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RESEARCH ARTICLE

Multi-temporal analysis of urban vegetation using deep learning and 3D reconstruction

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Abstract
Context Urban green spaces play a vital role in enhancing environmental quality and human well-being. However, traditional assessment methods, such as the green view index, primarily quantify green coverage while neglecting vegetation diversity, color richness, and seasonal dynamics, which are critical for urban livability.
Objectives This study develops a multi-temporal and multi-perspective analysis framework for urban green space visualization, introducing the Seasonal Species-Specific Plant View Index (S3PVI) to quantify plant coverage at the species level, capturing seasonal changes and visual diversity.
Methods The framework integrates computer vision, deep learning, and 3D reconstruction technologies, including structure from motion and 3D Gaussian splatting. To validate the S3PVI, case studies were conducted in Suita City, Japan, analyzing real-world seasonal vegetation patterns and testing the framework in a virtual park environment to assess its applicability in urban design.
Results The S3PVI effectively captured species-specific seasonal patterns, with cherry blossoms peaking at 45.61% visibility in spring and maples at 56.78% in autumn. Comparative analysis revealed distinctive vegetation strategies between streets, with Sanshiki-saido showing higher seasonal amplitude but lower consistency than Nakayoshido. Virtual simulations confirmed that multi-species schemes optimally balanced seasonal impact with year-round visual stability.
Conclusions The S3PVI framework advances urban vegetation assessment by providing species-specific and seasonally dynamic visual data, supporting evidence-based urban planning for ecological sustainability and livability. Potential applications include brownfield redevelopment, virtual park planning, and urban design simulations.

Keywords Urban green space · Vegetation visualization · Street view imagery · Semantic segmentation · 3D reconstruction · Multi-temporal analysis

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Introduction

Urban green spaces are fundamental components of sustainable cities, providing essential ecosystem services and enhancing urban environmental quality and human well-being (Pauleit et al. 2011; Richards and Edwards 2017). The visual characteristics of vegetation in these spaces, particularly the seasonal changes of ornamental species such as cherry blossoms, maples, ginkgo, and magnolias, generate important economic benefits while positively impacting environmental quality and human health (Asgarzadeh et al. 2014; Guan et al. 2017; Pratiwi et al. 2019). Research has demonstrated that vegetation characteristics, including color variation, species diversity, and seasonal dynamics, significantly enhance human psychological and physiological responses through stress reduction, mood enhancement, and improved cognitive function (Lindemann-Matthies and Brieger 2016; Hoyle et al. 2017). The aesthetic experience of urban vegetation is particularly influenced by visual diversity, with studies showing that both species richness and flower color diversity are key determinants of public preferences in urban settings (Tomitaka et al. 2021).

Current assessment methods for urban green spaces face several key limitations. Conventional metrics like the green view index (GVI) primarily focus on quantifying overall green coverage (Aoki et al. 1985), neglecting the nuanced visual characteristics of different vegetation types and their seasonal dynamics (Dutta et al. 2022; Shiraishi and Terada 2024). This oversimplification fails to capture the diverse contributions of various plant species to the urban landscape and their distinct seasonal patterns. Furthermore, traditional assessment methods often rely on single-perspective analyses, which may not adequately represent the comprehensive visual experience of urban green spaces (Zhou et al. 2016). These methodological limitations significantly restrict the ability to understand and manage the complex temporal and spatial dynamics of urban vegetation (Hoyle et al. 2017).

The growing complexity of urban environments and increasing demand for high-quality green spaces necessitate more sophisticated assessment tools (Wang et al. 2016; Xu et al. 2020). Studies highlight that visual diversity and seasonal variations significantly shape human experiences of urban landscapes, with factors such as color contrast, species composition, and structural complexity influencing preferences and perceived restorative potential (Du et al. 2016). While traditional methods provide basic quantification, urban designers need additional metrics to capture these nuanced aspects and temporal dynamics for better planning and management (Riechers et al. 2019).

To address these challenges, this study proposes a multi-temporal, multi-perspective framework for visualizing urban green space vegetation. The framework introduces a seasonal species-specific plant view index (S3PVI), which quantifies urban plant facade coverage while distinguishing species and seasonal variations. It integrates deep learning techniques, specifically DANet with an EfficientNet backbone (Fu et al. 2019; Tan and Le 2020), alongside 3D Gaussian splatting and structure from motion (SfM) technology (Schonberger and Frahm 2016) to improve vegetation assessment and visualization.

A case study in Suita City, Osaka Prefecture, Japan, tested the framework, analyzing vegetation visual characteristics across street green spaces. The results revealed spatiotemporal variations in S3PVI values, highlighting seasonal changes in visual impact. The framework's practical utility was demonstrated through virtual park simulations, supporting vegetation configuration decisions.

The remainder of this paper is structured as follows: Sect. "Literature review" reviews urban vegetation assessment and visualization techniques. Sect. "Methodology" details the methodological framework and data processing. Sect. "Experiments and results" presents empirical results. Sect. "Discussion" discusses theoretical and practical implications. Sect. "Conclusion" concludes with future research directions.

Literature review

Assessment methods of urban green spaces

Urban green spaces play a vital role in creating sustainable cities, leading to specific targets and indicators in master plans worldwide (Wolch et al. 2014; Bellè and Deserti 2024). Assessment methods have evolved significantly to better understand greenery's urban contributions. Traditional approaches ranged from field-based inventories to normalized difference vegetation index (NDVI) remote sensing (Ma et al. 2021; Aryal et al. 2022), with a shift toward streetscape analysis for extracting GVI between 2010 and 2022 (Lu et al. 2023). Recent advances include panoramic view green view index and semantic segmentation techniques (Xia et al. 2021; Hu et al. 2023).

However, these methods often treat urban vegetation as a homogeneous entity, overlooking crucial aspects of human perception and preference. Research has shown that visual diversity and specific characteristics of vegetation significantly influence people's experience of urban green spaces. For instance, Hoyle et al. (2017) found that visual diversity and colorful vegetation positively affected people's aesthetic preferences and perceived restorative potential of urban planting. Such findings underscore the limitations of current assessment methodologies, which tend to follow generalized frameworks that group multiple plant species into broad categories, overlooking their specific aesthetic and ecological contributions (Elsadek and Fujii 2014). Therefore, there is a pressing need to develop new assessment frameworks that can comprehensively evaluate both quantitative and qualitative aspects of urban green spaces, including key vegetation characteristics such as color, texture, and seasonal variations (Ma et al. 2020).

Visual perception and aesthetic experience of urban vegetation

Recent research on urban planting has identified what Hoyle et al. (2017) termed the 'wow factor', revealing that while colorful flowering plants provided immediate visual appeal, more subtle green planting contributed significantly to restorative effects. This finding suggests a complex relationship between aesthetic appreciation and ecological function, where different types of vegetation serve complementary roles in enhancing urban environments.

Studies have shown that aesthetic appreciation of urban vegetation is shaped by multiple visual characteristics. Lindemann-Matthies et al. (2016) found that people's perception and appreciation of species diversity increased with true species richness, although this relationship was not linear. Similarly, Tomitaka et al. (2021) revealed that both species richness and flower color diversity are key determinants of aesthetic preferences in urban park settings.

Through quantitative surveys and statistical analysis, Du et al. (2016) identified several key attributes affecting landscape visual aesthetic quality, including vegetation structure, plant density, height ratio, and color contrast. Their research demonstrated that both strong color contrast and the mixed use of evergreen and deciduous plants significantly enhanced visitor preference. Moreover, visitor characteristics such as education level, place of residence, and professional background significantly influenced landscape preferences.

Recent studies have also emphasized the role of temporal dynamics in shaping aesthetic experiences. Seasonal changes not only affect the physical appearance of green spaces but also influence people's perceptions and preferences (Półrolniczak et al. 2019). This temporal dimension adds another layer of complexity to vegetation assessment, suggesting the need for methods that can capture these seasonal variations effectively.

Seasonal dynamics in urban vegetation perception

The temporal dimension of urban vegetation, particularly seasonal changes, significantly influences how people perceive and experience urban green spaces. Recent research has emphasized that successful urban vegetation assessment must consider these seasonal variations, as they affect both the physical appearance of vegetation and people's psychological responses to urban environments (Palang et al. 2007; Junge et al. 2015).

Studies have demonstrated that seasonal changes in vegetation structure have distinct impacts on human well-being. For example, research on college students' responses to different vegetation types revealed that seasonal variations significantly influenced environmental perception scores, though physiological responses remained stable across seasons (Duan et al. 2024). Their findings showed that while canopy-only woodlands and tree-shrub-grass composite structures enhanced environmental perception in summer, canopy-only woodlands maintained their positive effect in winter. These results highlight the importance of selecting appropriate vegetation structures for year-round benefits in urban landscapes.

Eroğlu et al. (2012) investigated how seasonal changes in plant compositions affect visual perception and preferences in urban open-green areas. Their research employed the Delphi Method on photographs to identify visual effects of plant compositions across seasons. Their findings revealed that summer was the most influential season regarding design value and visual quality, while evergreen plants had a consistently positive effect on the design power and visual quality of compositions throughout the year. Importantly, they also found that perceptional differences toward seasonal plant changes were influenced by socio-economic factors, with form and texture playing significant roles in the overall perceptional effects. This research confirms that plant color variations can be recognized from considerable distances, providing different functional and aesthetic values in both short and long-term perspectives (Acar et al. 2007).

Weather conditions within the same season can also affect people's preferences for urban vegetation (Półrolniczak et al. 2019). A series of studies by Song et al. (2013, 2014, 2015) demonstrated consistent positive physical and psychological restorative effects of urban parks across different seasons, including spring, autumn, and winter. Notably, even brief exposure to natural environments during winter months enhanced positive emotions among participants (Bielinis et al. 2018).

The integration of seasonal considerations into vegetation assessment has practical implications for urban green space management. Stobbelaar and Hendriks (2007) argued that understanding seasonal variations in landscape appearance is essential for creating resilient urban green spaces. This temporal dimension suggests the need for more dynamic evaluation frameworks that can effectively capture seasonal nuances in vegetation characteristics. Such frameworks would be particularly valuable in regions with distinct seasonal changes, where urban vegetation undergoes significant visual and functional transformations throughout the year.

Spatiotemporal analysis using street view images

Street view imagery analysis has emerged as a promising tool for capturing the spatiotemporal dynamics of urban vegetation. Han et al. (2023) demonstrated that multi-temporal street view images can effectively track seasonal changes in urban greenery, providing insights from a pedestrian perspective that overcomes limitations of traditional remote sensing methods.

However, current applications face several critical challenges, including inconsistent perspectives from vehicle-mounted equipment and potential biases in street view coverage (Biljecki and Ito 2021; Fan et al. 2025). Recent technological developments have addressed some of these limitations through perspective correction methods and advanced 3D reconstruction techniques (Liu et al. 2024; Xie et al. 2024), enabling more detailed and consistent visual assessments of urban vegetation.

The integration of these advanced technologies with traditional assessment methods presents an opportunity to develop more comprehensive frameworks for evaluating urban vegetation. Such frameworks can capture both the spatial and temporal dynamics of urban green spaces while maintaining sufficient refinement in vegetation type characterization, bridging the gap between current practices and modern urban environmental requirements.

Methodology

This section introduces the methodology for multi-temporal urban green space vegetation visualization analysis, including key steps such as data collection, preprocessing, semantic segmentation, S3PVI calculation, and seasonal change analysis. Figure 1 shows the overall workflow of the method. The framework begins with high-resolution street view image collection, followed by SfM algorithm extraction of camera positions and 3D Gaussian splatting to create realistic scene reconstructions. Standardized views are then generated at fixed heights (1.6 m) and distances. These views are processed through EfficientNet-based classification to identify tree species and DANet semantic segmentation to determine plant locations. From segmentation results, the S3PVI index is calculated as the ratio of visible vegetation area (*Area_vi)* to total image area (*Area_ti*), enabling statistical analysis of seasonal vegetation changes. This approach integrates advanced image processing with 3D

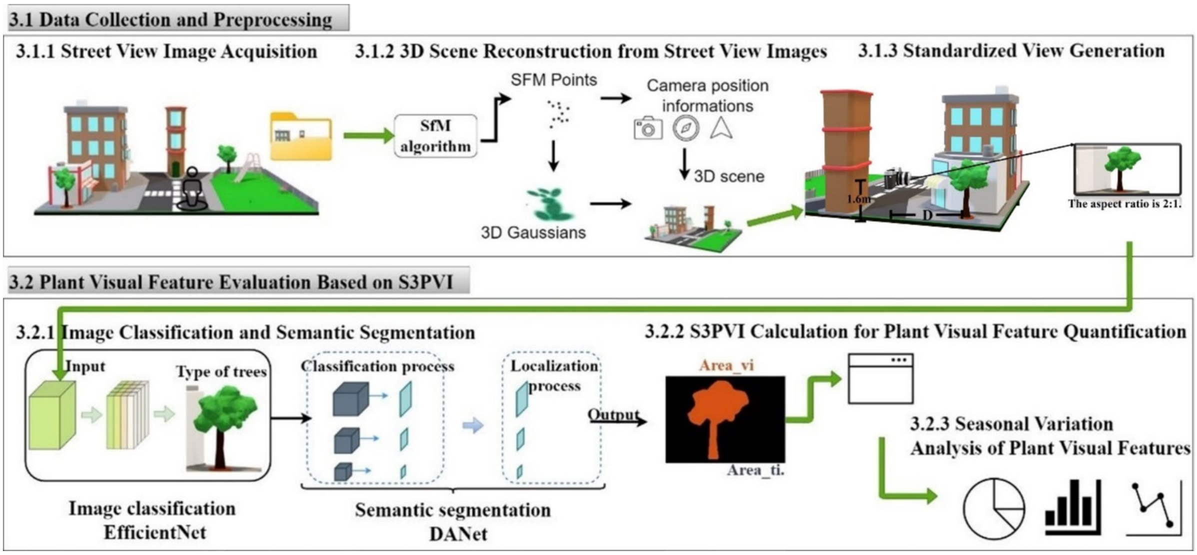


Fig. 1 Workflow diagram of the multi-temporal urban green space vegetation visualization analysis framework

reconstruction to achieve detailed multi-temporal analysis of urban vegetation.

Data collection and scene reconstruction

Street view image acquisition and processing

The temporal analysis utilizes street view imagery with historical coverage spanning multiple years. Since commercial street view platforms typically update imagery at irregular intervals (ranging from 1-3 years depending on the urban area's significance), the methodology accommodates this non-systematic temporal distribution. The framework is designed to integrate all available temporal data points within the study period, prioritizing imagery that captures key phenological events such as spring flowering and autumn coloration. This approach maximizes the capture of seasonal vegetation changes while working within the constraints of publicly available street view data resources. The multi-temporal urban green space vegetation visualization framework begins with spatial data integration and image acquisition. The process consists of three main stages: base map analysis, street view data evaluation, and view position optimization.

The first stage involves analyzing municipal base maps, which provide fundamental spatial information about urban vegetation distribution. These maps, maintained by local government agencies, document the general location and distribution patterns of street trees and other vegetation elements within the urban environment. While these maps may not provide precise coordinates for individual plants, they offer essential reference data for identifying target areas and understanding overall vegetation layouts.

The second stage focuses on street view image evaluation. For areas identified in the base maps, available street view data is systematically assessed based on three key aspects: temporal coverage (availability of historical imagery), spatial continuity (consistency of view positions), and image quality (resolution and clarity). This evaluation process identifies areas where sufficient temporal data exists to support meaningful analysis of seasonal vegetation changes.

The third stage involves optimizing view positions through detailed spatial analysis. Using the base map as a reference, each vegetation cluster identified is matched with available street view positions. The process considers both the physical constraints of street view capture points (typically available at 5–15 m intervals) and the optimal viewing conditions for vegetation documentation. Potential viewing positions are evaluated based on multiple factors including clear sight lines to target vegetation, appropriate viewing distances for capturing full plant forms, and minimal interference from urban infrastructure or other obstacles.

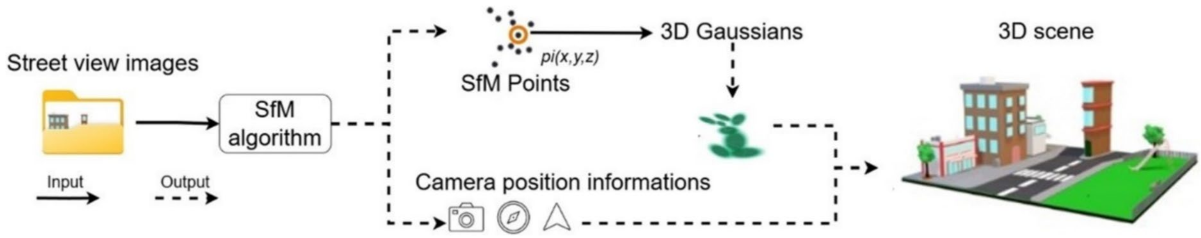


Fig. 2 Process of 3D scene reconstruction

3D scene reconstruction for complex environments

When direct street view imagery proves inadequate due to positioning limitations, incomplete coverage, or occlusion issues, the methodology employs 3D Gaussian splatting technology to reconstruct the scene (Kerbl et al. 2023). This reconstruction process enables the generation of new standardized views that overcome the limitations of raw street view data, particularly in cases where optimal viewing positions are not available from existing panorama points. This process includes the following steps shown in Fig. 2:

The reconstruction begins with SfM algorithm generating a 3D point cloud by matching features across images to estimate camera positions. To address gaps in this point cloud, 3D Gaussian splatting transforms discrete points into a continuous representation using Gaussian kernels Eq. (1):

$$G\left(p|p_i, \sigma\right) = exp\left(-\frac{\|p-p_i\|^2}{2\sigma^2}\right) \quad (1)$$

where *G(p|pi,σ)* represents the Gaussian kernel value with center at *pi* and standard deviation σ. This approach generates a (1) smoother, more realistic 3D scene from which new views can be generated, particularly valuable for areas where direct street view imagery is suboptimal.

Standardized view generation and quality assurance

The standardization of view generation implements a geometry-based optimization approach to ensure consistent and reproducible image capture across different urban environments. This method focuses on fundamental spatial relationships between camera, target plant, and surrounding environment to determine optimal viewing parameters. The parameters in Table 1 are used to generate standardized views.

The base viewing setup maintains established standards with the camera height at 1.6 m, representing average pedestrian eye level as illustrated in Fig. 3. The viewing distance calculation (D) is enhanced through a systematic positional optimization process, which varies according to plant height, is defined by Eq. (2).

$$D = \frac{H}{2\tan(\theta)} \quad (2)$$

where D is the optimal shooting distance from camera to plant base, H is plant height, and θ represents the elevation angle from camera to plant top. The optimal viewing zone is defined by the intersection of two geometric constraints: vertical viewing angle (θ) ranging from 20° to 40°, and horizontal angular span of the plant's crown width. Within this viewing

Table 1 Virtual camera parameter settings for standardized view generation

Parameter	Description
Camera height	The virtual camera is located at a height of 1.6 m (Osaka Prefectural Government 2020), representing the average eye level of pedestrians
Camera distance	The distance between the virtual camera and the target plant is calculated using Eq. (2) based on the plant height, ensuring full visibility of the plant
Image aspect ratio	The aspect ratio of the generated views is 2:1, simulating the human field of view
Plant positioning	The bottom edge of the plant trunk is aligned with the bottom of the image frame, and the top edge of the plant canopy touches the top of the image frame

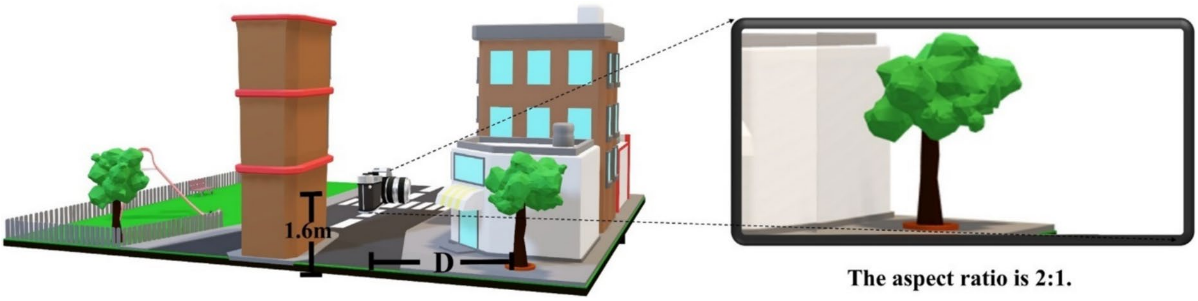


Fig. 3 Standardized imaging method for plant analysis

arc, positions are evaluated based on the ratios of plant height to frame height (Ph/Fh) and plant width to frame width (Pw/Fw). The ideal position maintains these ratios within predetermined ranges (typically 0.8–0.9 for height ratio and 0.6–0.7 for width ratio) to ensure consistent framing while preserving surrounding context.

The standardization process includes an occlusion check comparing visible plant outline against expected geometric profiles. All generated views maintain a 2:1 aspect ratio simulating human field of view, with the plant's trunk base aligned to the bottom of the image frame and canopy top approaching the upper boundary. Quality assurance employs quantitative metrics including peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), with processed images showing average improvements of 5.2 dB and 0.14 respectively (Hore and Ziou 2010). Figure 4 demonstrates how processed images align more closely with pedestrian perspective, with significantly reduced distortion. This standardization approach ensures consistent, high-quality visual data suitable for urban vegetation analysis while remaining practically implementable across different locations and time periods.

Virtual simulation environment for methodology validation

To validate the multi-temporal urban green space vegetation visualization framework in a controlled setting, a virtual simulation approach was developed as a complementary methodology. This approach applies the same principles outlined in Sects. "Street view image acquisition and processing"–"Standardized view generation and quality assurance" to a digitally constructed environment, maintaining methodological consistency while enabling greater experimental control.

(a) Original image: significant distortion, non-standard viewing angle, and distance.
(b) Preprocessed image: standardized plant observation angle and distance, improved image quality and consistency.

Fig. 4 Comparison of street view images before and after preprocessing

The simulation environment employs identical standardized view generation parameters with camera heights fixed at 1.6 m and viewing distances calculated using Eq. (2). Multiple strategic camera positions are established following the same geometric principles as real-world applications, defined by the intersection of vertical viewing angles (20–40°) and the horizontal angular span of plant crowns.

This virtual approach facilitates the systematic evaluation of multiple planting design schemes with different vegetation combinations. By implementing identical measurement protocols across all schemes, the simulation enables direct comparative analysis of different vegetation strategies' effects on seasonal visual characteristics of urban green spaces.

Plant visual feature evaluation based on S3PVI

In the multi-temporal urban green space vegetation visualization framework, the combination of image classification and semantic segmentation is a key step to accurately identify and separate the pixels of each plant species in standardized views. A deep learning-based image classification and semantic segmentation model is adopted, which is trained on a dataset containing 2,000 annotated images, covering 51 common plant species in urban environments, as shown in Table 2. The training dataset of 2,000 annotated images was specifically curated to emphasize plants during their peak ornamental display periods. For deciduous flowering species like cherry blossoms, images primarily captured spring blooming phases, while for species valued for autumn coloration such as maples, fall color peak periods were prioritized. Images were collected under consistent lighting conditions—clear, non-overcast days without direct backlighting—to minimize illumination variables while maintaining natural appearance. This intentional emphasis on optimal display conditions enhances the model's ability to recognize species during their most visually distinctive and ecologically significant phases.

Dataset development and characteristics

The dataset was curated following the Cityscapes dataset approach (Cordts et al. 2016), ensuring diverse representation of plant types and environmental conditions with emphasis on ornamental status. Each image underwent rigorous annotation by at least two individuals providing pixel-level labels, with the dataset divided into training, validation, and test subsets at a 70:15:15 ratio (Gomes and Zheng 2020).

Model architecture and selection

For plant species classification, the EfficientNet architecture was employed, with the EfficientNet-b4 variant achieving 97.9% accuracy on the dataset. For semantic segmentation, several models were evaluated using mean square error (MSE) as the criterion. DANet outperformed alternatives with the lowest MSE of 148.74, compared to ISANet (235.66) (Huang et al. 2019) and PSPNet (337.09) (Zhao et al. 2017), leading to the selection of EfficientNet-b4 for classification and DANet for segmentation tasks.

Training process and data augmentation

The model was trained using the Adam optimizer with an initial learning rate of 0.0001, a batch size of 8, and a total of 100 epochs (Kingma and Ba 2017). Various data augmentation techniques, including random flipping, scaling, and cropping, were implemented to enhance the model's robustness and generalization ability (Shorten and Khoshgoftaar 2019).

Model performance and analysis

The final model achieved a mean Intersection over Union (mIoU) of 82.17% on the test set, demonstrating effective distinction between plant species. IoU scores for the 51 plant species ranged from 69.10% to 92.50% as shown in Table 2. Highest accuracy was observed for lemon geranium (92.50%), cancer tree (91.70%), and acephala group (91.82%). Notable lower accuracy was found in Japanese cheese wood (69.10%), cherry blossoms (69.61%), and Sawara cypress (69.48%). Figure 5 illustrates the segmentation effectiveness, showing original photographs alongside corresponding segmented images where distinct colors represent different plant species. The relatively lower accuracy for cherry blossoms (69.61%) presents a limitation that must be considered when interpreting spring season analyses when these trees are visually dominant. Despite this limitation, the segmentation successfully identifies and separates plant species from backgrounds across diverse

Table 2 Intersection over Union (IoU) scores for common urban plant species in semantic segmentation

NUM	Botanical name	Common name	IOU (%)
1	Ternstroemia gymnanthera	Japanese Ternstroemia	90.74
2	Camptotheca acuminata	Cancer tree	91.70
3	Cupressus macrocarpa	Monterey cypress	89.04
4	Cinnamomum camphora	Camphor	81.38
5	Quercus acutissima	Quercus acutissima	70.97
6	Ligustrum lucidum	Glossy privet	78.38
7	Acer	Maple	81.63
8	Gardenia jasminoides	Cape jasmine	89.85
9	Hibiscus makinoi	Makino's mallow	88.29
10	Pinus thunbergii	Japanese black pine	79.51
11	Cortaderia selloana	Pampas grass	86.74
12	Paliurus ramosissimus	Thorny wingnic	79.07
13	Camellia japonica	Japanese camellia	77.34
14	Acacia baileyana	Cootamundra wattle	88.23
15	Lithocarpus edulis	Japanese stone oak	80.93
16	Castanopsis sieboldii	Itajii	73.29
17	Torreya nucifera	Japanese torreya	77.38
18	Quercus myrsinifolia	Japanese white oak	87.37
19	Ginkgo biloba	Ginkgo	74.79
20	Bassia scoparia	Kochia	81.71
21	Rhaphiolepis indica var. umbellata	Rhaphiolepis umbellata	81.64
22	Rosa spp.	Rosa	86.41
23	Cordyline spp.	Cordyline	79.72
24	Quercus glauca	Ring-cupped oak	87.55
25	Ceratonia siliqua	Arakashi	73.81
26	Jacaranda mimosifolia	Blue Jacaranda	83.17
27	Washingtonia filifera	California palm	80.21
28	Erythrina bidwillii	Coral tree	86.92
29	Paeonia lactiflora	Chinese peony	89.65
30	Styphnolobium japonicum var. pendulum	Japanese pagoda	84.75
31	Lavandula angustifolia	English lavender	73.21
32	Pelargonium crispum	lemon geranium	92.50
33	Salvia rosmarinus	Rosemary	90.48
34	Litsea japonica	Hamabiwa	82.25
35	Chamaecyparis pisifera 'Filifera'	Sawara cypress	69.48
36	Rhododendron spp.	Azalea	79.39
37	Eurya emarginata	Eurya emarginata	87.23
38	Juniperus rigida	Temple juniper	75.00
39	Cycas revoluta	Sago palm	83.68
40	Photinia fraseri	Christmas berry	85.22
41	Muhlenbergia capillaris	Muhly grass	90.78
42	Magnolia denudata	Lily tree	76.77
43	Prunus serrulata	Cherry blossoms	69.61
44	Picea abies	Norway spruce	81.13
45	Helianthus annuus	Common sunflower	75.49
46	Hedera canariensis	Canary ivy	87.57
47	Brassica oleracea var. acephala	Acephala group	91.82

Table 2 (continued)

NUM	Botanical name	Common name	IOU (%)
48	Forsythia suspensa	Weeping forsythia	74.69
49	Osmanthus fragrans	Sweet osmanthus	87.02
50	Pinus pinea	Stone pine	86.05
51	Pittosporum tobira	Japanese cheese wood	69.10

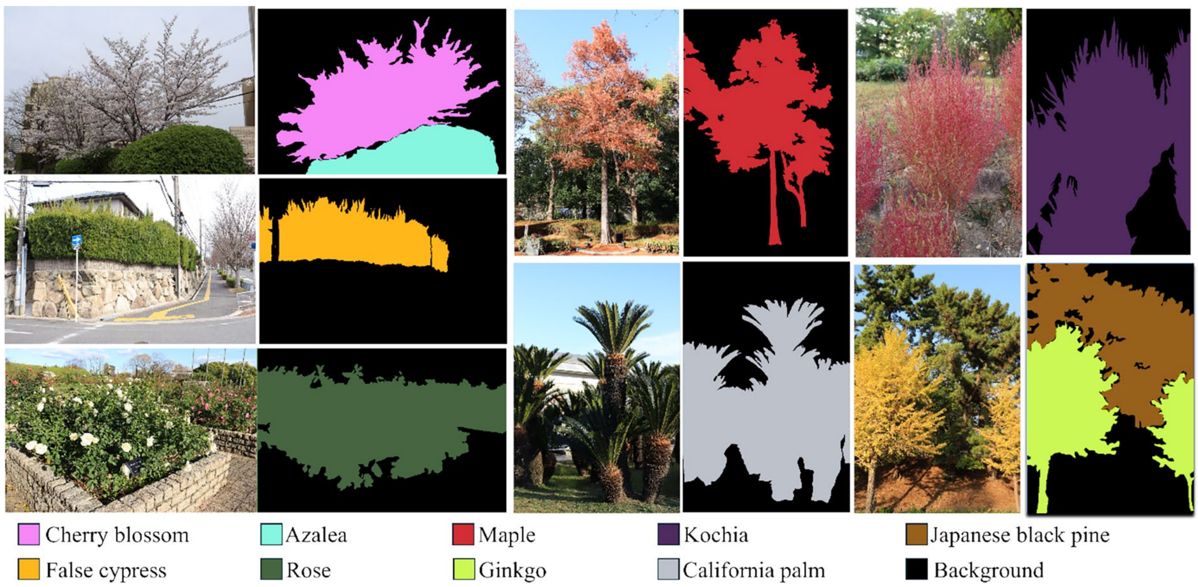


Fig. 5 Examples of original and segmented images

settings, enabling subsequent S3PVI calculation and temporal analysis of vegetation visual features.

S3PVI calculation for plant visual feature quantification

To ensure consistent and reliable data collection for S3PVI evaluation, standardized field photography procedures have been developed, drawing from best practices in urban vegetation assessment and visual quality analysis (Osaka Prefectural Government 2020). After semantic segmentation, the S3PVI of each plant species in the segmented image is calculated using Eq. (3):

$$S3PVI = \frac{\sum_{i=1}^{n} Area_{v_i}}{\sum_{i=1}^{n} Area_{t_i}} \times 100(\%) \tag{3}$$

where n is the total number of photos taken in the test area, $Area_{v_i}$ is the total number of pixels of the target plant in the image i took along the horizontal direction, and $Area_{t_i}$ is the total number of pixels in the image i. This ratio reflects the percentage of pixels attributed to the plant relative to the entire image, providing a VIPI value from 0 to 100%. The average of these values for all images quantifies the plant's visibility in the area.

The S3PVI is inspired by the GVI, which quantifies vegetation visibility in street-level images. While the GVI focuses on overall greenery visibility, the S3PVI extends this concept by quantifying the visibility of individual plant species across multiple seasons. This species-level, multi-temporal analysis provides a more detailed understanding of the visual characteristics and dynamics of urban green spaces. The average S3PVI values across all images quantify the visibility of each plant species in the study area. By evaluating multiple species in each image, the S3PVI enables a detailed assessment of their respective contributions to the aesthetics of urban green spaces.

To further quantify the differences in visual characteristics of vegetation across different areas and their temporal dynamics, this study introduces three quantitative indices based on the fundamental S3PVI metric: S3PVI seasonal amplitude (SA), S3PVI species diversity index (SDI), and year-round consistency (YRC).

The S3PVI SA is defined as the difference between the highest and lowest S3PVI values within a specific area over a year, calculated using the following Eq. (4):

$$SA = max\left(S3PVI_t\right) - min\left(S3PVI_t\right) \tag{4}$$

where $S3PVI_t$ represents the S3PVI value at a specific time point t. This index reflects the intensity of seasonal changes in vegetation visual characteristics within an area. Higher values indicate more significant seasonal visual changes in vegetation.

The S3PVI species diversity index (SDI) employs Simpson's diversity index to quantify the diversity level of vegetation visual contributions within an area, calculated as follows Eq. (5):

$$SDI = 1 - \sum \left(p_i^{\,2}\right) \tag{5}$$

where p_i represents the proportion of species i's S3PVI value relative to the total S3PVI value in the area. This index ranges from 0 to 1, with values closer to 1 indicating more balanced and diverse visual contributions from various species, while values closer to 0 suggest visual effects dominated by a few species.

The year-round consistency (YRC) index measures the stability of visual character throughout the year, calculated as the ratio between the minimum and maximum total S3PVI values across all time periods, as given by Eq. (6):

$$YCR = \frac{min\left(Total\, S3PVI_t\right)}{max\left(Total\, S3PVI_t\right)} \tag{6}$$

where Total $S3PVI_t$ is the sum of all species' S3PVI values at time point t. This index ranges from 0 to 1, with values closer to 1 indicating more consistent visual character throughout the year, while values closer to 0 suggest more dramatic fluctuations between peak and off-peak seasons. The YRC provides a complementary perspective to the seasonal amplitude, focusing on the overall stability of visual greenery rather than its maximum variation.

Experiments and results

Visual feature analysis of real street vegetation

The implementation of the multi-temporal urban green space vegetation visualization framework began with analyzing Suita City's municipal base maps, updated in 2020 (Suita City Official Website, n.d.). These maps provided comprehensive documentation of street tree distribution patterns throughout the study area. Based on this initial spatial data, the street network was systematically evaluated for available street view imagery. The intersection of Sanshikisaido and Nakayoshido in the Kita-senri residential area emerged as an ideal study location due to its well-documented vegetation patterns and comprehensive street view coverage. As illustrated in Fig. 6, this area covers approximately 700 m of urban streetscape. It is particularly notable for its carefully planned landscape design, featuring strategic combinations of deciduous and evergreen species that create dynamic visual transitions throughout the year.

The study area was systematically divided into five distinct zones, as illustrated in Fig. 6, which details the spatial relationship between street vegetation and urban infrastructure. Camera positions were established by carefully analyzing the base map vegetation patterns and available street view capture points. The selection process considered the spatial distribution of vegetation, viewing geometry constraints, and the need for comprehensive coverage of all documented plant specimens.

A total of 115 observation points were established across the five zones. Figure 7 demonstrates the application of 3D scene reconstruction techniques at position 1, where the reconstructed perspective provides enhanced visualization of otherwise difficult-to-document vegetation characteristics. The figure presents two comparative viewpoints: Fig. 7a shows the standard street-level perspective from position 1 captured in August 2022 via Street View mapping, where roadside vegetation is partially obscured by vehicles on the road. Due to the image being taken from the pedestrian walkway, the viewing distance is increased, making vegetation assessment challenging with frequent obstructions from passing vehicles. In response to these limitations, 3D Gaussian splatting technology was utilized to generate a reconstructed scene using 15 photographs from various angles. This

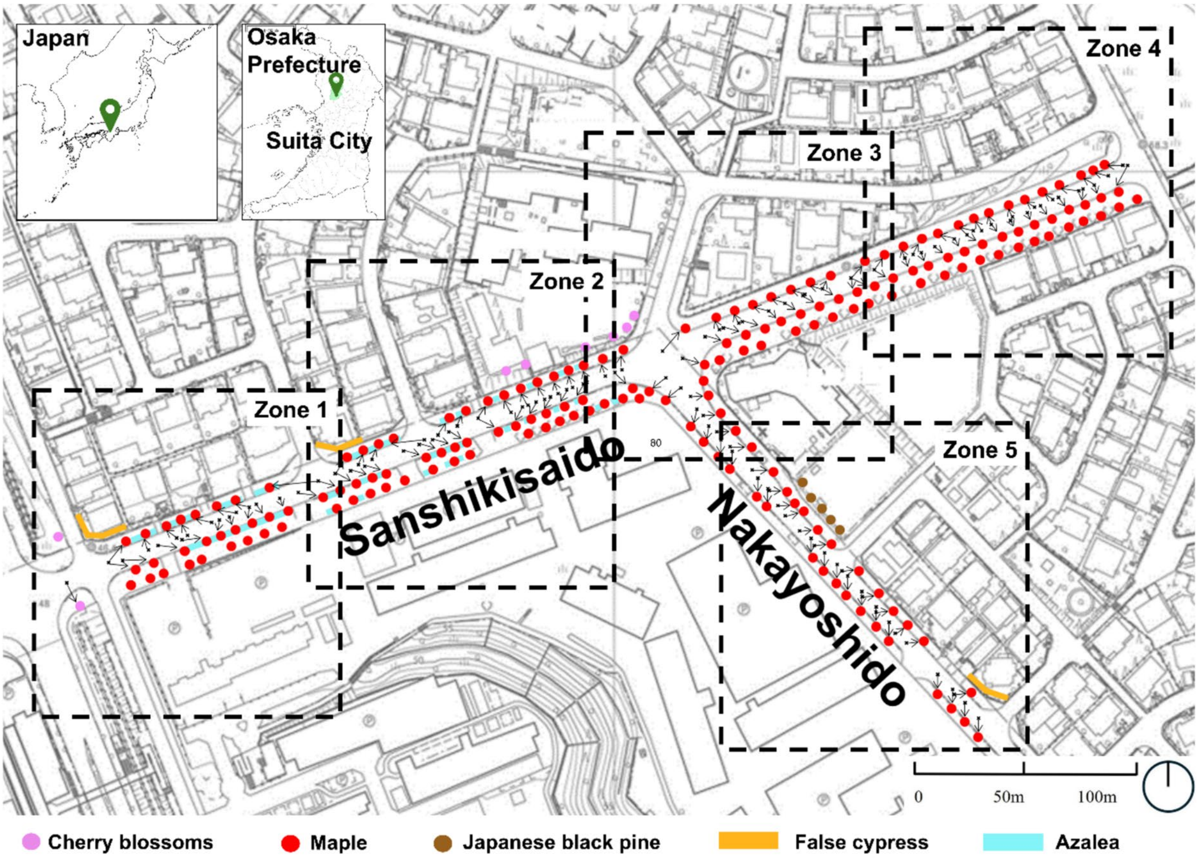
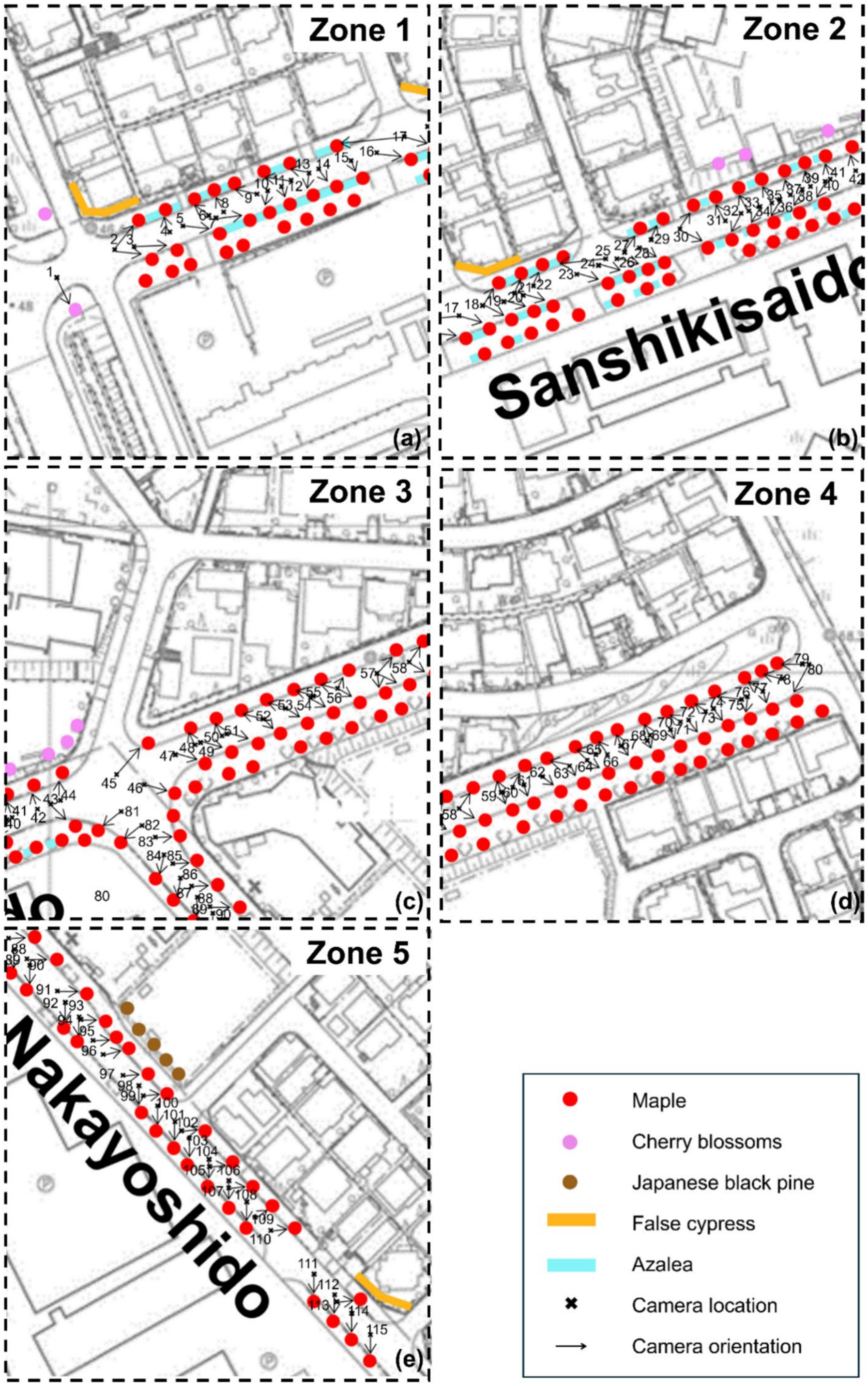


Fig. 6 Vegetation distribution along Sanshikisaido and Nakayoshido, Suita City

Fig. 7 Comparison between original Street View imagery and enhanced visualization at position 1 (August 2022)

process resulted in Fig. 7b, which provides an optimized viewing perspective that effectively reveals the spatial distribution and vertical stratification of tree canopies while minimizing obstructions. The enhanced perspective particularly highlights trees, allowing for a more accurate assessment of canopy dimensions, density, and species composition.

Fig. 8 Detailed vegetation map and camera placement of Sanshikisaido



Zone 1, detailed in Fig. 8a, features seventeen viewing positions capturing the characteristic mix of maple trees, azaleas, and false cypress trees, with cherry blossoms at both ends. Zone 2 (Fig. 8b) continues with positions 17 through 42, while Zone 3 (Fig. 8c) documents a curved section with positions

40 to 58, 81 to 90. Zone 4 (Fig. 8d) encompasses positions 58 through 80 along a maple-lined curve, and Zone 5 (Fig. 8e) extends along Nakayoshido with positions 88 through 115.

Each observation point maintained standardized documentation parameters, with camera height fixed at 1.6 m and viewing distances optimized according to vegetation height as specified in Fig. 3. In cases where physical constraints limited direct observation, 3D scene reconstruction techniques were employed to generate supplementary viewing angles, ensuring comprehensive documentation of all vegetation features.

The temporal analysis is extensively documented through a series of figures. This dataset represents all available Street View data for the region, ensuring thorough temporal coverage. Each image strictly follows the standardized view generation protocol outlined in Sect. "Standardized view generation and quality assurance", maintaining consistent camera parameters across all temporal instances. The resultant data was systematically processed through a multi-temporal evaluation framework to derive corresponding S3PVI values. Figure 9 's lower section displays both the original imagery and corresponding segmented visualizations, where cherry blossoms are distinctively highlighted in pink against a black background, facilitating clear temporal tracking of vegetation coverage patterns.

Similar detailed temporal analyses are presented for the remaining representative locations in Figs. 10, 11, and 12. Location 25 (Fig. 10) provides insights into azalea development patterns, with light blue segmentation highlighting temporal variations in presence and spatial distribution. Location 45 (Fig. 11) showcases maple tree evolution, with reddish-brown segmentation particularly emphasizing autumn foliage characteristics in the 2018.11 imagery. Location 113 (Fig. 12) focuses on the temporal dynamics of false cypress trees, represented in yellow in the segmented images, with a notable maple presence detected in the 2018.11 documentation.

The temporal analysis reveals distinct vegetation patterns across Sanshikisaido and Nakayoshido from 2010 to 2022 (Fig. 13). At Sanshikisaido, cherry blossoms peaked at 45.61% (April 2010) and 42.78% (April 2014) before disappearing until

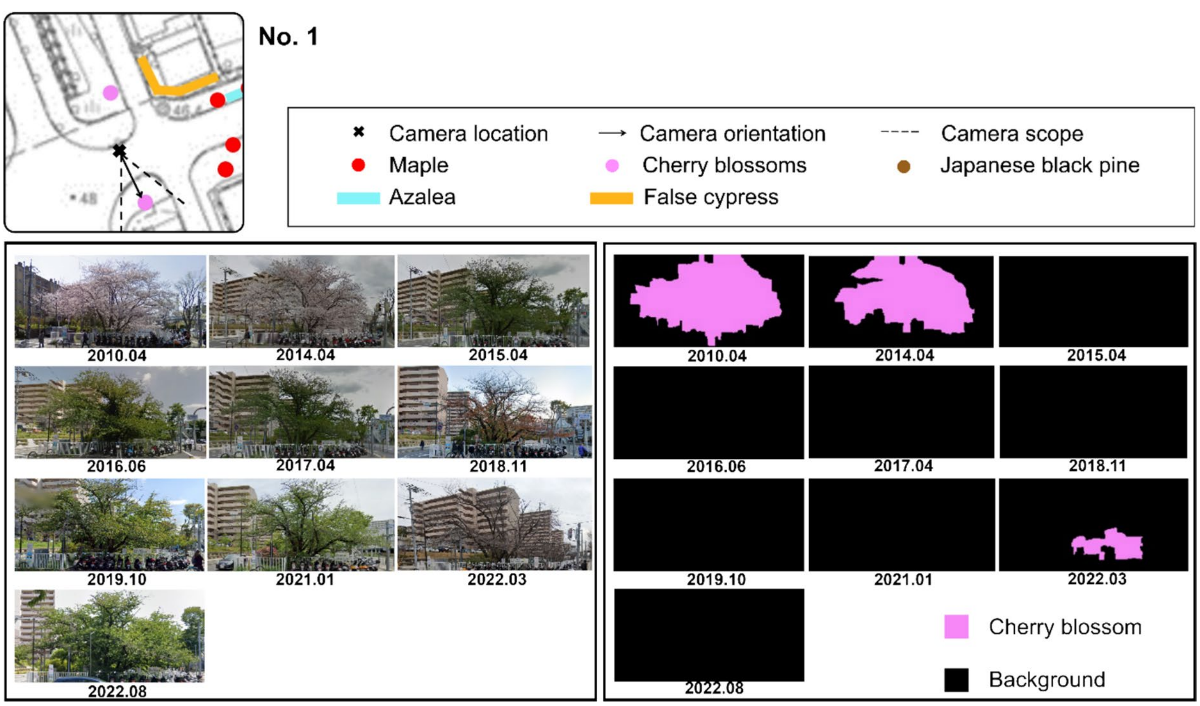


Fig. 9 Temporal analysis of vegetation presence at location 1 (2010–2022)

Fig. 10 Temporal analysis of vegetation presence at location 25 (2010–2022)

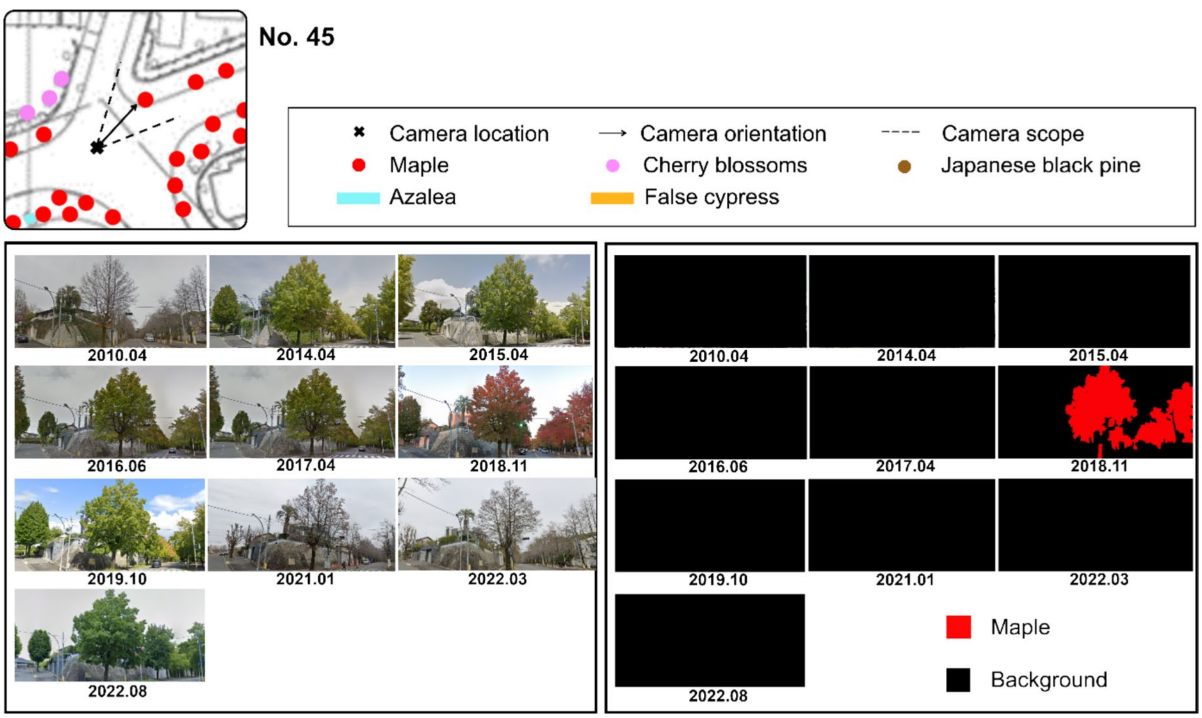


Fig. 11 Temporal analysis of vegetation presence at location 45 (2010–2022)

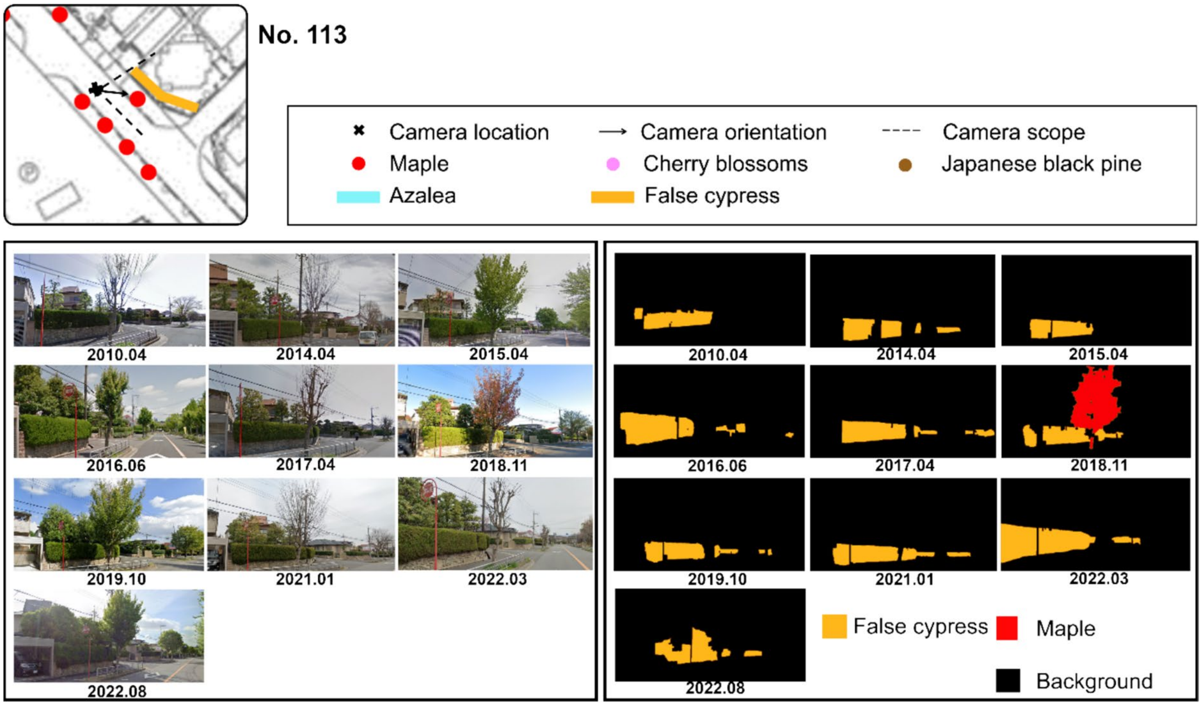


Fig. 12 Temporal analysis of vegetation presence at location 113 (2010–2022)

March 2022 (17.32%). Maple showed extreme seasonality with a major spike of 56.78% in November 2018, while false cypress maintained consistent presence (8.77–15.54%) throughout. Azalea gradually increased from 5.34% to 11.44%.

At Nakayoshido, cherry blossoms appeared only once (38.68%, April 2010), maple peaked at 23.57% in November 2018, and false cypress remained stable (10.38–16.54%). Japanese black pine showed an increasing trend from 12.16% to 21.74%. These measurements illustrate the contrast between ephemeral deciduous species and consistent evergreen species throughout seasonal cycles.

To enhance the quantitative comparison of vegetation visual characteristics between different street environments, the S3PVI SA, SDI, and YRC were calculated for Sanshikisaido and Nakayoshido based on the temporal data collected from 2010 to 2022 (Table 3).

The analysis revealed distinctive differences in vegetation visual characteristics between the two streets. Sanshikisaido exhibited a significantly higher seasonal amplitude (SA = 56.78) compared to Nakayoshido (SA = 38.68), indicating more pronounced seasonal variation in visual vegetation characteristics. This higher amplitude primarily resulted from the dramatic peaks of maple trees in autumn (56.78% in November 2018) and cherry blossoms in spring (45.61% in April 2010), creating more dynamic seasonal transformations in the visual landscape.

The S3PVI Species Diversity Index showed slightly higher diversity in Sanshikisaido (SDI = 0.530) than Nakayoshido (SDI = 0.514). This marginal difference suggests that both streets maintain relatively similar levels of diversity in species' visual contributions, with multiple plant species playing significant roles in shaping the streetscape appearance.

However, the year-round consistency index revealed more substantial differences in temporal stability, with Nakayoshido demonstrating higher consistency (YRC = 0.29) than Sanshikisaido (YRC = 0.19). This indicates that while Sanshikisaido offers more dramatic seasonal highlights, Nakayoshido maintains a more stable visual character throughout the year. The higher YRC value for Nakayoshido can be attributed to the consistent presence of evergreen species, particularly Japanese black

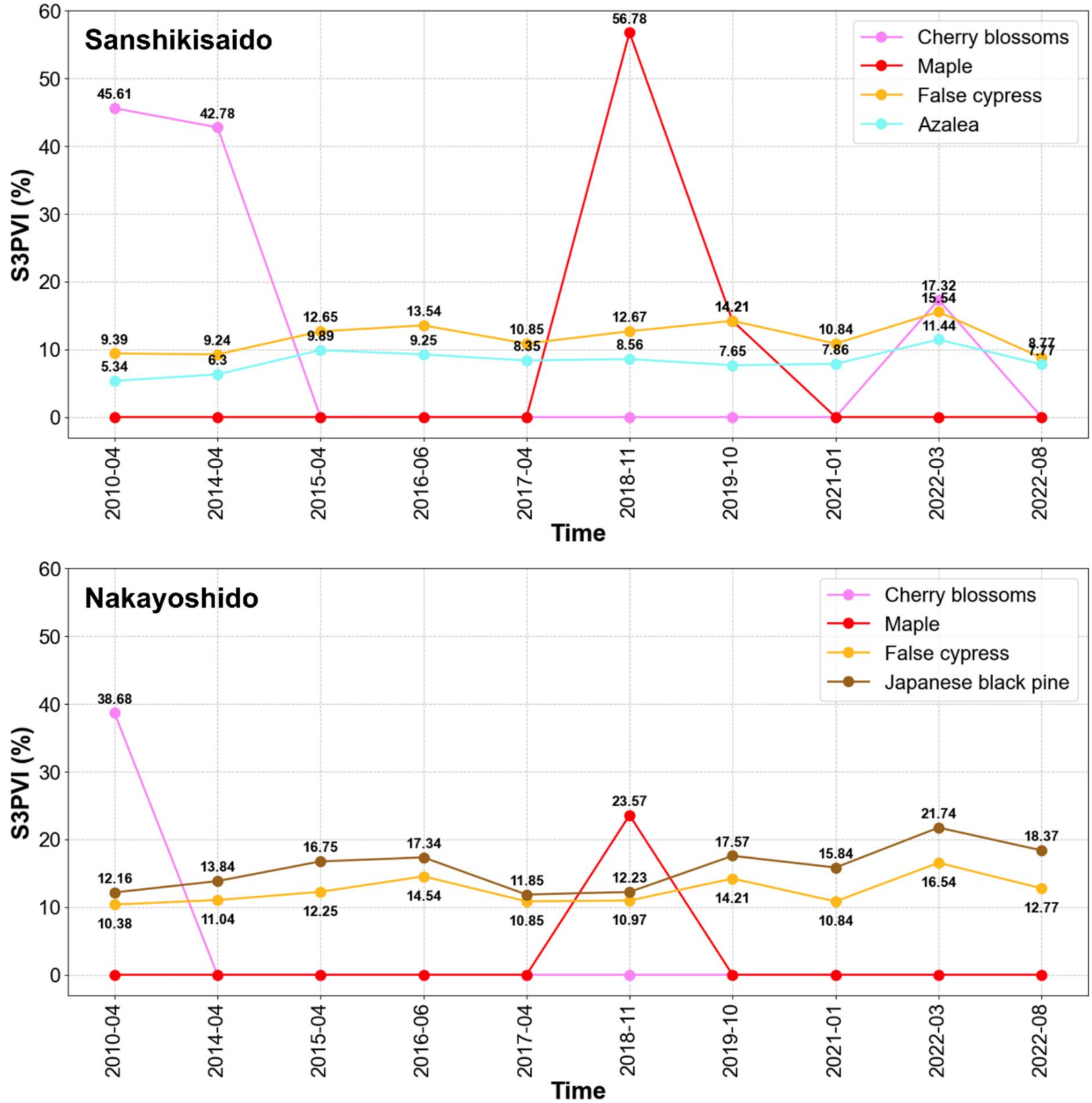


Fig. 13 Seasonal change curves of S3PVI values for major plant species

Table 3 S3PVI quantitative indices for Sanshikisaido and Nakayoshido (2010–2022)

Street	SA	SDI	YRC
Sanshikisaido	56.78	0.53	0.19
Nakayoshido	38.68	0.51	0.29

pine and false cypress, which provide visual continuity even during non-peak seasons.

Multi-temporal visualization evaluation of virtual park vegetation design schemes

A 7,000 square meter virtual park was designed as a testbed for evaluating the multi-temporal vegetation visualization framework (Fig. 14), featuring water

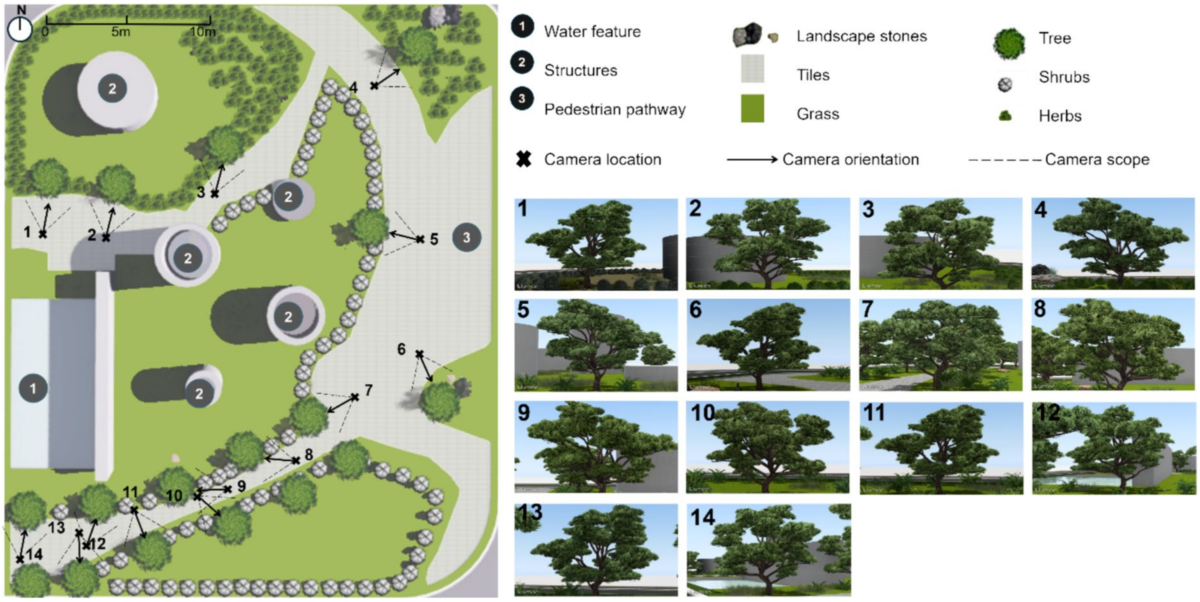


Fig. 14 Virtual park design layout with camera positions and corresponding vegetation views

features, structures, pathways, and strategic vegetation placement. The implementation included 14 camera locations positioned to capture diverse visual perspectives while maintaining consistent measurement conditions. Each location included directional indicators and precise vegetation viewing distances calculated according to Sect. "Standardized view generation and quality assurance" methodology. The right side of Fig. 14 displays the corresponding vegetation views, demonstrating the range of plant perspectives analyzed.

Seven distinct planting design schemes with different combinations of cherry blossoms, maples, and Japanese pines were evaluated (Fig. 15). Schemes 1–3 tested single-species approaches, Schemes 4–6 explored dual-species combinations, and Scheme 7 incorporated all three species.

The S3PVI analysis (Fig. 16) showed that single-species schemes delivered seasonal peaks but temporal inconsistency: Scheme 1 (cherry blossoms) excelled in spring but declined elsewhere, Scheme 2 (maple) peaked in autumn, while Scheme 3 (Japanese pine) maintained the most consistent values (40–50%) year-round. Dual-species combinations achieved better seasonal balance, with Scheme 5 (cherry blossoms and Japanese pine) providing both spring impact and year-round interest. Scheme 7, with all three species, delivered the most comprehensive visual appeal with both seasonal peaks and sustained interest throughout the year.

The three S3PVI-based indices were applied to evaluate the seven planting design schemes for the virtual park (Table 4).

Single-species deciduous approaches (Schemes 1–2) showed high seasonal amplitude but minimum diversity and year-round consistency, indicating dramatic but ephemeral visual impact. The evergreen approach (Scheme 3) demonstrated high consistency but limited seasonal variation.

Multi-species approaches (Schemes 4–7) provided more balanced performance. Notably, Scheme 7 achieved the highest diversity (SDI = 0.67) while maintaining good year-round consistency (YRC = 0.74). Scheme 6 balanced high consistency (YRC = 0.77) with good diversity (SDI = 0.51), while Scheme 5 offered moderate seasonal amplitude (SA = 35.12) with some diversity.

Discussion

The multi-temporal urban green space vegetation visualization analysis framework constructed in this study demonstrates its capability to assess current

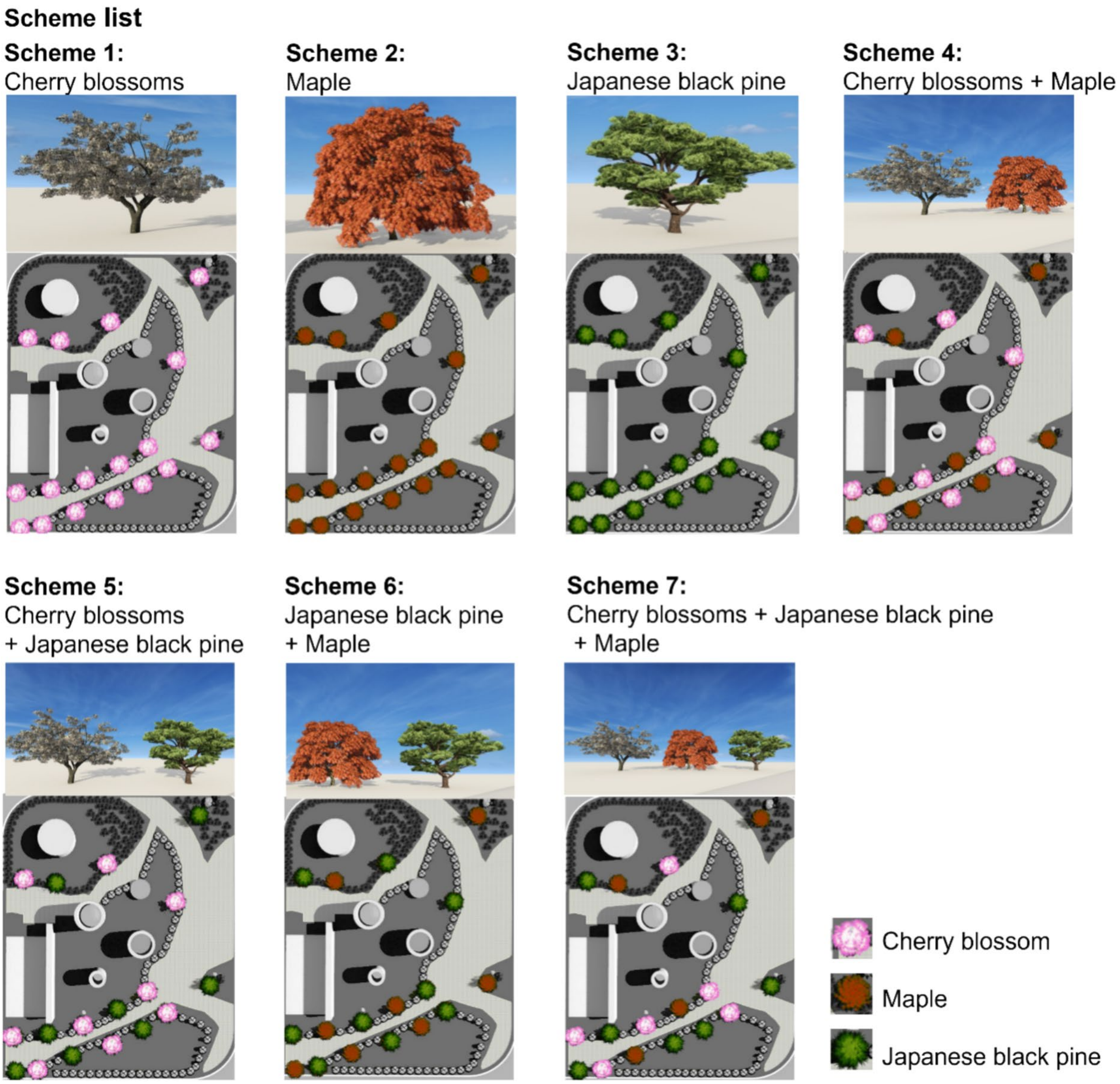
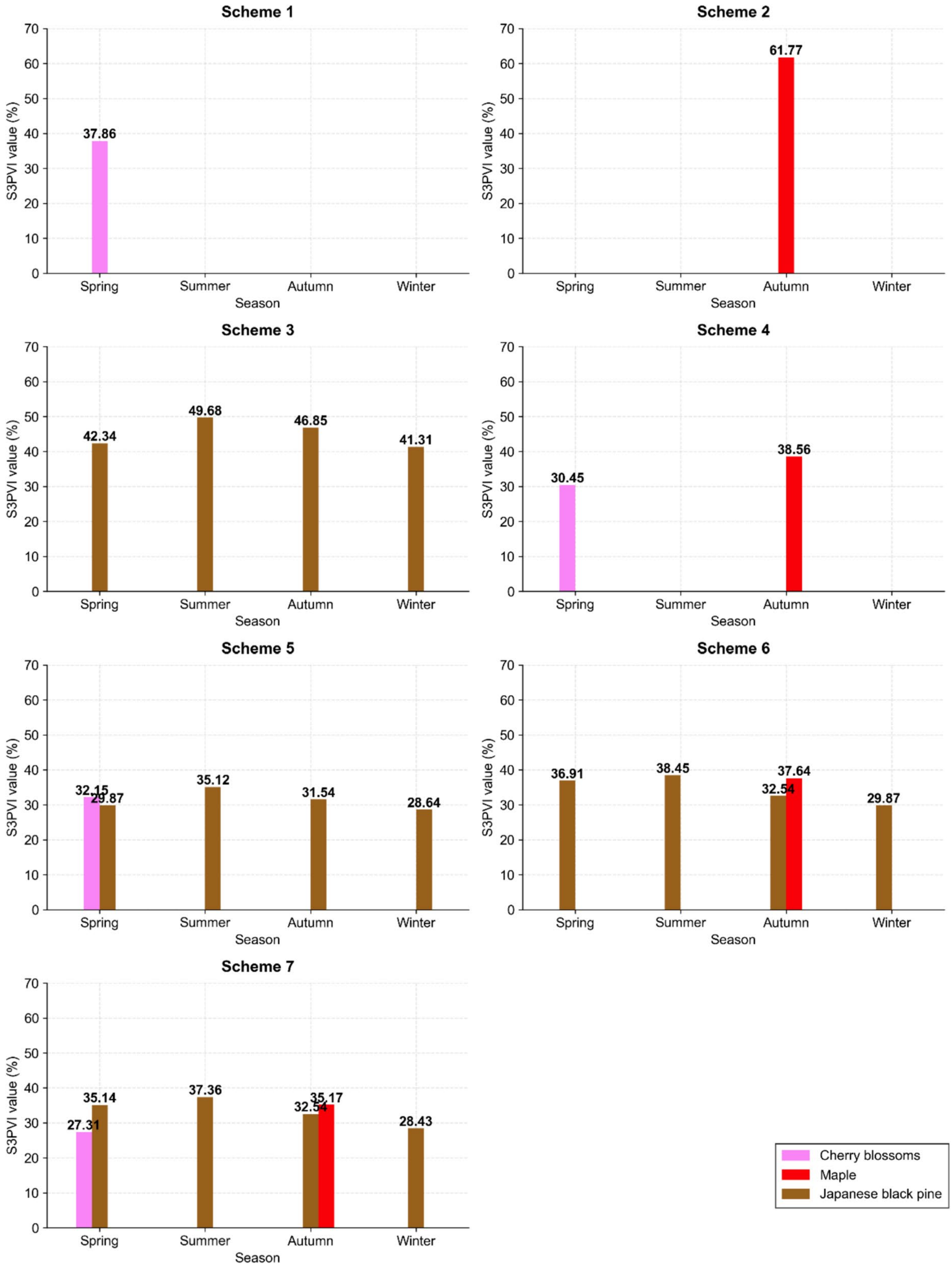


Fig. 15 Seven planting design schemes for the virtual park

conditions through the analysis of the Sanshikisaido case study, particularly suitable for initial assessments of brownfield projects. Quantitative indicators such as the S3PVI index and visual contribution rate reveal the differential roles of various plant types in shaping the visual effect of street landscapes. Based on the street view photo data of Sanshikisaido, this study analyzed the temporal changes of vegetation visual features with monthly precision. The virtual park project further validates the framework's potential in planning and designing vegetation layouts on 3D ground surfaces, offering a new perspective for urban green space planning and design decision-making.

Advantages and limitations of the multi-temporal urban green space vegetation visualization analysis framework

This research framework provides insights into the changes of urban vegetation visual characteristics


Scheme 1
37.86
Scheme 2
61.77
Scheme 3
42.34
49.68
46.85
41.31
Scheme 4
30.45
38.56
Scheme 5
32.15
29.87
35.12
31.54
28.64
Scheme 6
36.91
38.45
32.54
37.64
29.87
Scheme 7
27.31
35.14
37.36
32.54
35.17
28.43
S3PVI value (%)
Season
Spring
Summer
Autumn
Winter
Cherry blossoms
Maple
Japanese black pine

◂**Fig. 16** Seasonal S3PVI values for seven planting design schemes in the virtual park

by introducing a temporal dimension. Compared to traditional assessment methods such as GCR and GVI, S3PVI focuses on the plant type scale and can distinguish the visual contributions of different plant species. This feature gives S3PVI a unique advantage in assessing the diversity and seasonal changes of plant landscapes, directly addressing the research gap identified by previous studies that suggest visual diversity and colorful vegetation substantially affect aesthetic preferences (Du et al. 2016; Wang et al. 2016).

The application of 3D Gaussian splatting for data processing and optimization in this framework addresses a critical issue in urban vegetation analysis: the inconsistency of street view images. Traditional methods often rely directly on street view images for calculations like GVI, which can lead to significant errors due to variations in camera angles, distances, and distortions. This framework's approach of using 3D Gaussian splatting to reconstruct 3D scenes from street view images, followed by the generation of standardized views, represents an advancement in data preprocessing for urban green space analysis.

The research framework also has some limitations. The current plant dataset is limited in scale, which may affect the accuracy of the model in identifying diverse vegetation types. Moreover, existing technology still faces challenges in capturing plant features during periods of non-significant visual characteristics, which may lead to biases in identifying certain plant species in some seasons.

The relatively low IoU score for cherry blossoms (69.61%) significantly impacts spring season analyses when these trees are visually dominant. This identification challenge stems from high variability in blooming density, diverse viewing angles, and subtle differences among cultivars. The spring S3PVI measurements, particularly the peak values in Sanshikisaido (45.61% in April 2010 and 42.78% in April 2014), likely underestimate the actual visual contribution of cherry blossoms due to their distinctive coloration and high visual contrast. Consequently, the calculated seasonal amplitude (SA) of 56.78 for Sanshikisaido may underrepresent the true magnitude of seasonal visual change, potentially understating the comparative difference with Nakayoshido. The temporal inconsistency in cherry blossom detection—absent between 2014 and 2022, then reappearing (17.32%) in March 2022—combines actual phenological variations with detection limitations, requiring cautious interpretation of temporal trends for this species. Similarly, in virtual simulations, Scheme 1's visual impact may be underestimated relative to schemes dominated by more accurately identified species. Future improvements should include season-specific models for flowering species, integration of phenological data, and expanded training datasets representing diverse blooming stages to enhance identification accuracy for visually distinctive yet variable species like cherry blossoms.

The significance of the S3PVI for quantitative evaluation

In constructing the multi-temporal visualization analysis framework, this research created a dataset containing 51 common urban environmental plants, providing a crucial data foundation for the development and validation of the S3PVI index. The construction of this dataset involved street view image collection, expert labeling, and multiple rounds of validation, ensuring the quality and representativeness of the data. These 51 plants cover common street trees, park plants, and seasonal ornamental plants, providing rich training and testing samples for the S3PVI index.

The introduction of complementary indices—SA, SDI, and YRC—enhances the analytical capabilities of the S3PVI framework, addressing previous limitations in quantitative comparison. These metrics enable objective evaluation of key landscape characteristics: seasonal variation intensity, species contribution diversity, and visual stability throughout the year. The application to both real-world streets and virtual design schemes demonstrates how these indices effectively quantify the different strategies in urban vegetation planning. Sanshikisaido's higher SA but lower YRC compared to Nakayoshido reveals its emphasis on seasonal highlights rather than year-round consistency, while the comparative analysis of virtual schemes clearly identifies the trade-offs between seasonal impact and continuous visual presence.

It should be noted that the S3PVI framework provides quantitative outcomes beyond the visual representations. The SA, SDI, and YRC indices offer specific numerical values that enable direct comparison

Table 4 S3PVI quantitative indices for virtual park planting schemes

Planting scheme	Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5	Scheme 6	Scheme 7
S3PVI SA	37.86	61.77	8.34	38.56	35.12	8.58	9.93
S3PVI SDI	0.00	0.00	0.00	0.44	0.49	0.51	0.67
YRC	0.00	0.00	0.83	0.00	0.19	0.77	0.74

between different streets and vegetation configurations. These quantitative measures allow for systematic evaluation of plant color diversity and seasonal changes across urban landscapes. Future research could further develop standardized scales for these indices to facilitate more intuitive interpretation and comparison.

Application of the multi-temporal analysis framework in empirical case studies

The current focus of the multi-temporal visualization analysis framework is primarily on the visual aesthetic features of vegetation, with insufficient attention to other green space functions such as ecological functions and recreational activities. Future studies should aim to integrate the S3PVI index with other ecological and recreational assessment indicators to achieve a comprehensive assessment of the multi-functional attributes of urban green spaces.

While this study focused on two streets as detailed case studies to demonstrate the methodology's capabilities, the framework is designed to be scalable and applicable to larger urban areas. Future studies will extend the application to multiple streets and entire built-up areas to validate the framework's effectiveness at different spatial scales. Additionally, while the dataset contains 51 plant species, the presentation focused on five representative types to clearly illustrate the methodology's key capabilities. Comprehensive analysis of all species would strengthen future research applications.

The camera locations used in this study were based on systematic criteria including uniform spatial distribution along the street, consistent distance from vegetation features, standard height (1.6 m) to simulate pedestrian perspective, and orientation toward key vegetation features. This approach aims to balance objective representation with relevant pedestrian viewpoints. Future studies could incorporate more sophisticated methods for determining optimal camera positions, including eye-tracking studies or pedestrian flow analysis to better reflect actual human visual experience.

Variations in topography, climate, and culture across different regions may influence people's preferences for plant landscapes (Hoyle et al. 2017). As the samples in this study are mainly from Japanese cities, the generalizability of the assessment results needs to be validated across a broader range. Future research should enhance the diversity of vegetation types and urban environments considered and incorporate influences from more diverse cultural backgrounds to improve the robustness and applicability of the assessment framework.

Multi-temporal vegetation visualization analysis supporting 4D vegetation landscape modeling

Compared to traditional field surveys and manual interpretation methods, multi-temporal visualization analysis offers significant advantages in efficiency and cost-effectiveness for data acquisition and automated processing. However, the accuracy of image processing and semantic segmentation still needs further improvement. Future research can explore integrating street view images with other data sources, such as high-resolution satellite images and LiDAR point cloud data, to provide more comprehensive and multi-scale information on urban green space vegetation.

Future research could explore integrating generative technology systems to achieve more complex 4D seasonal change simulations, further enhancing decision support capabilities in planning and design processes. This integration could allow for more accurate predictions of how vegetation will change over time, taking into account factors such as growth rates, seasonal variations, and environmental influences. Such advancements would provide planners and designers with a more dynamic and realistic view of their proposed green spaces over extended periods.

The accessibility of analytical tools significantly impacts their adoption rate in professional practice, making this an important consideration for the future evolution of the S3PVI framework. While the S3PVI method offers valuable analytical capabilities, its current implementation requires considerable computational expertise in deep learning, image processing, and 3D scene reconstruction. Future developments could focus on creating simplified interfaces, pre-trained models for common urban vegetation, and automated processing pipelines that practitioners can deploy with minimal technical expertise. The development of web-based applications and simplified mobile tools could allow on-site assessments, similar to existing GVI calculators. Reducing these technical barriers would transform S3PVI into a practical decision-support tool that complements existing vegetation indices in everyday planning and design practices.

Conclusion

This study proposes a multi-temporal urban green space vegetation visualization framework based on street view images, introducing the S3PVI to quantify visual characteristics of different plant species across seasons. The framework advances beyond greenness-focused assessment to characterize vegetation types, spatial distributions, and temporal dynamics. Through deep learning and 3D reconstruction integration, it enables automated analysis from multiple perspectives and temporal phases, enhancing urban green space assessment efficiency.

Empirical analysis of Sanshikisaido revealed significant differences in vegetation visualization features across time and space, accurately characterizing the dynamics of cherry blossoms and maple trees through different phenological periods. Virtual scenario simulations verified the framework's potential for evaluating different vegetation configuration schemes.

This research contributes to landscape ecology and urban management by expanding assessment dimensions to include species-specific and seasonal considerations while establishing methodological foundations for studying vegetation-human interactions. Practically, it provides quantitative guidance for planning, species selection, and maintenance strategy development, while enhancing stakeholder communication through visualization of design outcomes.

The S3PVI index offers valuable planning references by quantifying different species' visual contributions during seasonal periods, enabling designers to optimize plant selection and spatial layouts for year-round visual richness. Despite challenges in sample diversity, species identification accuracy, and temporal resolution, integration with emerging technologies like digital twins and virtual reality presents opportunities for immersive, interactive platforms supporting urban green space planning and management.

Author contributions Anqi Hu: Conceptualization, Methodology, Software, Formal analysis, Resources, Writing—Original draft, Visualization, Funding acquisition. Nobuyoshi Yabuki: Conceptualization, Methodology, Writing—Review & Editing, Supervision, Project administration. Tomohiro Fukuda: Conceptualization, Methodology, Writing—Review & Editing, Supervision.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

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

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