Principles) (2011), https://www.icomos.org/charters-and-doctrinal-texts/

TABLE A3 Coding results of research methodologies (Cohen's κ = 0.64).

Core methods	Tools	Data	Literature
(Overlay-based) Multi-criteria evaluation framework 17 publications (8.37%)	- Risk assessment framework - Landscape characteristics - evaluation framework - Landscape visual quality - assessment framework - Landscape sensitivity assessment framework - Perception assessment framework - Design, policy and decision-making framework - Visual impact assessment framework	- Field-based data (e.g., field research data, on-site photo/video) - Expert-based data Survey/interview/discussion data - Spatial and remote sensing data (e.g., land cover/use data, terrain data, urban spatial data) - Risk and environmental data (e.g., hazard/risk data, climate data) - Historical and archival data (e.g., historical records)	6, 18, 36, 56, 62, 64, 73, 80, 99, 112, 119, 122, 158, 163, 184, 187, 189
AI-based, AI-related technologies 10 publications (4.93%)	- AI-based analysis and decision tools - Image analysis using ML/DL Visualization and modeling tools using ML/DL - GIS-integrated AI methods	- User-generated and participatory data (e.g., text, image) - Field-based data (e.g., on-site image/video) - 3D spatial data (e.g., point cloud, multi-view image) - Remote sensing and spatial datasets (e.g., satellite imagery, Urban spatial data) - Archival and historical records	5, 19, 57, 76, 93, 128, 130, 134, 177, 199
Case study 3 publications (1.48%)	- Field research - Content/image analysis - Interview/Survey	- Field-based data (e.g., field research data, on-site photo/video) - Document-based data (e.g., historical records) - Expert-based data	146, 154, 180
Content analysis 9 publications (4.43%)	- Manual and conceptual content analysis methods (e.g., Philosophical content analysis, grounded theory-based content analysis, semantic differential method) - Computational and software-based text analysis (e.g., Coding-based tools, ROST CM, Python, NLP technology) Spatial supported content analysis (e.g., visual/textual content analysis with GIS)	- User-generated content (e.g., text content, image, geo-tag) - Field-based data (e.g., field research data, on-site photo/video) Spatial data (e.g., Urban spatial data) - Historical and archival data	33, 51, 133, 135, 144, 150, 167, 188, 198
Design and planning approaches 4 publications (1.97%)	- Design thinking tools - Diagram-based tools	- Field-based data (e.g., field research data, on-site photo/video) - Design record - Historical and archival data (e.g., historical records)	46, 120, 137, 200

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TOC

TABLE A3 Coding results of research methodologies (Cohen's κ = 0.64).

Core methods	Tools	Data	Literature
Empirical research methods (perception, behavior) 57 publications (28.08%)	- Psychological-based tools (e.g., survey, self-report, interview, group discussion, photo-based survey) - Physiological-based tools (e.g., eye-tracking, physiological response analysis) - Phenomenological-based tools (e.g., field observation, participatory preference/mapping methods) - Combination with GIS-based tools (e.g., PPGIS) - Combination with immersive/ virtual technologies Combination with assessment framework	- Psychological data (perception, behavior, attitude) - Physiological data (e.g., eye-tracking, heart rate) - Phenomenological data (e.g., behavior data) - Field-based data (e.g., field research data, on-site photo/ video) - 3D spatial data (e.g.,point cloud, multi-view image, 3d model) - Remote sensing and terrain data (e.g., topographic /terrain data, satellite remote sensing imagery)	8, 12, 14, 16, 17, 24, 26, 27, 32, 35, 40, 41, 42, 50, 52, 53, 54, 60, 61, 63, 65, 67, 68, 75, 81, 89, 91, 98, 101, 105, 111, 114, 117, 126, 127, 131, 139, 148, 151, 153, 161, 162, 165, 168, 169, 173, 179, 181, 182, 185, 191, 193, 195, 196, 201, 202, 203
GIS-based technologies 35 publications (17.24%)	- GIS-based visibility analysis tools (e.g., viewshed) - GIS-based spatial analysis tools (e.g., accessibility, connectivity, raster-based spatial analysis, geospatial analysis) - GIS-based modeling tools (e.g., CityEngene) - Multi-source integration (e.g., point cloud, remote sensing) - Field-supported or participatory GIS - Expert- and framework-integrated approaches	- Terrain and topographic data (e.g., DEM, DTM, topographic data) - Remote sensing and land cover data (e.g., e.g., Landsat, NDVI, time-series of multi-spectral visible light, NIR, thermal imagery) - On-site and photographic data Point cloud and 3D spatial data Survey, participatory, and perceptual data - Historical and archival data (e.g., historical records)	10, 15, 20, 22, 25, 31, 37, 44, 66, 78, 79, 82, 88, 90, 95, 100, 103, 104, 107, 110, 118, 132, 140, 143, 155, 156, 157, 159, 160, 164, 166, 170, 174, 190, 197
Image analysis 2 publications (0.99%)	- Color measurement methods	- Field-based data (e.g., on-site photo/video)	4, 23
Immersive technologies (VR, AR, MR) 8 publications (3.94%)	- Virtual reality technologies Augmented reality and mixed media tools - Point cloud and immersive spatial tools - 3D modeling and rendering tools	- 3D model and visualization data Point cloud (e.g., LiDAR, Airborne, TLS, MLS) - Multi-view image data (e.g., UAV photogrammetry) - Perceptual data	9, 30, 58, 87, 106, 113, 116, 172
Literature review 9 publications (4.43%)	- Network analysis tools (e.g., CiteSpace, VOSviewer) - Content analysis tools (e.g., coding)	- Web of Science - CNKI - CSSCI	2, 7, 11, 13, 34, 92, 123, 149, 176
Photogrammetry-based technologies 5 publications (2.46%)	- Photogrammetry and point cloud-based tools	- Point cloud (e.g., LiDAR, Airborne, TLS, MLS) - Multi-view image data (e.g., UAV photogrammetry)	69, 74, 77, 152, 178

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TOC

TABLE A3 Coding results of research methodologies (Cohen's κ = 0.64).

Core methods	Tools	Data	Literature
Point cloud-based techniques 2 publications (0.99%)	- Photogrammetry and point cloud-based tools (e.g., Structure-from-Motion (SfM)) - GIS-based modeling with point cloud data - Building structural analysis with point cloud data	- Point cloud (e.g., LiDAR, Airborne, TLS, MLS) - Multi-view image data (e.g., UAV photogrammetry)	55, 109
Digital twin 1 publication (0.49%)	- Digital twin - Reality capture for digital twins	- Point cloud (e.g., LiDAR, Airborne, TLS, MLS)	124
Rendering/ visualization/ modeling methods 2 publications (0.99%)	- 3D modeling tools (e.g., Mesh technique) - 3D rendering tools (e.g., Blender for rendering)	- 3D model and visualization data Point cloud (e.g., LiDAR, Airborne, TLS, MLS) - Multi-view image data (e.g., UAV photogrammetry) - Perceptual data	71, 108
Mixed methods 39 publications (19.21%)	**Mixed methods-1:** Point cloud-based techniques + Photogrammetry		1, 38, 43, 45, 47, 147
	Mixed methods-2: Case study + Literature review		141
	Mixed methods-3: Content analysis + Multi-criteria evaluation framework + Literature review		115
	Mixed methods-4: Empirical research methods + Content analysis		39
	Mixed methods-5: GIS + AI-based, AI-related technologies		96
	Mixed methods-6: GIS + Content analysis		72, 129
	Mixed methods-7: GIS + Empirical research methods		3, 28, 59, 70, 83, 84, 86, 97, 102, 125, 142, 192
	Mixed methods-8: GIS + Empirical research methods + Multi-criteria evaluation framework		136, 194
	Mixed methods-9: GIS + Multi-criteria evaluation framework		21, 85, 138
	Mixed methods-10: GIS +Point cloud-based techniques		94, 145, 171
	Mixed methods-11: GIS +Point cloud-based techniques + Empirical research methods		175
	Mixed methods-12: GIS +Point cloud-based techniques + Photogrammetry		29
	Mixed methods-13: Immersive technologies + Empirical research methods		121, 183
	Mixed methods-14: Immersive technologies + Point cloud-based techniques + Empirical research methods		186
	Mixed methods-15: Immersive technologies +Point cloud-based techniques		48
	Mixed methods-16: Point cloud-based techniques+ Empirical research methods		49

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
1	3d cameras acquisitions for the documentation of cultural heritage	M. Pulcrano; S. Scandurra; G. Minin; A. di Luggo	**2019**	https://doi.org/10.5194/isprs-archives-XLII-2-W9-639-2019
2	3d point cloud for cultural heritage: a scientometric survey	Tianyi Zhang; Yuguo Gu; Ruoyu Guo; Xuebin Deng; Fengjiao Wang; Shunyi Zheng; Lei Wang; Shuqing Zhou; Lingfei Xu; Huiyu Wang	**2022**	https://doi.org/10.3390/rs14215542
3	A bi-scale assessing framework for aesthetic ecosystem services of villages in a world heritage site	Yin-ping Ding; Zhi-lin Liu; Yuan-mei Jiao; Qiu-e Xu; Kan-feng Zhang; Cheng-jing Liu; Fan Chen	**2022**	https://doi.org/10.1007/s11629-021-6996-8
4	A cheap protocol for colour measure and for diagnostic in planning a cultural heritage restoration	M. P. Sammartino; C. Genova; S. Ronca; G. Cau; G. Visco	**2017**	https://doi.org/10.1007/s11356-016-8160-5
5	A method for measuring the visual coherence of buildings in residential historic areas	Yipin Xu; Zejia Pan	**2024**	https://doi.org/10.3390/buildings14061595
6	A multi-criteria and multi-group analysis for historic district quality assessment	Raffaele Attardi; Fortuna De Rosa; Maria Di Palma; Claudia Piscitelli	**2013**	https://doi-org.tudelft.idm.oclc.org/10.1007/978-3-642-39649-6_39
7	A review: how deep learning technology impacts the evaluation of traditional village landscapes	Tao Wang; Jingjing Chen; Li Liu; Lingling Guo	**2023**	https://doi.org/10.3390/buildings13020525
8	A study on the sustainable development of historic district landscapes based on place attachment	Xiaoyang Zhu; Shang-Chia Chiou	**2022**	https://doi.org/10.3390/su141811755
9	A virtual tour for the promotion of tourism of the city of bari	Valerio De Luca; Giorgia Marcantonio; Maria Cristina Barba; Lucio Tommaso De Paolis	**2022**	https://doi.org/10.3390/info13070339
10	Accelerated stone deterioration induced by forest clearance around the angkor temples	Marie-Françoise André; Franck Vautier; Olivier Voldoire; Erwan Roussel	**2014**	https://doi.org/10.1016/j.scitotenv.2014.05.141
11	Advances and prospect in natural beauty evaluation: insights for the world heritage karst	Xi Zhao; Kangning Xiong; Meng Zhang	**2024**	https://doi.org/10.1186/s40494-024-01479-9
12*	Aesthetic heterogeneity on rural landscape: pathway discrepancy between perception and cognition	Jun Qi; Yanmei Zhou; Li Zeng; Xueqiong Tang	**2022**	https://doi.org/10.1016/j.jrurstud.2022.05.004

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
13	Aesthetic value protection and tourism development of the world natural heritage sites	Shirong Zhang; Kangning Xiong; Guangyu Fei; Haipeng Zhang; Yongbi Chen	**2023**	https://doi.org/10.1186/s40494-023-00872-0
14	Agricultural heritage systems and landscape perception among tourists	Antonio Santoro; Martina Venturi; Mauro Agnoletti	**2020**	https://doi.org/10.3390/su12093509
15	An algorithmic approach to viewsheds analysis for cultural landscape manziana and the bracciano lake area	Matteo Flavio Mancini	**2020**	https://doi.org/10.1007/978-3-030-20216-3_16
16	An assessment of ordinary landscapes by an expert and by its residents	Évelyne Vouligny; Gérald Domon; Julie Ruiz	**2009**	https://doi.org/10.1016/j.landusepol.2008.10.016
17	Analysis of cultural ecosystem services using text mining of residents??Opinions	Jae-Hyuck Lee; Hong-Jun Park; Ilkwon Kim; Hyuk-Soo Kwon	**2020**	https://doi.org/10.1016/j.ecolind.2020.106368
18	Analysis of the technical condition of a late 19th century public building in lodz	Wioletta Grzmil; Justyna Zapała-Sławeta; Jagoda Juruś	**2023**	https://doi.org/10.3390/ma16051983
19	Application of neural graphics primitives models for 3d representation of devastation caused by russian aggression in ukraine	Illia Oholtsov; Yuri G. Gordienko; Mariia Ladonia; Sergii Telenyk; Grzegorz Nowakowski; Sergii G. Stirenko	**2024**	https://doi.org/10.1007/978-3-031-63751-3_23
20	Archaeological remote sensing using multi-temporal, drone-acquired thermal and near infrared (nir) imagery	Austin Chad Hill; Elise Jakoby Laugier; Jesse Casana	**2020**	https://doi.org/10.3390/rs12040690
21	Assessing railway landscape by ahp process with gis: a study of the yunnan-vietnam railway	Kun Sang; Giovanni Luigi Fontana; Silvia Elena Piovan	**2022**	https://doi.org/10.3390/rs14030603
22	Assessing the optimality of landscape structure in a landscape plan (a lithuanian example)	Darijus Veteikis; Paulius Kavaliauskas; Ričardas Skorupskas;	**2016**	https://www.lvb.lt/permalink/370LABT_NETWORK/5bfnq8/alma9913068363108451
23*	Assessing the visual landscape of istanbul bosphorus: exploring the role of vegetation and built environment characteristics	Hüseyin Ögçe; Elif Nur Sarı; Meltem Erdem Kaya	**2024**	https://doi.org/10.1016/j.landusepol.2024.107288
24	Assessing the visual quality of rural and urban-fringed landscapes surrounding livestock farms	Ayfer Kaplan; Tuncay Taşkın; Ahmet Önenç	**2006**	https://doi.org/10.1016/j.biosystemseng.2006.07.011

** Anchor papers*

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TOC

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
25	Assessment of geosites and geotouristic sites for mapping geotourism: a case study of al-soudah, asir region, saudi arabia	Jamilah Al Mohaya; Mena Elassal	**2023**	https://doi.org/10.1007/s12371-022-00774-w
26	Assessment of society?? Per-ceptions on cultural ecosystem services in a cultural landscape in nanchang, china	Ning Kang; Guanhong Xie; Chunqing Liu	**2023**	https://doi.org/10.3390/su151310308
27	Assessment of visual quality and social perception of cultural landscapes: application to anyi traditional villages, china	Ning Kang; Chunqing Liu	**2024**	https://doi.org/10.1186/s40494-024-01326-x
28	Assessment of visual values as a tool supporting the design decisions of the cultural park protection plan: the case of kazimierz and stradom in krak?W	Urszula Forczek-Brataniec	**2021**	https://doi.org/10.3390/su13136990
29	As-textured as-built bim using sensor fusion, zee ain historical village as a case study	Yahya Alshawabkeh; Ahmad Baik; Ahmad Fallatah	**2021**	https://doi.org/10.3390/rs13245135
30	Augmented reality and 3d printing for archaeological heritage evaluation of visitor experience	Valeria Garro; Veronica Sundstedt	**2022**	https://doi.org/10.1007/978-3-031-15553-6_25
31	Balancing cultural heritage conservation: visual integrity assessment to support change management in the buffer zone of chiang mai historic city using gis and computer-generated 3d modeling	Janjira Sukwai; Nobuo Mishima; Nattasit Srinurak	**2022**	https://doi.org/10.3390/land11050666
32*	Beautiful agricultural land-scapes promote cultural ecosystem services and biodi-versity conservation	Giacomo Assandri; Giuseppe Bogliani; Paolo Pedrini; Mattia Brambilla	**2018**	https://doi.org/10.1016/j.agee.2018.01.012
33	Between history, politics and economy: the problematic heritage of former border railway stations in poland	Weronika Dragan; Mirek Dymitrow; Robert Krzysztofik	**2019**	https://doi.org/10.1553/moegg161s229
34	Bibliometric and visual analysis of sustainable preservation of heritage gardens	Janjira Sukwai; Nattasit Srinurak	**2024**	https://doi.org/10.1186/s40494-024-01483-z

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
35	Biodiversity and wind energy in kenya: revealing landscape and wind turbine perceptions in the world's wildlife capital	Erik Nordman; Jane Mutinda	**2016**	https://doi.org/10.1016/j.erss.2016.05.020
36	Characterisation of naturally and artificially weathered pine tar coatings by visual assessment and gas chromatography-mass spectrometry	Inger Marie Egenberg; Ann Katrin Holtekjølen; Elsa Lundanes	**2003**	https://doi.org/10.1016/S1296-2074(03)00048-7
37	Characteristic and marks of cultural landscape of slovakia	Ján Supuka; Radmila Štěpánková	**2004**	https://www-proquest-com.tudelft.idm.oclc.org/scholarly-journals/characteristic-marks-cultural-landscape-slovakia/docview/203483834/se-2
38	Comparative analysis of point clouds acquired from a tls survey and a 3d virtual tour for hbim development	J. Liu; D. Willkens; C. López; L. Cortés-Meseguer; J. L. García-Valldecabres; P. A. Escudero; S. Alathamneh	**2023**	https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-959-2023
39	Conservation and sustainable tourism development of the natural world heritage site based on aesthetic value identification: a case study of the libo karst	Kangning Xiong; Shirong Zhang; Guangyu Fei; Ao Jin; Haipeng Zhang	**2023**	https://doi.org/10.3390/f14040755
40	Cultivated terraces in slovenian landscapes	Mateja Šmid Hribar; Matjaž Geršič; Primož Pipan; Peter Repolusk; Jernej Tiran; Maja Topole; Rok Ciglič	**2017**	https://doi.org/10.3986/AGS.4597
41	Cultural elements' influence on visual preferences in urban waterfronts' walkways in malaysia	Tun Liu; Mohd Yazid Mohd Yunos; Adam Aruldewan S. Muthuveeran; Riyadh Mundher; Nor Atiah Ismail	**2024**	https://doi.org/10.3389/fbuil.2024.1393187
42	Cultural heritage readability: children?? Perception of cultural landscape, laodikeia ancient city, denizli	Ayşe Özdemir	**2018**	https://doi.org/10.17475/kastorman.312904
43	Damage assessment and digital 2d-3d documentation of petra treasury	Fadi Bala'awi; Yahya Alshawabkeh; Firas Alawneh; Eyad Almasri	**2012**	https://www.maajournal.com/index.php/maa/article/view/664
44	Determining suitable ecotourism areas in protected watershed area through visibility analysis	S. Demir	**2019**	https://aperta.ulakbim.gov.tr/record/69797

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
45	Developing a documentation system for desert palaces in jordan using 3d laser scanning and digital photogrammetry	Sharaf Al-kheder; Yahya Al-shawabkeh; Norbert Haala	**2009**	https://doi.org/10.1016/j.jas.2008.10.009
46	Development of post-industrial heritage landscape design based on visual cognitive schema theory	Yan Wang; Bojun Hou	**2024**	https://doi.org/10.3390/buildings14103194
47	Digital documentation of complex architectures by integration of multiple techniques - the case study of valer castle	Fabio Voltolini; Sabry El-Hakim; Fabio Remondino; Stefano Girardi; Alessandro Rizzi; Marco Pontin; Luigi Gonzo	**2007**	https://doi.org/10.1117/12.702727
48	Digital mont'e prama: 3d cultural heritage presentations in museums and anywhere	Marcos Balsa Rodriguez; Marco Agus; Fabio Bettio; Fabio Marton; Enrico Gobbetti	**2015**	https://doi.org/10.1109/DigitalHeritage.2015.7419573
49	Digital replica of cultural landscapes: an experimental reality-based workflow to create realistic, interactive open world experiences	Emanuel Demetrescu; Enzo d'Annibale; Daniele Ferdani; Bruno Fanini	**2020**	https://doi.org/10.1016/j.culher.2019.07.018
50	Does metaverse stimulate tourism prosocial behavior? A mindfulness-driven model with a psychological ownership perspective	Ruiying Cai; Yao-Chin Wang; Ting (C.) Zhang	**2024**	https://doi.org/10.1108/ijchm-08-2023-1130
51	Empirical study on emotional perception and restorative effects of suzhou garden landscapes text mining and statistical analysis	Zhenyu Zhang; Xiaomeng Wang; Mu Jiang	**2025**	https://doi.org/10.3390/land14010122
52	Empowering public participation in assessing the indicators of aesthetic value for historical landscape a case study on melaka, malaysia	Mohd Sufian Fauzi Rosley; Mohammad Nazli Md Shah; Yusni Yusof; Siti Aisyah Mohamed Nor	**2024**	https://doi.org/10.1080/23311983.2024.2380114
53	Erbil citadel as a brand for the city: the role of residents' awareness and perceptions	Haval Sami Ali; Mahmood Khayat	**2024**	https://doi.org/10.3390/su16198529
54	Ergonomics and cultural heritage the palatina chapel in palermo, italy	Salvatore Barbaro; Rosario Caracausi; Bénédicte Chaix; Rosa Maria Chisesi	**2007**	https://doi.org/10.6092/issn.1973-9494/1229
55	Error-aware construction and rendering of multi-scan panoramas from massive point clouds	Comino Trinidad; Andujar; Chica; Brunet	**2017**	https://doi.org/10.1016/j.cviu.2016.09.011

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
56	Estimation on aesthetic value of tourist landscapes in a natural heritage site: kanas national nature reserve, xinjiang, china	Di; Yang; Liu; Wu; Ma	**2010**	https://doi.org/10.1007/s11769-010-0059-3
57	Evaluating activation functions in gan models for virtual in-painting a path to architectural heritage restoration	Petito; Iannace; Morrone; De Rosa	**2024**	https://doi.org/10.3390/app14166854
58	Evaluating cultural landscape remediation design based on vr technology	Lin; Zhang; Tang; Song; Ye	**2021**	https://doi.org/10.3390/ijgi10060423
59	Evaluation for landscape aesthetic value of the natural world heritage site	Ha; Yang	**2019**	https://doi.org/10.1007/s10661-019-7607-9
60	Evaluation of cultural ecosystem services in moun-tain-type scenic areas: an im-portance-performance analysis of the road of tang poetry in eastern zhejiang	Fan; Wu; Jin; Lu; Zhao; Wang	**2024**	https://doi.org/10.1080/13467581.2023.2270031
61	Evaluation of state of cultural and historical objects in jekabpils city in context of sustainable development	Jankava; Palabinska; Pastare	**2018**	https://doi.org/10.22616/ESRD.2018.076
62	Evaluation of the geological heritage of the dray nur and dray sap waterfalls in the central highlands of vietnam	Ta Hoa Phuong; Nguyen-Thuy Duong; Quang Hai Truong; Bui Van Dong	**2016**	https://doi.org/10.1007/s12371-016-0176-1
63	Evaluation of the quality of par-ticipatory landscape perception in neighborhoods of cultural landscape to achieve social sustainability	Golestani; Khakzand; Faizi	**2022**	https://doi.org/10.36253/aestim-13527
64	Evaluation on tourism ecolog-ical security in nature heritage sites: case of kanas nature reserve of xinjiang, china	Xuling Liu; Zhaoping Yang; Feng Di; Xuegang Chen	**2009**	https://doi.org/10.1007/s11769-009-0265-z
65	Exploring perceived naturalness and diverse landscape service appreciation: a q methodology study in ansan city park	Do-Eun Kim; Yong-Hoon Son; Kyu-Chul Lee	**2024**	https://doi.org/10.1080/13416979.2024.2370690
66	Exploring the impact of urban development on mountain view visualization using a gis-based landscape assessment model: a case study in lishui, china	Yinchao Xie; Yijia Zhao; Wei Liu; Xuefeng Bai; Hao Xu	**2024**	https://doi.org/10.1080/10106049.2024.2322697

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
67	Exploring the link between landscape perception and community participation: evidence from gateway communities in giant panda national park, china	Nian Li; Dongmei Gu; Yifei Li; Xinyu Huang; Qibing Chen; Xi Li; Bingyang Lv	**2024**	https://doi.org/10.3390/land13122216
68*	Factors influencing visual landscape quality perceived by the public: results from a national survey	Flurina M. Wartmann; Jacqueline Frick; Felix Kienast; Marcel Hunziker	**2021**	https://doi.org/10.1016/j.landurbplan.2020.104024
69	From analogue to digital photogrammetry: documentation of padise abbey in two different time stages	Adam Dlesk; Andres Uueni; Karel Vach; Jüri Pärtna	**2020**	https://doi.org/10.3390/app10238330
70	From traditional to contemporary: revelations in chinese garden and public space design	Bo Yang; Nancy J. Volkman	**2010**	https://doi.org/10.1057/udi.2010.13
71	Garden cultural heritage spatial functionalities: the case of anamorphosis abscondita at vaux-le-vicomte	Mihailo Grbić; Aleksandar Čučaković; Biljana Jović; Miloš Tripković	**2016**	https://doi.org/10.1016/j.culher.2015.08.007
72	Geo-archaeo-routes on the island of lemnos	Eustathios Ilia; Artemios Gratsias; Kalliopi Antonopoulou; Panagiotis Zagkas	**2023**	https://doi.org/10.3390/geosciences13050143
73	Geodiversity and geological treasure of tabas unesco global geopark for geotourism development, new uggp from iran	Vesal Yahya Sheibani; Ehsan Zamanian	**2023**	https://doi.org/10.1007/s12371-023-00873-2
74	Graphic study and geovisualization of the old windmills of la mancha (spain)	Enrique Pérez-Martín; Tomás Ramón Herrero-Tejedor; Miguel Ángel Gómez-Elvira González; José Ignacio Rojas-Sola; Miguel Ángel Conejo-Martín	**2011**	https://doi.org/10.1016/j.apgeog.2011.01.006
75	Harmony in nature: exploring the multisensory impact of classical gardens on individuals??Well-being	Zihan Gong; Sixiang Dai; Sumeyra Kasapoglu; Xuchu Qiu; Amaël Frankl	**2024**	https://doi.org/10.1177/19375867241276299
76	Harnessing artificial intelligence technology and social media data to support cultural ecosystem service assessments	Lukas Egarter Vigl; Thomas Marsoner; Valentina Giombini; Caroline Pecher; Heidi Simion; Egon Stemle; Erich Tasser; Daniel Depellegrin	**2021**	https://doi.org/10.1002/pan3.10199
77	Heritage and technology: novel approaches to 3d documentation and communication of architectural heritage	Mariateresa Galizia; Laura Inzerillo; Cettina Santagati	**2015**	https://hdl.handle.net/10447/160823

** Anchor papers*

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TOC

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
78	Historic gardens restoration - preliminary outcomes from a synergistic application of visual assessment and geomatic techniques to optimize the management of arboreal heritages	Enrico Felice; Michaela De Giglio; Marco Dubbini; V. Vignoli	**2022**	https://doi.org/10.17660/ActaHortic.2022.1345.15
79	How can a complex geosite be enhanced? A landscape-scale approach to the deep-seated gravitational slope deformation of pointe leysser (aosta valley, nw italy)	M. Gabriella Forno; Franco Gianotti; Marco Gattiglio; Manuela Pelfini; Gaia Sartori; Irene Bollati; et al.	**2022**	https://doi.org/10.1007/s12371-022-00730-8
80	How can landscape visual assessment inform landscape planning and management? Alto douro wine region case study, portugal	Ana Medeiros; Cláudia Fernandes; João Gonçalves; Paulo Farinha-Marques; Isabel Martinho da Silva; et al.	**2024**	https://doi.org/10.1016/j.apgeog.2024.103203
81	How do rural landscapes support place attachment in refugees? Results from a photo elicitation	Mahsa Bazrafshan; Adrienne Grêt-Regamey; Felix Kienast	**2024**	https://doi.org/10.1080/01426397.2024.2354363
82	I walk an ancient road: a straightforward methodology for analyzing intra- and inter-regional connectivity systems along roman frontier zones (c. 1st??Th century ad)	Dominik Hagmann	**2025**	https://doi.org/10.1016/j.jas.2024.106151
83	Identification and evaluation of landscape as a precondition for planning revitalization and development of mediterranean rural settlements: case study mrkovi village, bay of kotor, montenegro	Željka Čurović; Milić Čurović; Velibor Spalević; Milorad Janic; Paul Sestras; Svetislav G. Popović	**2019**	https://doi.org/10.3390/su11072039
84	Identification of important terraced visual landscapes based on a sensitivity-subjectivity preference matrix for agricultural cultural heritage in southwestern china	Luanyu Zhou; Yuluan Zhao; Xue Yang; Jun He; Hong Wang	**2023**	https://doi.org/10.1016/j.ecolind.2023.110573
85	Identification of priority conservation areas for natural heritage sites integrating landscape ecological risks and ecosystem services: a case study in the bogda, china	Tian Wang; Xiaodong Chen; Xin Zheng; Yayan Lu; Fang Han; Zhaoping Yang	**2022**	https://doi.org/10.3390/ijerph19042044

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
86	Identifying and mapping the tourists??Perception of cultural ecosystem services: a case study from an alpine region	Brenda Maria Zoderer; Erich Tasser; Karl-Heinz Erb; Paola S. L. Stanghellini; Ulrike Tappeiner	**2016**	https://doi.org/10.1016/j.landuse-pol.2016.05.004
87	Immersive virtual reality and computer vision for heritage visual evaluation and percep-tion of the industrial heritage sites along the yunnan-vietnam railway (yunnan section)	Yingxue Wang; Shuoyi Wang; Jin Wang	**2024**	https://doi.org/10.1186/s40494-024-01145-0
88	Impact assessment and protec-tion of outstanding landscape integrity in a natural heritage site: fairy valley, kanas nature reserve, xinjiang, china	Fang Han; Zhaoping Yang; Xinyu Liu; Feng Di	**2011**	https://doi.org/10.1007/s11629-011-2067-x
89	Impact of artificial elements on mountain landscape perception: an eye-tracking study	Suling Guo; Wei Sun; Wen Chen; Jianxin Zhang; Peixue Liu	**2021**	https://doi.org/10.3390/land10101102
90	Implications of urban growth and farmland loss for ecosystem services in the western united states	Jenna Narducci; Cristina Quin-tas-Soriano; Antonio Castro; Rosa Som-Castellano; J. S. Brandt	**2019**	https://doi.org/10.1016/j.landuse-pol.2019.04.029
91	Individual views and shared landscapes of folklore in reyk-holtsdal, iceland	Laura Puolamäki	**2012**	https://doi.org/10.2478/v10091-012-0021-8
92	Intangible cultural heritage in china: a visual analysis of research hotspots, frontiers, and trends using citespace	Qiong Dang; Zhongming Luo; Chuhao Ouyang; Lin Wang; Mei Xie	**2021**	https://doi.org/10.3390/su13179865
93	Land cover and landscape structural changes using extreme gradient boosting, random forest, and fragmenta-tion analysis	Charles Matyukira; Paidamwoyo Mhangara	**2023**	https://doi.org/10.3390/rs15235520
94	Landmarks as cultural heritage assets: affecting the distri-bution of settlements in rural areas	Barbara Prus; Magdalena Wilko-sz-Mamcarczyk; Tomasz Salata	**2020**	https://doi.org/10.3390/rs12111778
95	Landscape analysis and regain functionality of gulistan garden in the historic van castle	Feran Aşur; Şevket Alp	**2020**	https://doi.org/10.31407/ijees10.108

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
96	Landscape management and planning as a spatial organization method connecting ces supply-demand assessment and sustainable tourism development	Chang Li; Qifan Liang; Beiduo Lin; Jun Zhai	**2023**	https://doi.org/10.1016/j.jort.2023.100705
97	Landscape perception and public participation for the conservation and valorization of cultural landscapes: the case of the cinque terre and porto venere unesco site	Antonio Santoro; Daniele Venturi; Mauro Agnoletti	**2021**	https://doi.org/10.3390/land10020093
98	Landscape perception in marginalized regions of europe: the outsiders' view	Katalin Solymosi	**2011**	https://doi.org/10.3167/nc.2011.060104
99	Landscape risk assessment model and decision support system for the protection of the natural and cultural heritage in the eastern mediterranean area	Maria Gabriella Trovato; Dana Ali; Jessica Nicolas; Ammar El Halabi; Sarah Meouche	**2017**	https://doi.org/10.3390/land6040076
100	Landscape visual sensitivity assessment of historic districts: a case study of wudadao historic district in tianjin, china	Ya-Nan Fang; Jian Zeng; Aihemaiti Namaiti	**2021**	https://doi.org/10.3390/ijgi10030175
101	Local perceptions of ecosystem services and protection of culturally protected forests in southeast china	Hong Gao; Yi Xiao; C.S.A. (Kris) van Koppen; Zhiyun Ouyang	**2023**	https://doi-org.tudelft.idm.oclc.org/10.1080/20964129.2018.1546126
102	Making a cultural landscape: the case of dongshan river basin, taiwan	Shu-Chun Lucy Huang; William P. Stewart; Pao-Ning Yin	**2017**	https://doi.org/10.1080/08941920.2017.1364450
103	Mapping and assessment of karst landscape aesthetic value from a world heritage perspective: a case study of the huangguoshu scenic area	Meng Zhang; Kangning Xiong; Xi Zhao; Xiaoxi Lyu	**2024**	https://doi.org/10.1186/s40494-024-01312-3
104	Mapping landscape perception: an assessment with public participation geographic information systems and spatial analysis techniques	Amalia Vaneska Palacio Buendía; Yolanda Pérez-Albert; David Serrano Giné	**2021**	https://doi.org/10.3390/land10060632
105	Measuring visual attractiveness of urban commercial street using wearable cameras: a case study of gubei gold street in shanghai	Yihua Huang; Yuanquan Ouyang	**2022**	https://doi.org/10.1007/978-3-031-05900-1_28

** Anchor papers*

>>>

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
106	Mesh retopology applied to 3d models of cultural heritage for interactive visualization enhancement in virtual reality and augmented reality	Manuel Drago Díaz Alemán	**2023**	https://doi.org/10.37558/gec.v24i1.1147
107	Method for selecting viewpoints of architectural heritage land-scapes	Yungang Hu; Yutang Feng; Ran Zhao; Yuhua Wu; Pinjun Nie	**2024**	https://doi.org/10.1186/s40494-024-01235-z
108	Methods and application for photorealistic rendering and lighting of ancient buildings	Maurizio Rossi; Daniele Marini; Alessandro Rizzi	**2004**	https://doi.org/10.1016/j.culher.2003.12.004
109	Methods for measuring buildings using laser scanning (on the example of two objects of cultural heritage of the novo-sibirsk region)	Anna Y. Maynicheva; Evgeniya A. Gruzdeva; Elena Y. Orlova	**2023**	https://doi.org/10.17223/22220836/51/22
110	Mitigating visual impacts of built structures: the contribu-tion of mayors in the collabo-rative managing of a unesco cultural landscape	Fabrizio Aimar	**2024**	https://doi.org/10.1108/JCHMSD-02-2021-0017
111	New life for mondonico: from ghost village to agro-forest university campus	Alessia Silvetti; Chiara Bonaiti; Francesca Andrulli	**2020**	https://doi.org/10.14633/AHR301
112	On the evolution of the aesthetic advantages of cultural landscapes	Elena V. Golosova; Olga V. Shelepova; Anastasia A. Nikolaeva	**2025**	https://amazoniainvestiga.info/index.php/amazonia/article/view/813
113	Optimization of building thermal environment and vr industrial heritage landscape design enhanced by computer vision algorithms	Lv You	**2024**	https://doi.org/10.1016/j.tsep.2024.102926
114	Perceptions of cultural land-scapes: exploring tourist satis-faction in traditional villages	Huaheng Shen; Xueqin Tan; Xinmei Liu; Xiting Yu; Yu Luo	**2025**	https://doi.org/10.3934/geosci.2025002
115	Perspectives on landscape identity: a conceptual challenge	Derk Jan Stobbelaar; Bas Pedroli	**2011**	https://doi.org/10.1080/01426397.2011.564860
116	Photorealistic rendering over the internet for restoration support of ancient buildings	Maurizio Rossi; Daniele Marini; Alessandro Rizzi	**2001**	https://doi.org/10.1117/12.411894
117	Placemaking in informal settlements: the case of france colony, islamabad, pakistan	Ramisa Shafqat; Dora Marinova; Shahed Khan	**2021**	https://doi.org/10.3390/urbansci5020049

** Anchor papers*

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TOC

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
118	Planning a greenway based on an evaluation of visual landscape attractiveness	Łukasz Sarnowski; Zbigniew Podgórski; Dariusz Brykała	**2016**	https://doi.org/10.1515/mgr-2016-0017
119	Planning in sharp's town and countryside	Izaskun Aseguinolaza-Braga	**2009**	https://doi.org/10.15581/014.11.25898
120	Plants as design material in gardens of le notre	M. van den Toorn	**2010**	https://doi.org/10.17660/ActaHortic.2010.881.153
121	Pointxr: a toolbox for visualization and subjective evaluation of point clouds in virtual reality	Evangelos Alexiou; Nanyang Yang; Touradj Ebrahimi	**2020**	https://doi.org/10.1109/qomex48832.2020.9123121
122	Preservation and renewal: a study on visual evaluation of urban historical and cultural street landscape in quanzhou	Yang Zhao; Junhan Liu; Yali Zheng	**2022**	https://doi.org/10.3390/su14148775
123	Progress of gentrification research in china: a bibliometric review	Fengbao Liu; Xigang Zhu; Jianshu Li; Jie Sun; Qinshi Huang	**2019**	https://doi.org/10.3390/su11020367
124	Progressive dilution of point clouds considering the local relief for creation and storage of digital twins of cultural heritage	Martin Štroner; Tomáš Křemen; Rudolf Urban	**2022**	https://doi.org/10.3390/app122211540
125	Public perception influence on the reshaping urban heritage: a case study of port said historic quarters	Sara S. Fouad; Shahira Sharaf Eldin	**2023**	https://doi.org/10.1177/12063312211018397
126	Public perception of accommodation structures in the cultural landscape: an exploration of integration and significance	Raul-Catalin Oltean; Felix Horatiu Arion	**2024**	https://doi.org/10.3390/buildings14061822
127*	Public support for river restoration: a mixed-method study into local residents??-Support for and framing of river management in the dutch floodplains	Arjen E. Buijs	**2009**	https://doi.org/10.1016/j.jenvman.2009.02.006
128	Quantitative analysis and evaluation of winter and summer landscape colors in the yangzhou ancient canal utilizing deep learning	Yanyan Wang; Jiangling Qian; Jiajie Cao; Rong Fan; Xunyu Han	**2025**	https://doi.org/10.1038/s41598-025-91483-1
129	Quantitative research on aesthetic value of the world heritage karst based on ugc data: a case study of huangguoshu scenic area	X. Zhao; K. Xiong; M. Zhang	**2005**	https://doi.org/10.1371/journal.pone.0317304

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
130	Recognition of street landscape patterns in kunming city based on intelligent decision algorithm and regional cultural expression	Xingxiao Zhu; Zhizhong Xing; Xia Chen; Jing Wang; Xinyue Yang; Lei Yang; Lin Wang; Ruimin Li; Yayu Wang	**2024**	https://doi.org/10.3390/electronics13214183
131*	Relationship between landscape visual attributes and spatial pattern indices: a test study in mediterranean-climate landscapes	Gonzalo de la Fuente de Val; José A. Atauri; José Vicente de Lucio	**2006**	https://doi.org/10.1016/j.landurbplan.2005.05.003
132	Remnants of medieval field patterns in the czech republic	Petr Sklenicka; Kristina Molnarova; Elizabeth Brabec; Peter Kumble; Blanka Pittnerova; Katerina Pixova; Miroslav Salek	**2009**	https://doi.org/10.1016/j.agee.2008.10.026
133	Representation of butchulla cultural heritage values in communication of k'gari (fraser island) as a tourism destination	Sarah Brown; Clare Baldwin; Lisa Chandler	**2014**	https://doi.org/10.1080/14486563.2014.985266
134	Research on landscape perception and visual attributes based on social media data?? Case study on wuhan university	Xia Zhang; Danning Xu; Ni Zhang	**2022**	https://doi.org/10.3390/app12168346
135	Research on the perception of cultural ecosystem services in urban parks via analyses of online comment data	Qianzi Jiang; Guangxing Wang; Xueyuan Liang; Na Liu	**2025**	https://doi.org/10.15302/J-LAF-1-020072
136	Research on visual experience evaluation of fortress heritage landscape	Xiang Xu; Rui Dong; Zhixing Li	**2024**	https://doi.org/10.1186/s40494-024-01397-w
137	Research-based design approaches in historic garden renovation	Albert Fekete; László Kollányi	**2019**	https://doi.org/10.3390/land8120192
138	Scenic routes linking and protecting natural and cultural landscape features	Richard L. Kent; Cynthia L. Elliott	**1995**	https://doi.org/10.1016/0169-2046(94)02027-D
139	Seeking lost memories: application of a new visual methodology for heritage protection	Min Wang; Meiting Zhao; Mingliang Lin; Wei Cao	**2020**	https://doi.org/10.1080/00167428.2020.1715800
140*	Settlement models, land use and visibility in rural landscapes: two case studies in greece	Marjanne Sevenant; Marc Antrop	**2007**	https://doi.org/10.1016/j.landurbplan.2006.09.004
141	Socio-cultural appropriateness of the use of historic persian gardens for modern urban edible gardens	Majid Amani-Beni; Gaodi Xie; Qingjuan Yang; Alessio Russo; Mohammad Reza Khalilnezhad	**2022**	https://doi.org/10.3390/land11010038

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
142	Spatial analysis of visitor preferences in the outdoor recreational niche of mediterranean cultural landscapes	María F. Schmitz; Itziar de Aranzabal; Francisco D. Pineda	**2025**	https://doi.org/10.1017/S0376892907004249
143	Spatial planning and the traditional settlements management: evidence from visibility analysis of traditional settlements in cyclades, greece	Georgios Tsilimigkas; Evangelia-Theodora Derdemezi	**2025**	https://doi.org/10.1080/02697459.2019.1687202
144	Study on multidimensional perception of national forest village landscape based on digital footprint support??Nhui xidi village as an example	Feifan Weng; Xufang Li; Yanqiu Xie; Zhengduo Xu; Fanzhuo Ding; Zheng Ding; Yushan Zheng	**2023**	https://doi.org/10.3390/f14122345
145	Terrestrial laser scanning digitalization in underground constructions	César Porras-Amores; Fernando R. Mazarrón; Ignacio Cañas; Paola Villoria Sáez	**2019**	https://doi.org/10.1016/j.culher.2019.01.007
146	The 21st-century islamic garden: connecting the present to the past	Amer Habibullah; D. Fairchild Ruggles	**2024**	https://doi.org/10.3368/lj.43.2.1
147	The 3d reconstruction and visualization of seokguram grotto world heritage site	Jin Ho Park; Tufail Muhammad; Jae-Hong Ahn	**2014**	https://doi.org/10.1109/VSMM.2014.7136646
148	The aesthetic value of a mountain landscape: a study of the mt. Everest trek	Beau Beza	**2010**	https://doi.org/10.1016/j.landurbplan.2010.07.003
149	The aesthetic value of world heritage karst: a literature review and implication for huangguoshu scenic area outstanding universal value	Xin Wang; Kangning Xiong; Meng Zhang; Xi Zhao	**2022**	https://doi.org/10.3390/su142315961
150	The appropriation and transformation of the landscape: the urbanization process resulting from the cultivation of the erva mate in paran? (brazil)	Carlos Smaniotto Costa; Eliana do Pilar Rocha	**2025**	https://doi.org/10.1080/13563475.2015.1119672
151	The assessment of the tourism potential of the tagus international nature reserve landscapes using methods based on the opinion of the demand	Dora Isabel Rodrigues Ferreira; José-Manuel Sánchez-Martín	**2022**	https://doi.org/10.3390/land11010068
152	The bust of the emperor hadrian	Josefina García-León; Filippo Fantini; Jesús A. González García	**2022**	https://doi.org/10.1007/978-3-031-04632-2_37

** Anchor papers*

>>>

TOC

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
153	The cantonese ancestral clan building as a social integration platform	Rachel Suet Kay Chan	**2020**	https://doi.org/10.18055/finis17553
154	The colors of mzab cities: heritage, culture, and symbolism	Meriem Benkhedda	**2023**	https://doi.org/10.6092/issn.1973-9494/20042
155	The contribution of digital data to the understanding of ritual landscapes: the case of calicantone (sicily)	Francesca Buscemi; Marianna Figuera	**2019**	https://doi.org/10.1515/opar-2019-0029
156	The cultural landscape of rural cemeteries on the polish??Zech borderlands: multi-faceted visual analysis as an element of tourism potential assessment	Anna Dzikowska; Anna Zaręba; Alicja Krzemińska; Kamil Pawłowski	**2023**	https://doi.org/10.3390/su151813730
157	The emerging role of visual resource assessment and visualization in landscape planning in switzerland	Willy A. Schmid	**2001**	https://doi.org/10.1016/S0169-2046(01)00137-2
158	The evaluation of the cultural values of edirne city in the frame of urban aesthetics	E. Erdoğan; N. Kuter	**2010**	https://dergipark.org.tr/tr/pub/jotaf/issue/19044/201427
159	The hidden cairns?? Case study of drone-based als as an archaeological site survey method	Johanna Roiha; Vili Einari Heinaro; Markus Holopainen	**2021**	https://doi.org/10.3390/rs13102010
160	The impact of land use and depopulation on burial mounds in the kazanlak valley, bulgaria	Martin Eftimoski; Shawn A. Ross; Adela Sobotkova	**2017**	https://doi.org/10.1016/j.culher.2016.10.002
161	The importance of ecosystem services in coastal agricultural landscapes: case study from the costa brava, catalonia	Emma Soy-Massoni; Johannes Langemeyer; Diego Varga; Marc Sáez; Josep Pintó	**2015**	https://doi.org/10.1016/j.ecoser.2015.11.004
162	The influence of interpretation on learning about architectural heritage and on the perception of cultural significance	Márcia Costa; Maria João Carneiro	**2020**	https://doi.org/10.1080/14766825.2020.1737705
163	The key to improving the beauty of the giant retaining wall in valleys	Jialu Song; Yanzuo Zhou; Weiyang Xiao; Qin Zeng; Yixuan Wu; Huixing Song	**2023**	https://doi.org/10.1371/journal.pone.0287251
164	The past in the present: the anthropized landscape as an instrument of memory legacy	Manlio MONTUORI	**2019**	http://www.leviedeimercanti.it/proceedings-xvii-forum/

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
165	The perception of abandoned farmland by local people and experts: landscape value and perspectives on future land use	Anda Ruskule; Oļģerts Nikodemus; Raimonds Kasparinskis; Simon Bell	**2013**	https://doi.org/10.1016/j.landurbplan.2013.03.012
166	The perception of agrarian historical landscapes: a study of the veneto plain in italy	Tiziano Tempesta	**2010**	https://doi.org/10.1016/j.landurbplan.2010.06.010
167	The portrayal of greenland: a visual analysis of its digital storytelling	Francesc Fusté-Forné	**2022**	https://doi.org/10.1080/13683500.2021.1974359
168	The restorative potential of green cultural heritage: exploring cultural ecosystem services??Impact on stress reduction and attention restoration	Jing Xie; Shixian Luo; Katsunori Furuya	**2023**	https://doi.org/10.3390/f14112191
169	The visual quality effects of historical building gardens on urban texture in the sustainable landscape	Kübra Yazici; Bahriye Gülgün Aslan	**2019**	https://www.prt-parlar.de/download_feb_2019/
170	Tourist landscape vulnerability assessment in mountainous world natural heritage sites: the case of karajun-kurdening, xinjiang, china	Xiaodong Chen; Zhaoping Yang; Fang Han	**2023**	https://doi.org/10.1016/j.ecolind.2023.110038
171	Towards a framework for point-cloud-based visual analysis of historic gardens: jichang garden as a case study	Y. Peng; Guanting Zhang; Steffen Nijhuis; Giorgio Agugiaro; Jantien E. Stoter	**2023**	https://doi.org/10.1016/j.ufug.2023.128159
172	Towards tangible cultural heritage experiences - enriching VR-based object inspection with haptic feedback	Stefan Krumpen; Reinhard Klein; Michael Weinmann	**2022**	https://doi.org/10.1145/3470470
173	Traditional village perception and protection behavior: the mediating role of local identity and the impact of different population differences	Xiaoxue Lu; Donghao Tan; Yuchen Zhou; Yanqiu Xie; Zujian Chen	**2024**	https://doi.org/10.1080/13467581.2024.2418499
174	Transdisciplinary approach of transboundary landscape studies: a case study of an austro-hungarian transboundary landscape	Anke Hahn; Éva Konkoly-Gyuró; Sonja Völler; Pál Balázs; Gregor Torkar; Julia Ellis Burnet	**2019**	https://doi.org/10.1080/00167223.2019.1581628
175	Transformation of the jeruzalem hills cultural landscape with modern vineyard terraces	Primož Pipan; Žiga Kokalj	**2017**	https://doi.org/10.3986/AGS.4629

** Anchor papers*

>>>

TOC

TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
176	Trends and future directions in research on the protection of traditional village cultural heritage in urban renewal	Jun Xia; Xuefei Gu; Tianru Fu; Yangzhi Ren; Yazhen Sun	**2024**	https://doi.org/10.3390/buildings14051362
177	Understanding the visual relationship between function and facade in historic buildings using deep learning?? Case study of the chinese eastern railway	Peilun Li; Zhiqing Zhao; Bocheng Zhang; Yuling Chen; Jiayu Xie	**2023**	https://doi.org/10.3390/su152215857
178	Unmanned aerial vehicles (uav) photogrammetry in the conservation of historic places	Alex Federman; Sujan Shrestha; Mario Santana Quintero; Davide Mezzino; John Gregg; Shawn Kretz; Christian Ouimet	**2018**	https://doi.org/10.3390/drones2020018
179	Unraveling the benefits of urban heritage greenery	Hung-Ming Tu	**2025**	https://doi.org/10.1007/s11355-025-00649-6
180	Urban heritage facility management - a conceptual framework for the provision of urban-scale support services in norwegian world heritage sites	Bintang Noor Prabowo; Alenka Temeljotov Salaj; Jardar Lohne	**2024**	https://doi.org/10.3390/heritage7030066
181	Urban spaces quality enrichment based on aesthetic values of historical fabrics of isfahan, iran	Fatemeh Mehdizadeh Saradj; Farhang Mozafar; Maryam Taefnia; Reihaneh A. Sajad	**2018**	https://doi.org/10.1680/jurdp.18.00005
182	User experience centered application design of multivariate landscape in kulangsu, xiamen	Fengze Lin; Fengming Chen; Mingjian Zhu	**2021**	https://doi.org/10.1007/978-3-030-78224-5_4
183	Using 360-degree panoramic technology in traditional villages	Huaheng Shen; Nor Fadzila Aziz; Xianyang Lv	**2025**	https://doi.org/10.1016/j.ecoinf.2025.103036
184	Using a new pdp modelling approach for land-use and land-cover change predictions: a case study in the stubai valley (central alps)	Cristian Fondevilla; M. Àngels Colomer; Federico Fillat; Ulrike Tappeiner	**2015**	https://doi.org/10.1016/j.ecolmodel.2015.11.016
185	Value-based profiles of visitors to a world heritage site: the case of suwon hwaseong fortress (in south korea)	Hwasung Song; Hyun Kim	**2018**	https://doi.org/10.3390/su11010132
186	Virtual valcamonica: collaborative exploration of prehistoric petroglyphs and their surrounding environment in multi-user virtual reality	Alexander Kulik; André Kunert; Stephan Beck; Carl-Feofan Matthes; Andre Schollmeyer; Adrian Kreskowski; Bernd Fröhlich; Sue Cobb; Mirabelle D'Cruz	**2017**	https://doi.org/10.1162/pres_a_00297

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
187	Visual analysis method for cultural heritage site risk assessment	Kun Qian; Jizhou Sun; Hui Chen; Jiawan Zhang	**2016**	https://doi.org/10.1007/s12650-015-0325-7
188	Visual analysis of social media data on experiences at a world heritage tourist destination: historic centre of macau	Mengyan Jia; Jingzhao Feng; Yile Chen; Chunxi Zhao	**2024**	https://doi.org/10.3390/buildings14072188
189	Visual analysis of the cultural landscape for revitalization of rural areas	Sylwia Szefler	**2021**	https://doi.org/10.54740/ros.2021.020
190	Visual analysis of the cultural landscape in terms of veg-etation for the purposes of revitalization of rural areas	Sylwia Szefler	**2023**	https://doi.org/10.54740/ros.2021.020
191	Visual assessment of rural landscape with different char-acters	Esra Özhancı; Hasan Yılmaz	**2019**	https://doi.org/10.26650/forestist.2019.040219
192	Visual capacity assessment of open landscape in poland	Anna Górka	**2020**	https://doi.org/10.3390/su12166319
193	Visual effect of modern buildings on a traditional japanese garden	Buket Senoglu; Hilmi Ekin Oktay; Isami Kinoshita	**2018**	https://doi.org/10.21834/e-bpj.v3i8.1393
194	Visual impact assessment method for cultural heritage: west lake cultural landscape in hangzhou, china	Huaiyun Kou; Longchang Zhang; Sichu Zhang	**2024**	https://doi.org/10.3390/land13101596
195	Visual landscape evaluation of kastamonu clock tower environment	Sevgi Öztürk; Elif Ayan Çeven; Öznur Işınkaralar	**2018**	https://www.prt-parlar.de/download_feb_2018/
196	Visual landscape quality as-sessment in historical cultural landscape areas	Emine Keleş; Damla Atik; Gökçen Bayrak	**2018**	https://doi.org/10.14207/ejsd.2018.v7n3p287-300
197	Visual perception of the rural landscape: a case study in val di chiana, tuscany	Veronica Alampi Sottini; Iacopo Bernetti; Matteo Pecchi; Maria Cipollaro	**2018**	https://doi.org/10.13128/Aestimum-23967
198	Visual preferences assessment of landscape character types using data mining	F. Aşur; S. Deniz Sevimli; K. Yazıcı	**2020**	http://jast.modares.ac.ir/article-23-31642-en.html
199	Visualization system of hlai ethnic village landscape design based on machine learning	Jun Liu; Xiaoli Wu; Yi Zhang; Li Wang	**2023**	https://doi.org/10.1007/s00500-023-08196-8
200	Viticultural landscape patterns - embedding contemporary wineries into the landscape site	Olga Harea; Anna Eplényi	**2017**	https://doi.org/10.22616/j.landarchart.2017.10.01

** Anchor papers*

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TABLE A4 Selected papers for literature analysis.

	Title	Author	Year	Doi & Link
201*	What attracts tourists to press the shutter in cultural heritage tourism? An analysis of visitor-employed photography and visual attributes: a case study on japan's kairakuen garden	Huixin Wang; Shixian Luo; Katsunori Furuya	**2023**	https://doi.org/10.1080/02508281.2022.2153993
202	What do we visually focus on in a world heritage site? A case study in the historic centre of prague	Fangfang Liu; Jian Kang; Yue Wu; Da Yang; Qi Meng	**2022**	https://doi.org/10.1057/s41599-022-01411-1
203	What is attractive rural landscape? Differences in the social and expert assessment	Agata Gajdek; Barbara Krupa; Anna Nowak	**2023**	https://doi.org/10.1007/s11629-022-7377-7

* *Anchor papers*

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APPENDIX B

For Chapter 4

APP. B.1

Details of calculation for visual indicators

A Depth

1 Layered Depth Index (LDI)

- **Step 1:** Divide viewing distances into several intervals (e.g., near, middle, far, very far).
- **Step 2:** Calculate proportions p_i of sightlines in each interval:

$$p_i = \frac{n_i}{N}, \quad \text{where} \quad \sum p_i = 1$$

- **Step 3:** Compute entropy H to represent layering complexity:

$$H = -\sum_i (p_i \log(p_i))$$

- **Step 4:** Calculate coefficient of variation (CV) of viewing distances:

$$CV = \frac{\sigma_D}{\mu_D}$$

where σ_D is the standard deviation and μ_D the mean of viewing distances.

- **Step 5:** Compute the LDI as the product of entropy and CV:

$$LDI = H \times CV$$

2 Absolute Depth Index (ADI)

Defined as the ratio of the maximum observed viewing distance (D_{max}) to a reference or maximum possible distance (D_{ref}):

$$ADI = \frac{D_{\max}}{D_{\mathrm{ref}}}$$

3 Combined Depth Index (DI)

Integrate normalized LDI and ADI with equal weighting (0.5 each):

$$DI = 0.5 \times LDI_{\mathrm{norm}} + 0.5 \times ADI_{\mathrm{norm}}$$

Interpretation:

- Higher LDI indicates greater complexity in spatial layering.
- Higher ADI indicates longer viewing distances.
- Higher DI values represent spaces with pronounced layering and extensive visibility.

B Orientation

- **Step 1:** Divide the horizontal 360° range into 36 intervals (10° each).
- **Step 2:** Compute the weighted proportions p_k of sightline lengths in each interval:

$$p_k = \frac{D_{\mathrm{sum},k}}{\sum_k D_{\mathrm{sum},k}}$$

- **Step 3:** Calculate directional entropy ($H_{direction}$):

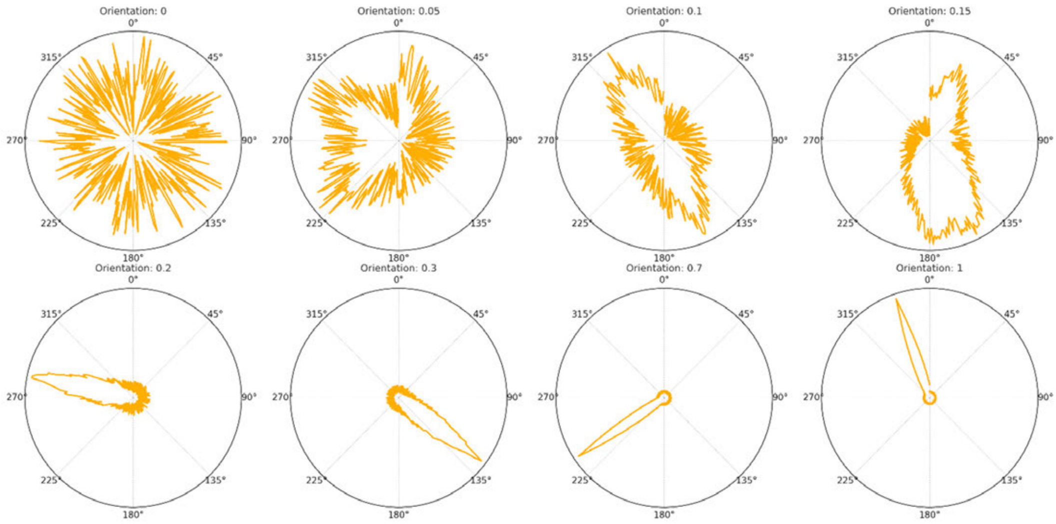
$$H_{\mathrm{direction}} = -\sum_k (p_k \log(p_k))$$

- **Step 4:** Normalize entropy and derive the orientation indicator:

$$\mathrm{Orientation} = 1 - \frac{H_{\mathrm{direction}}}{\log(36)}$$

Interpretation:

- Values approaching 1 indicate clear directional guidance.
- Values approaching 0 indicate uniform distribution with no directional bias.



Examples of different level of orientation value

C Openness

Computed using spherical area approximation:

- **Step 1:** Calculate spherical areas corresponding to each unobstructed sightline.
- **Step 2:** Sum these unobstructed spherical areas.
- **Step 3:** Define openness as the ratio of unobstructed area to total potential spherical area:

$$\text{Openness} \approx \frac{\text{Unobstructed spherical area}}{\text{Total spherical area}}$$

Interpretation:
- High openness implies extensive visibility and fewer obstructions.
- Low openness implies limited visibility and significant visual blockage.

D Complexity

Complexity integrates both class proportions and spatial scale variations.

Step 1: Calculate class proportion entropy (H_{class}), reflecting the evenness of element types:

$$H_{\text{class}} = -\sum_i q_i \log(q_i), \quad q_i = \frac{n_i}{N}$$

where Q_i is the proportion of class *i*.

- **Step 2:** Calculate scale diversity within each class using weighted Shannon entropy ($H_{distance}$):

- Compute coefficient of variation (*CV*) for each landscape element type.
- Calculate weighted proportions p_i:

$$p_i = \frac{CV_i}{\sum_j CV_j}$$

Compute scale diversity entropy:

$$H_{\text{distance}} = -\sum_i p_i \log(p_i)$$

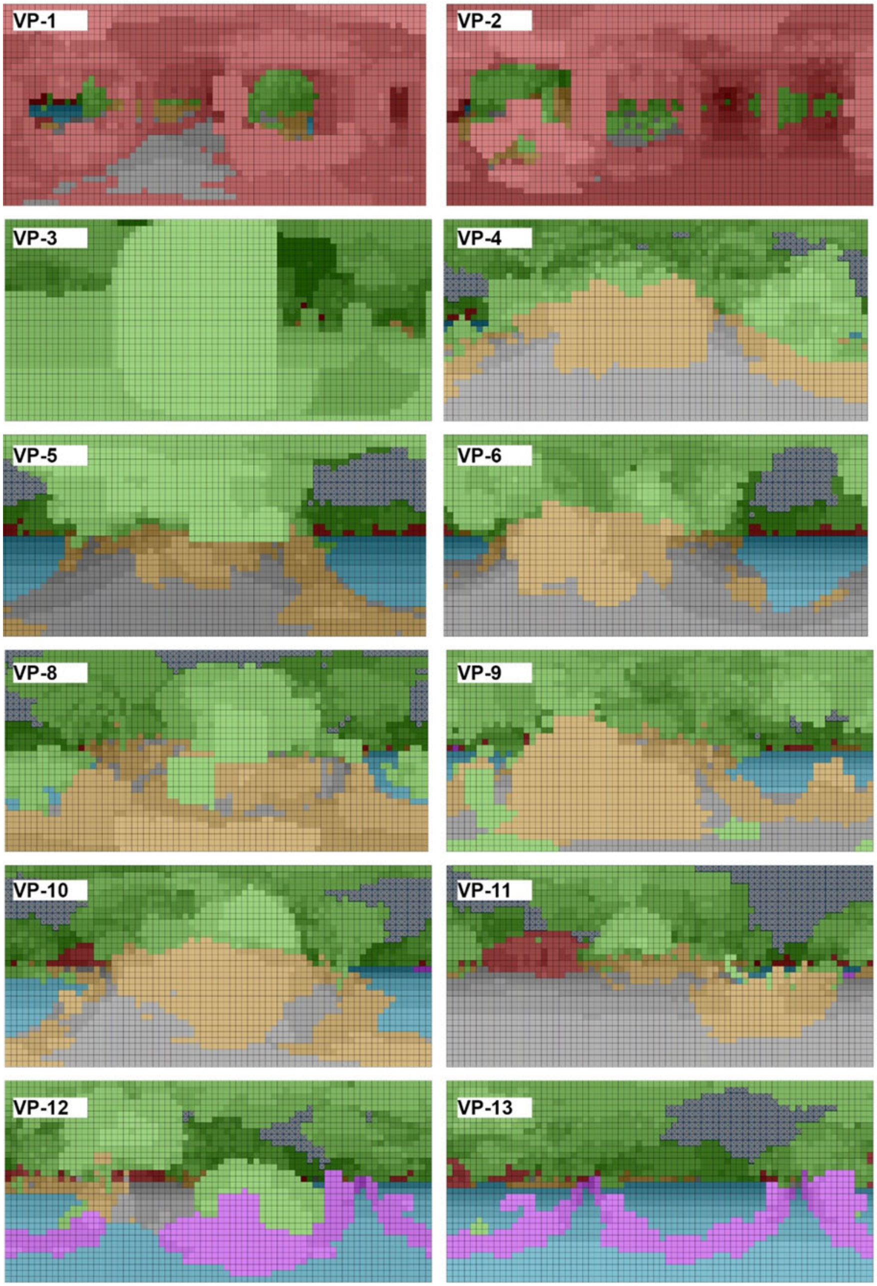
- **Step 3:** Combine class and scale entropies into a final Complexity Index, using normalized values and equal weighting:

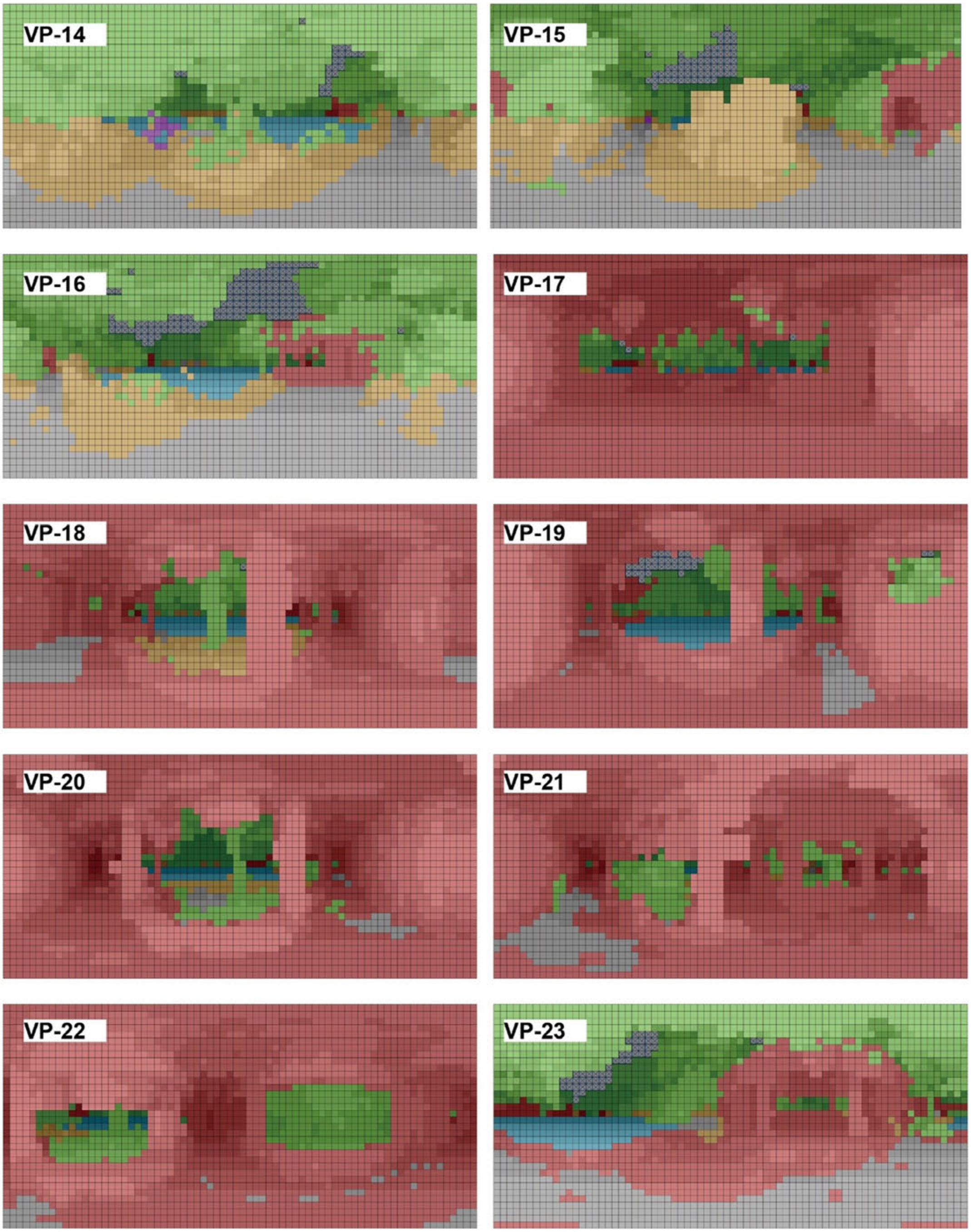
$$\text{Complexity}_{\text{final}} = w_1 \cdot \frac{H_{\text{class}}}{\log(m)} + w_2 \cdot \frac{H_{\text{distance}}}{\log(m)}$$

Interpretation:

- High complexity indicates rich diversity in landscape elements and scales, providing intricate visual experiences.
- Low complexity indicates fewer elements and less variation, resulting in visually simple environments.

APP. B.2 LiDAR-based computation results

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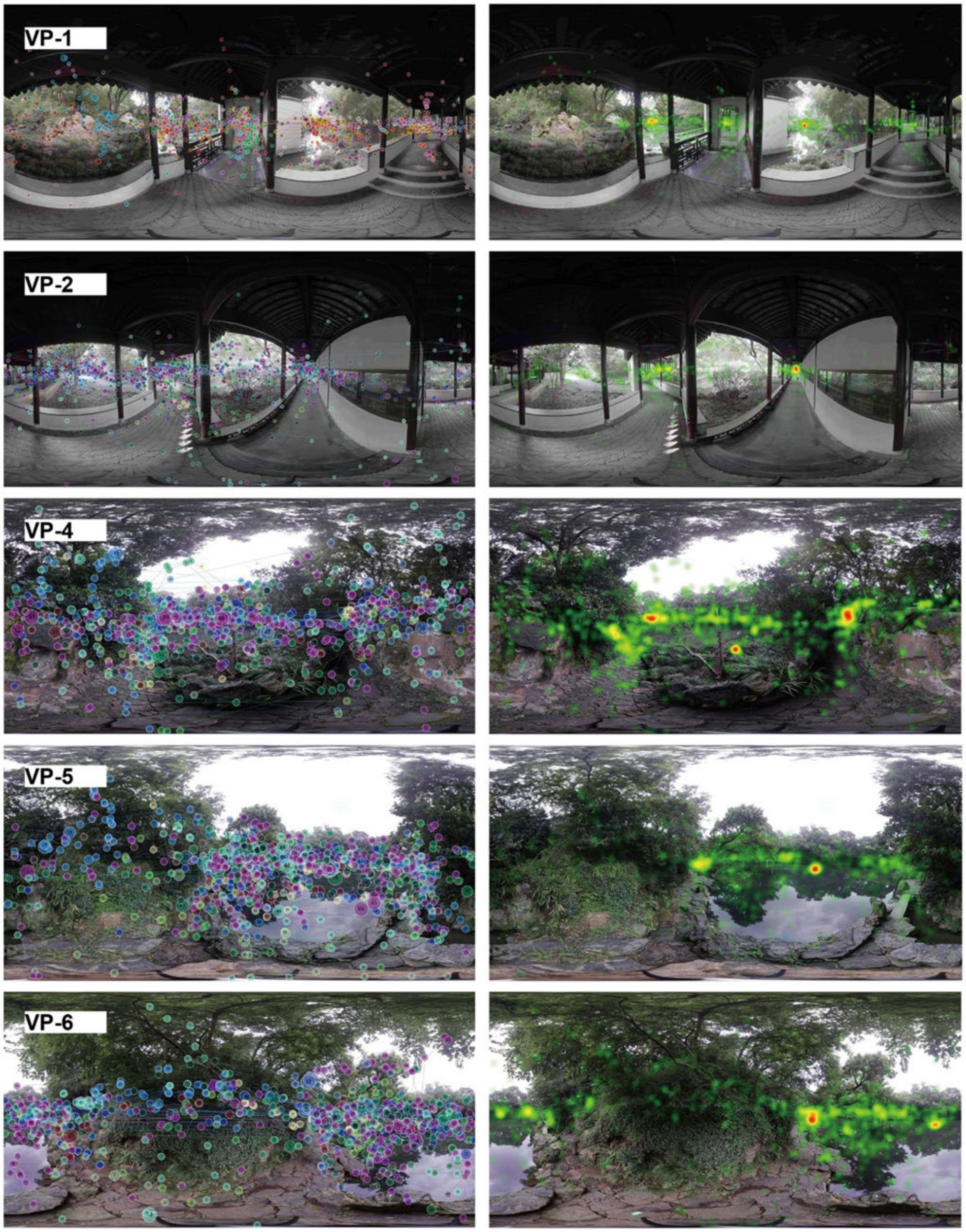
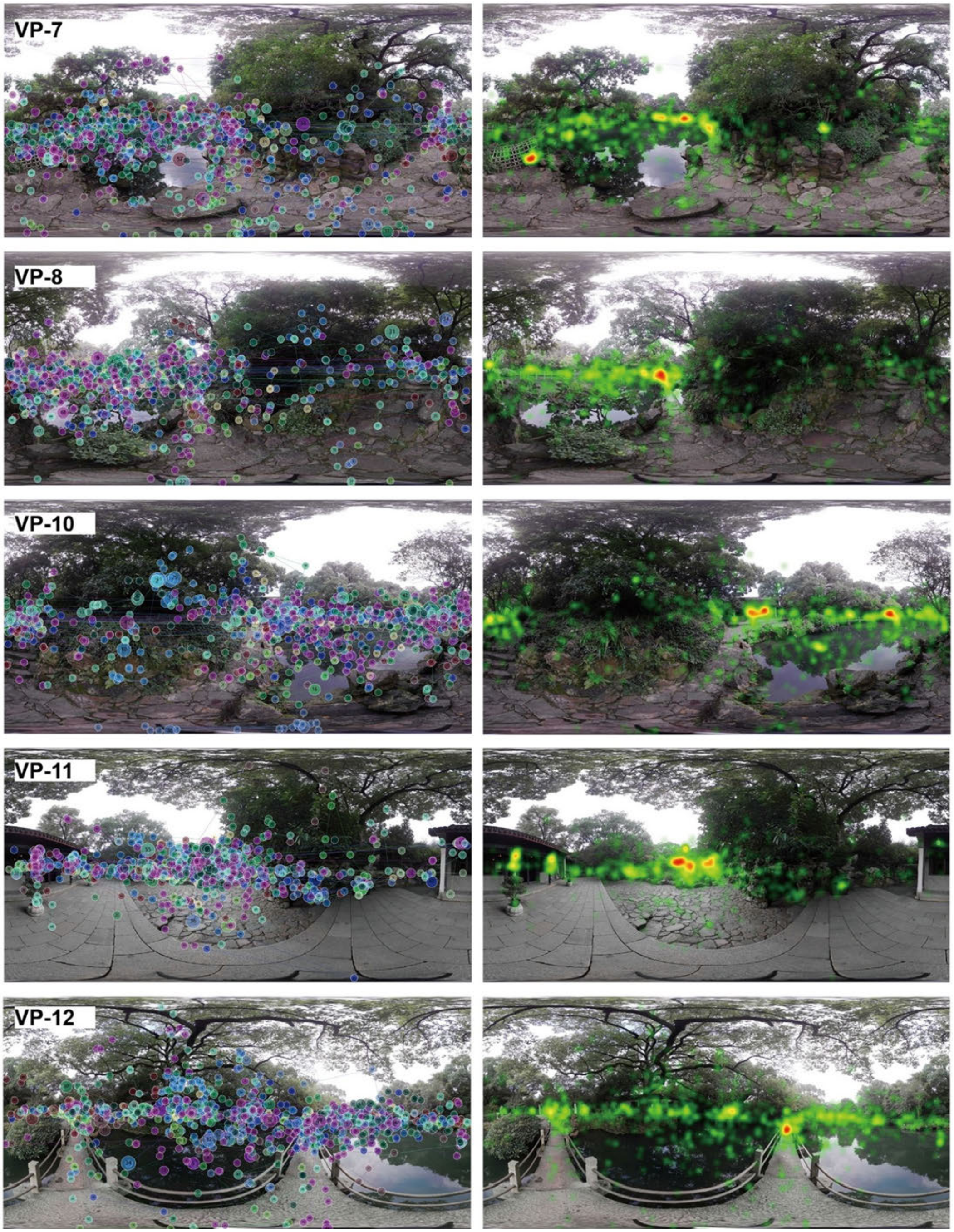
APP. B.3

Eye-tracking results

(heatmaps and scanpath)

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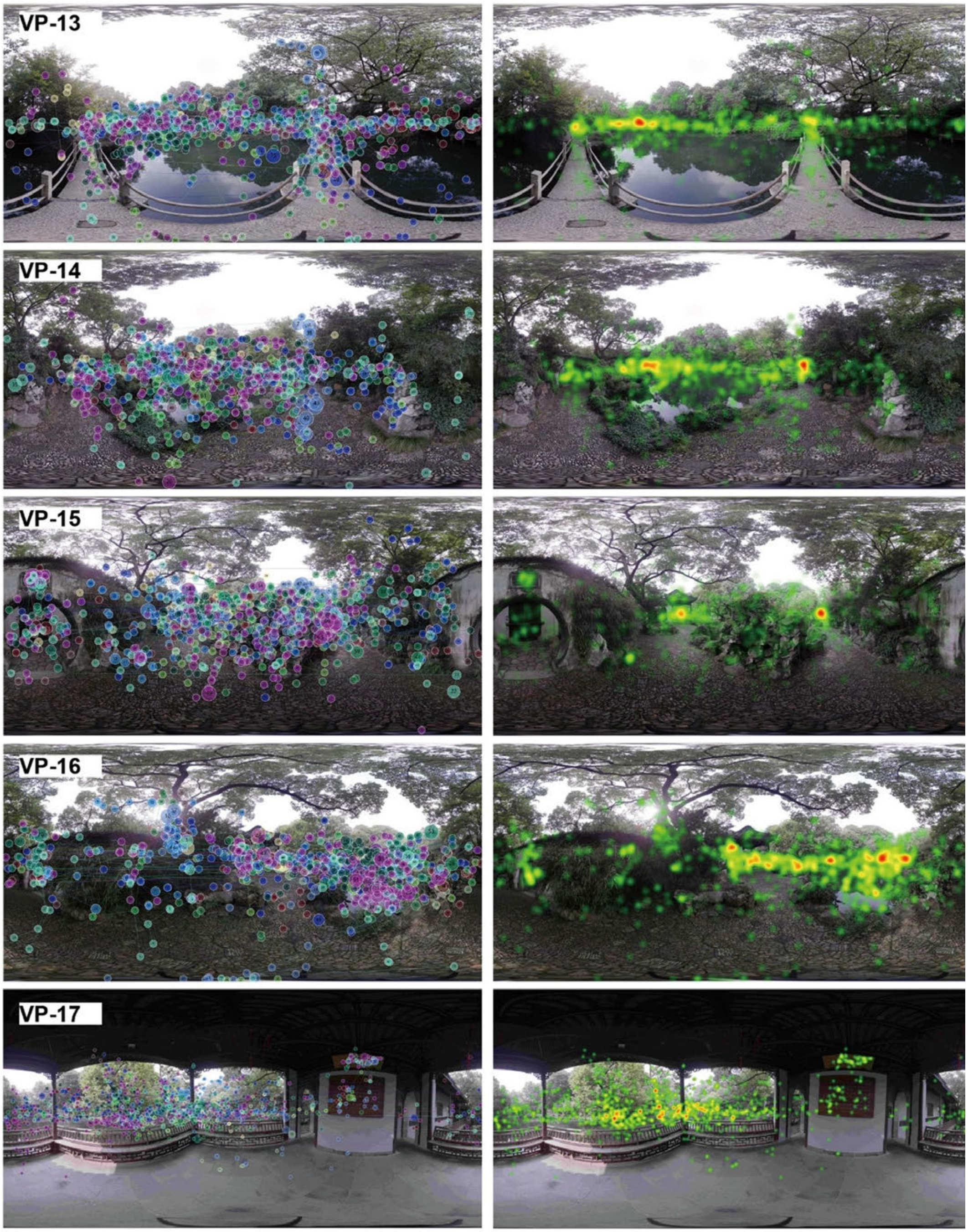
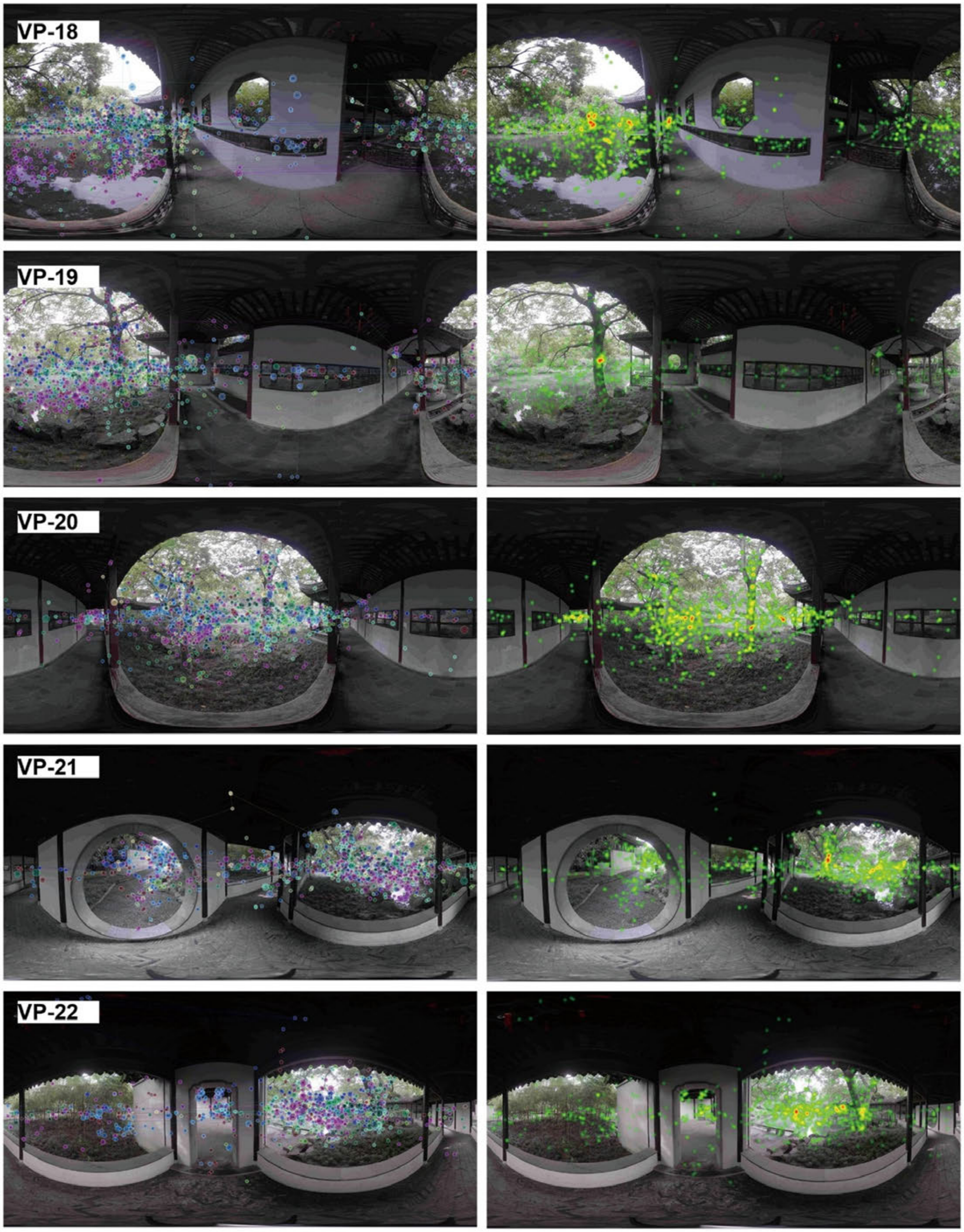


TOC


VP-18
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APPENDIX C

For Chapter 5

APP. C.1

Eye-tracking heatmaps

(Right ones for general public, left for experts)

TOC

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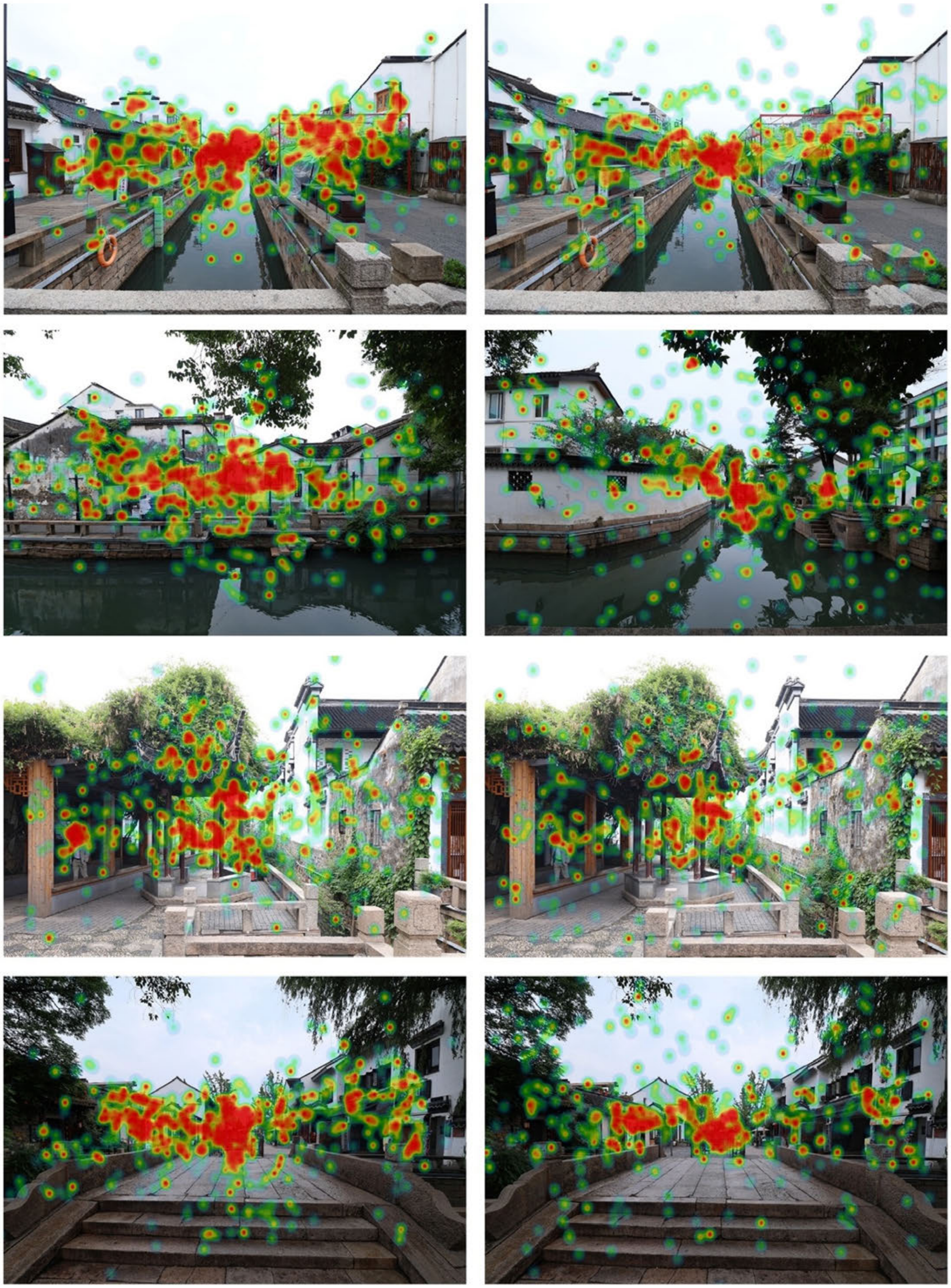

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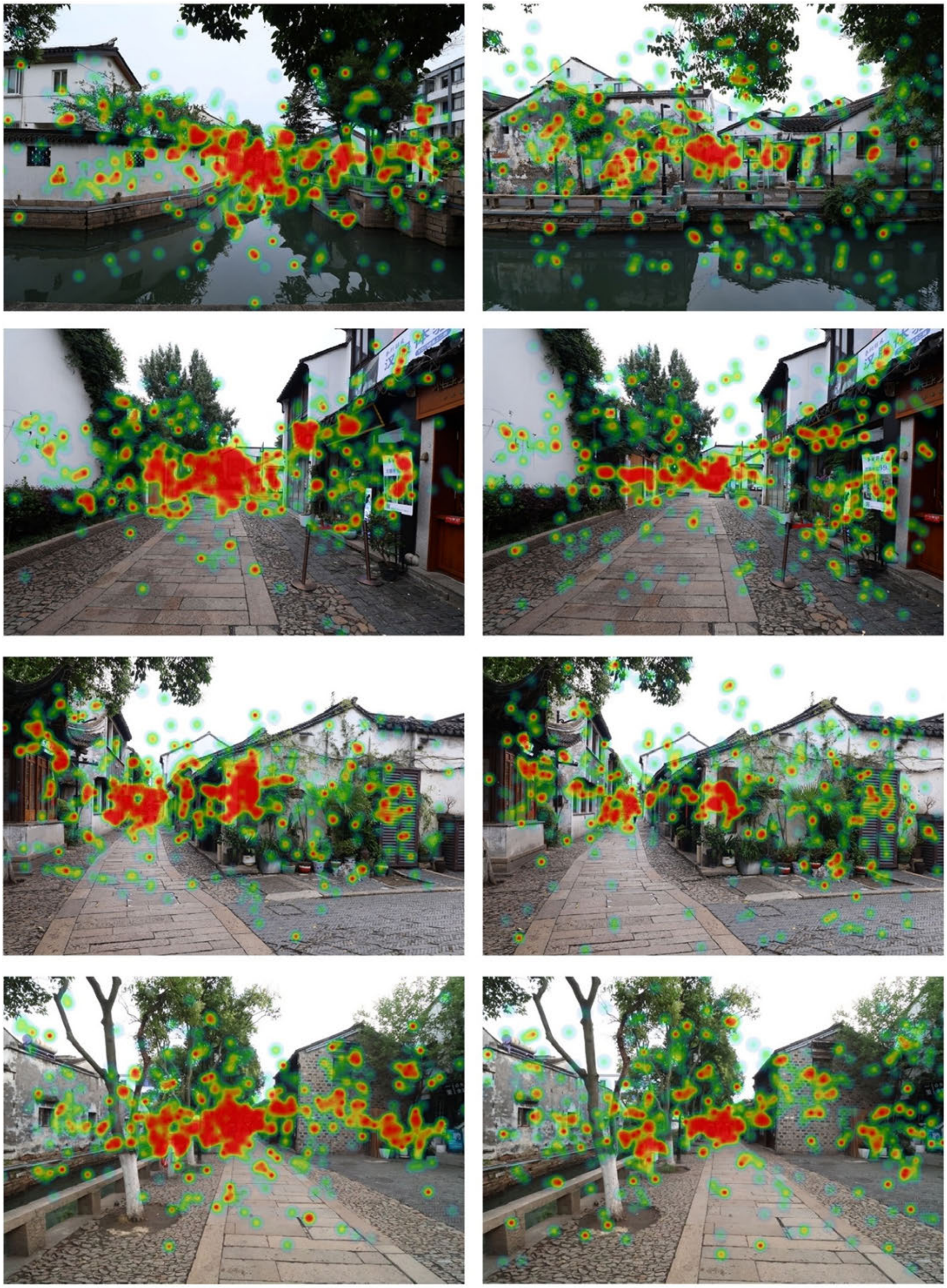

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APP. C.2

LMM results for fixation durations

BGI X AOIs X Groups	Coef	Std_Err	P>|z|	CI_lower	CI_upper
AOI_Name[T.historical and cultural elements]	0.783755	0.025925	9.11E-201	0.732942	0.834568
AOI_Name[T.perspective focal points]	0.517073	0.025836	4.21E-89	0.466434	0.567713
AOI_Name[T.buildings/struc-tures]	0.318083	0.025804	6.48E-35	0.267508	0.368658
BI_Level:AOI_Name[T.historical and cultural elements]	-0.1236	0.013573	8.50E-20	-0.15021	-0.097
AOI_Name[T.paved ground]	0.213342	0.025804	1.36E-16	0.162766	0.263917
GI_Level:AOI_Name[T.historical and cultural elements]	-0.06444	0.01516	2.13E-05	-0.09415	-0.03472
GI_Level:AOI_Name[T.GI]	0.062982	0.015126	3.13E-05	0.033336	0.092629
AOI_Name[T.GI]	0.096826	0.025804	0.000175153	0.046251	0.147402
AOI_Name[T.commercial elements]	0.093491	0.025804	0.000291042	0.042915	0.144066
GI_Level:AOI_Name[T.perspective focal points]	-0.04837	0.015135	0.001392853	-0.07804	-0.01871
BI_Level:AOI_Name[T.perspective focal points]	-0.03996	0.013553	0.003192115	-0.06653	-0.0134
Group[T.Public]:AOI_Name[T.historical and cultural elements]	-0.08737	0.03665	0.017125282	-0.15921	-0.01554
Group[T.Public]:AOI_Name[T.perspective focal points]	-0.07943	0.036547	0.029746456	-0.15106	-0.0078
BI_Level:GI_Level:AOI_Name[T.paved ground]	-0.01739	0.008142	0.032649066	-0.03335	-0.00144
Group[T.Public]:GI_Level:AOI_Name[T.paved ground]	0.043401	0.021391	0.042467684	0.001474	0.085328
Group[T.Public]:BI_Level:GI_Level:AOI_Name[T.historical and cultural elements]	-0.02335	0.011538	0.042956288	-0.04597	-0.00074
BI_Level:GI_Level:AOI_Name[T.commercial elements]	-0.01621	0.008137	0.046353677	-0.03216	-0.00026
BI_Level	0.01896	0.009574	0.047663002	0.000195	0.037724

APP. C.3

Cronbach's Alpha of the questionnaire

Cronbach's Alpha for the eight factors among the 20 scenes (Each group)

Group	Factor	cronbach_alpha
expert	F11	0.950435
expert	F12	0.956048
expert	F13	0.962844
expert	F21	0.953892
expert	F22	0.962062
expert	F31	0.960374
expert	F32	0.966456
expert	F33	0.967393
public	F11	0.893205
public	F12	0.896701
public	F13	0.92677
public	F21	0.893715
public	F22	0.913584
public	F31	0.919032
public	F32	0.935807
public	F33	0.930454

APP. C.4 LMM results for questionnaire

BI_coef	GI_coef	BI_p	GI_p	group	factor
0.195255	0.148519	5.57E-269	3.80E-93	Expert	F11
0.267995	0.128229	0	1.51E-84	Expert	F12
0.25537	0.157731	0	7.61E-131	Expert	F13
0.08795	0.140551	7.49E-63	9.42E-94	Expert	F21
0.56269	0.534508	0	0	Expert	F22
0.635427	0.429206	0	1.49E-279	Expert	F31
0.43178	0.279621	0	9.37E-303	Expert	F32
0.24721	0.350089	0	0	Expert	F33
0.104336	0.251096	4.73E-53	1.10E-176	Public	F11
0.179414	0.223904	1.62E-160	1.16E-147	Public	F12
0.184967	0.26487	4.04E-170	2.21E-205	Public	F13
-0.01079	0.220586	0.097736826	4.83E-149	Public	F21
0.429982	0.658679	0	0	Public	F22
0.514411	0.601392	0	0	Public	F31
0.31154	0.437411	0	0	Public	F32
0.130995	0.451481	1.56E-78	0	Public	F33

TOC

APP. C.5 Summaries of the interview-based coding

The table for the public

source	target	value
BI	Ecological Aesthetics	6
BI	Ecological Function	3
BI	Genius Loci	7
BI	Social/Symbolic	14
BI	Spatial Function	11
BI	Spatial Memory	16
BI	Visual Aesthetics	11
BI	Well-being Function	8
GI	Ecological Aesthetics	8
GI	Ecological Function	12
GI	Genius Loci	22
GI	Social/Symbolic	14
GI	Spatial Function	7
GI	Spatial Memory	5
GI	Visual Aesthetics	15
GI	Well-being Function	22
Ecological Aesthetics	T3	14
Ecological Function	T3	15
Genius Loci	T1	29
Social/Symbolic	T3	28
Spatial Function	T3	18
Spatial Memory	T1	21
Visual Aesthetics	T2	26
Well-being Function	T2	29
Well-being Function	T3	1

The table for the expert

source	target	value
BI	Ecological Aesthetics	5
BI	Ecological Function	6
BI	Genius Loci	6
BI	Social/Symbolic	11
BI	Spatial Function	14
BI	Spatial Memory	11
BI	Visual Aesthetics	8
BI	Well-being Function	6
GI	Ecological Aesthetics	7
GI	Ecological Function	19
GI	Genius Loci	7
GI	Social/Symbolic	10
GI	Spatial Function	4
GI	Spatial Memory	4
GI	Visual Aesthetics	23
GI	Well-being Function	19
Ecological Aesthetics	T2	12
Ecological Function	T3	25
Genius Loci	T1	13
Social/Symbolic	T1	21
Spatial Function	T3	18
Spatial Memory	T1	15
Visual Aesthetics	T2	31
Well-being Function	T3	25

APPENDIX D
For Chapter 7

APP. D.1
Participants information

Group	Features	Count	Native
Age	18-25	11	2
	26-30	14	3
	31-35	5	0
Gender	Male	16	3
	Female	14	2
Education	Bachelor's	13	2
	Master's	14	3
	PhD	3	0

Note: All experimental participants provided informed consent, and the human-subject components of the study were approved by the institutional ethics committee.

APP. D.2 Visibility analysis

Filename	Low (1)	Medium (2)	High (3)	Integrated	Low %	Medium %	High %
M-0_route	6734636	846763	176009	7757408	86.82	10.92	2.27
M-0_context	1441840	574920	30184	2046944	70.44	28.09	1.47
M-0_ZTV	61828	12077	29807	103712	59.62	11.64	28.74
M-1_route	6863411	993881	74750	7932042	86.53	12.53	0.94
M-1_context	1623831	421368	6742	2051941	79.14	20.54	0.33
M-1_ZTV	179351	101384	83142	363877	49.29	27.86	22.85
M-2_route	6918978	987597	105880	8012455	86.35	12.33	1.32
M-2_context	1405694	452631	62391	1920716	73.19	23.57	3.25
M-2_ZTV	251837	68537	899	321273	78.39	21.33	0.28
M-3_route	6865362	1026046	162165	8053573	85.25	12.74	2.01
M-3_context	1491123	514427	49767	2055317	72.55	25.03	2.42
M-3_ZTV	163987	124661	120217	408865	40.11	30.49	29.4

Note: each raster means 1 m^2.

APP. D.3 Eye- and head-tracking results

TABLE D3.1 Summary of LMM (near view)

Block	Metric	Stage	Mean	95% CI
Eye (dwell time, ms)	Building	2020-phase	153.8	[118.6, 199.5]
Eye (dwell time, ms)	Building	2023-phase	211.1	[162.8, 273.6]
Eye (dwell time, ms)	Building	2025-phase	126.2	[115.2, 138.2]
Eye (dwell time, ms)	Building	Present	756.3	[593.4, 963.9]
Eye (dwell time, ms)	New constructions	2020-phase	0	[-0.1, 0.1]
Eye (dwell time, ms)	New constructions	2023-phase	0	[-0.1, 0.1]
Eye (dwell time, ms)	New constructions	2025-phase	0	[-0.1, 0.1]
Eye (dwell time, ms)	New constructions	Present	1901.6	[1880.7, 1922.7]
Eye (dwell time, ms)	Polder land	2020-phase	3816	[3438.6, 4234.7]
Eye (dwell time, ms)	Polder land	2023-phase	3302.7	[2823.0, 3863.9]
Eye (dwell time, ms)	Polder land	2025-phase	2823.9	[2489.7, 3202.9]
Eye (dwell time, ms)	Polder land	Present	78.2	[66.6, 91.8]
Eye (dwell time, ms)	Sky	2020-phase	585.5	[464.6, 737.8]
Eye (dwell time, ms)	Sky	2023-phase	1226	[999.3, 1504.0]
Eye (dwell time, ms)	Sky	2025-phase	1720	[1457.2, 2030.2]
Eye (dwell time, ms)	Sky	Present	30.1	[23.3, 38.8]
Eye (dwell time, ms)	Total	2020-phase	12346.7	[11736.7, 12988.5]
Eye (dwell time, ms)	Total	2023-phase	12596.1	[11899.0, 13334.1]
Eye (dwell time, ms)	Total	2025-phase	12311.4	[11979.8, 12652.0]
Eye (dwell time, ms)	Total	Present	9439	[8922.3, 9985.7]
Head (movement std, °)	pitch_std	2020-phase	42.9	[42.0, 43.8]
Head (movement std, °)	pitch_std	2023-phase	43.8	[42.9, 44.7]
Head (movement std, °)	pitch_std	2025-phase	43.4	[43.3, 43.6]
Head (movement std, °)	pitch_std	Present	43.8	[42.9, 44.7]
Head (movement std, °)	roll_std	2020-phase	92.4	[89.6, 95.3]
Head (movement std, °)	roll_std	2023-phase	89.2	[86.4, 92.0]
Head (movement std, °)	roll_std	2025-phase	91.2	[90.4, 92.1]
Head (movement std, °)	roll_std	Present	82.5	[79.8, 85.3]
Head (movement std, °)	yaw_std	2020-phase	101.4	[98.5, 104.3]
Head (movement std, °)	yaw_std	2023-phase	97.1	[94.2, 100.0]
Head (movement std, °)	yaw_std	2025-phase	96.7	[95.4, 98.0]
Head (movement std, °)	yaw_std	Present	93.8	[90.9, 96.7]

TABLE D3.2 Summary of LMM (far view)

Stage	AOI	pred_mean	ci_low	ci_high
20-phase	Building	153.822914	120.0192	197.0689
20-phase	Polder land	3815.96152	2982.573	4882.136
20-phase	Sky	585.499395	457.4442	749.3237
23-phase	Building	211.057166	164.757	270.2901
23-phase	Polder land	3302.69863	2581.375	4225.506
23-phase	Sky	1225.95472	958.0637	1568.675
25-phase	Building	126.196817	98.4249	161.7261
25-phase	Polder land	2823.88791	2207.107	3612.951
25-phase	Sky	1720.02112	1344.257	2200.746
20-phase	Total	12347	11800	12900
23-phase	Total	12596	12000	13200
25-phase	Total	12311	11700	12900
20-phase	yaw_std	4.68307188		
23-phase	yaw_std	0.36302636		
25-phase	yaw_std	9.48E-16		
20-phase	roll_std	1.19352171		
23-phase	roll_std	-2.00122406		
25-phase	roll_std	-4.22E-15		

TABLE D3.3 Summary of LMM (proposed constructions and present-phase)

Block	Metric	Scenario	Mean	95% CI
Eye (dwell time, ms)	Building	M-1	167.21	[115,242]
Eye (dwell time, ms)	Building	M-2	567.81	[351,917]
Eye (dwell time, ms)	Building	M-3	1788.73	[957,3342]
Eye (dwell time, ms)	Building	Present	1360.28	[1255.31,1465.25]
Eye (dwell time, ms)	New constructions	M-1	87.74	[56,138]
Eye (dwell time, ms)	New constructions	M-2	239.35	[142,403]
Eye (dwell time, ms)	New constructions	M-3	112.54	[31,402]
Eye (dwell time, ms)	New constructions	Present	2721.5	[2482.44,2960.56]
Eye (dwell time, ms)	Polder land	M-1	8.28	[6,11]
Eye (dwell time, ms)	Polder land	M-2	17.72	[11,27]
Eye (dwell time, ms)	Polder land	M-3	125.87	[46,341]
Eye (dwell time, ms)	Polder land	Present	350.89	[307.24,394.54]
Eye (dwell time, ms)	Sky	M-1	250.73	[169,371]
Eye (dwell time, ms)	Sky	M-2	125.8	[88,180]
Eye (dwell time, ms)	Sky	M-3	563.25	[338,938]
Eye (dwell time, ms)	Sky	Present	224.66	[188.51,260.81]
Eye (dwell time, ms)	Total	M-1	3808.48	[3064,4734]
Eye (dwell time, ms)	Total	M-2	5524.26	[4201,7264]
Eye (dwell time, ms)	Total	M-3	6134.06	[3297,11412]
Eye (dwell time, ms)	Total	Present	10049.74	[9676.23,10423.25]
Head (movement std, °)	pitch_std	M-1	36.8	[33.30, 40.31]
Head (movement std, °)	pitch_std	M-2	36.38	[32.61, 40.15]
Head (movement std, °)	pitch_std	M-3	40.76	[38.26, 43.25]
Head (movement std, °)	pitch_std	Present	43.75	[42.77,44.73]
Head (movement std, °)	roll_std	M-1	64.82	[55.01, 74.63]
Head (movement std, °)	roll_std	M-2	77.44	[68.21, 86.67]
Head (movement std, °)	roll_std	M-3	64.5	[55.21, 73.79]
Head (movement std, °)	roll_std	Present	82.52	[79.41,85.64]
Head (movement std, °)	yaw_std	M-1	72.59	[59.50, 85.67]
Head (movement std, °)	yaw_std	M-2	82.2	[71.30, 93.09]
Head (movement std, °)	yaw_std	M-3	63.07	[51.91, 74.22]
Head (movement std, °)	yaw_std	Present	93.8	[90.59,97.02]

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Curriculum vitae

Yuyang Peng was born in Chengdu, China in 1993. He received his Bachelor of Engineering from Sichuan University in 2016, graduating with an Honored Bachelor degree from the same institute (top 1.5% cohort). He then pursued a Master's degree in Landscape Architecture at Southeast University and completed his MEng in 2019, earning the Excellent Master's Thesis award. Since April 2020, he has been a PhD researcher at the Department of Urbanism, Faculty of Architecture and the Built Environment, Delft University of Technology (TU Delft), The Netherlands. His doctoral project investigates how digital data and computational methods can support the understanding, assessment, and design of visual heritage landscapes. His research interests include digital landscape, heritage landscapes and buildings, visual landscape research, perception of built environment, and data-driven urbanism. His work has been presented at international venues such as the Digital Landscape Architecture (DLA) conference series and has contributed to publications and manuscripts in journals including *Landscape and Urban Planning, Sustainable Cities and Society, Computers Environment & Urban Systems, Automation in Construction, Advanced Engineering Informatics, Frontiers of Architectural Research, Urban Forestry & Urban Greening, npj Heritage Science, Journal of Environmental Psychology, Landscape Architecture and Sustainability*, and *Environmental Impact Assessment Review*, among others.

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26#10

Visual Heritage Landscape Research

A Pathway Framework for Integrating Data, Methods, and Content

Yuyang Peng

Heritage landscapes are shaped, experienced, and interpreted through vision. Visual qualities such as openness, enclosure, depth, skyline continuity, landmark prominence, and view accessibility strongly influence how heritage values are perceived and how spatial change is judged. However, research on visual heritage landscapes remains fragmented: studies often prioritize either spatial-technical analysis or perception-based evaluation, while the relationships among data, methods, and research aims remain implicit. This limits methodological comparability, transferability, and practical application. This dissertation develops a pathway-oriented framework for visual heritage landscape research by integrating three core components: data, methods, and content. Rather than treating methods as isolated techniques, it conceptualizes research as structured pathways that connect evidence, analytical procedures, and intended outputs. Based on a systematic review and typological synthesis, four expanded pathways are proposed and tested through case studies of a historic garden, a historic urban area, an urban heritage landscape, and a rural heritage landscape.

Across these cases, the thesis demonstrates how spatial modelling, multi-source geo-data, immersive technologies, and perception-based methods can be combined to explain visual mechanisms, assess environmental preferences, strengthen cross-scale interpretation, and support decision-making in conservation, planning, and design. The dissertation further develops a navigational model that helps researchers and practitioners select and adapt pathways according to research objectives, data availability, and implementation needs. Overall, the thesis contributes a coherent and transferable framework that translates visual evidence into structured, interpretable, and actionable knowledge for heritage landscape conservation, planning, and design.

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