

Article

Exploring the Long-Term Changes in Visual Attributes of Urban Green Spaces Using Point Clouds

Xiaohan Zhang ¹ , Yuhao Fang ² , Guanting Zhang ³ and Shi Cheng ^{2,4,*} 

¹ Department of Architecture, Technical University of Munich, 80333 Munich, Germany; xiao-han.zhang@tum.de

² Department of Architecture, Southeast University, Nanjing 210096, China; fangyuhao@seu.edu.cn

³ College of Architecture, Nanjing Tech University, Nanjing 211816, China; guanting_zhang@163.com

⁴ Chinese National Visual Image Research Base, Southeast University, Nanjing 210096, China

* Correspondence: 101300063@seu.edu.cn

Abstract: The visual attributes of urban green spaces influence people's perceptions, preferences, and behavioural activities. While many studies have established correlations between landscape perception and visual attributes, they often focus on specific timeframes and overlook dynamic changes in the spatial form of urban green spaces. This study aims to explore the long-term changes in the visual attributes of urban green spaces. We propose a method to quantitatively analyse changes in visual attributes using point clouds to simulate visual interfaces. Using an unmanned aerial vehicle, we conducted a five-axis tilt photography survey of Qinglv Yuan Park in Nanjing, China, in August 2018 and September 2023. Point cloud models were generated for the two periods, and five visual attribute indicators, openness (OP), depth variance (DV), green view ratio (GVR), sky view ratio (SVR), and skyline complexity (SC), were analysed for long-term changes. The results indicate that OP, DV, and SVR decreased after five years, while GVR increased. The maximum increase in GVR was 26.6%, and the maximum decrease in OP was 12.8%. There is a positive correlation between GVR and its change (d_GVR). Conversely, there are negative correlations between SC and its change (d_SC), as well as between SVR and d_GVR. Tree growth emerged as a primary factor influencing changes in the visual attributes of urban green spaces. This study highlights the importance of adopting a long-term and dynamic perspective in visual landscape studies, as well as in landscape design and maintenance practices. Future research on predicting long-term changes in the visual attributes of urban green spaces should focus on understanding the relationships between tree properties and environmental conditions.

Keywords: urban green spaces; visual attributes; long-term changes; point clouds; dynamic design and maintenance



Citation: Zhang, X.; Fang, Y.; Zhang, G.; Cheng, S. Exploring the Long-Term Changes in Visual Attributes of Urban Green Spaces Using Point Clouds. *Land* **2024**, *13*, 884. <https://doi.org/10.3390/land13060884>

Academic Editors: Fabrizio Battisti and Maria Rosa Trovato

Received: 30 April 2024

Revised: 29 May 2024

Accepted: 14 June 2024

Published: 18 June 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

With rapid urbanisation, city residents are increasingly susceptible to various mental and physical ailments, such as anxiety, depression, and obesity [1–3]. Urban green space serves as a crucial urban green infrastructure capable of alleviating stress and restoring attention [4–6]. Evidence has shown that living in areas with more urban green spaces leads to lower stress levels and better mental health outcomes [7]. Furthermore, urban green space with good spatial quality can positively impact people's outdoor activities, which can also contribute to reducing the risk of chronic physical diseases [8]. Therefore, creating high-quality urban green spaces to promote people's health and well-being has become one of the critical concerns of urban designers.

The visual quality of urban green space is one of the key factors influencing landscape preferences and attracting human activities [9]. Previous studies have proposed various theories to understand the relationship between human perceptions and preferences in landscape environments. For example, Appleton proposed the Prospect–Refuge theory,

which suggests that in a landscape environment, people play the roles of “prey” and “hunter” at the same time and need to be in a space with a sense of shelter and safety while looking at the landscape from a distance [10]. Information processing theory, proposed by Kaplan and Kaplan, suggests that favoured landscapes require “Making sense” and “Involvement” [11]. Since then, with the development of the field of landscape visual quality assessment, the analysis framework and quantitative assessment indicator system for visual landscapes have been gradually built up. For instance, Grahn and Stigsdotter proposed the theory of PSD (perceived sensory dimensions), which includes eight perceptual dimensions, such as nature, scene, shelter, and space [12]. Tveit et al. developed a theoretical terminology for visual quality, including four levels (concepts, dimensions, landscape attributes, and indicators [13]. Naturalness is regarded as one of the critical factors of visual quality. Related indicators include water surface rate and green visibility [14–16]. Visual scale can describe the visibility and openness of landscape space, and indicators include sky view, openness, etc., [17,18].

The relationship between the various visual attributes of landscape spaces and landscape preference has been established. Zhang et al. explored the relationship between the four visual attribute indicators (openness, richness, order, and depth) and landscape preference by using a photographic questionnaire and found that the landscapes with high openness and order had a higher preference [19]. Similarly, studies have shown that landscapes with appropriate openness are preferred more, and they can promote residents’ outdoor activities and communication [20]. Furthermore, Zhu et al. experimentally determined that scenes were most suitable for the human brain when the green view ratio reached 60–80% [21]. The visual attributes of landscape spaces have been found to play an essential role in predicting people’s preferences for specific landscape spaces and potential behaviour [19]. Therefore, an in-depth study of the visual attributes of landscapes can not only help designers understand the spatial and visual characteristics of a site and assess the visual quality of landscapes but also help in landscape planning and design, management decisions, and related policymaking [22].

However, previous studies on the visual attributes and preferences of urban green space have tended to overlook the dynamic changes in landscape space. Landscape spaces at a particular time have often been used as the experimental material for landscape perception and preference studies. While monitoring the dynamic change in landscapes has long been an important issue in the field of urban environmental resource management and spatial planning, it tends to focus on the dynamic change in landscapes at large scales, such as cities or regions [23–25]. Although we have limited exploration of the long-term changes in the visual attributes of landscape spaces, dynamic changes in landscape space are objective. For example, Ode et al. proposed a measure of visual scale using a fusion data source in which two photographs of the same landscape space taken 20 years apart showed huge differences [26].

The dynamic growth of plants, the renewal and renovation of green spaces, and the pruning and death of trees are the objective causes of changes in the spatial form of the landscape. Changes in vegetation occur due to factors such as resident preferences and activity needs [27]. Factors such as tree species, age, and habitat conditions can also lead to variations in tree growth rate [28–30]. Pruning is a common maintenance practice for urban trees. Although trees could grow better without intervention, periodic pruning is necessary to maintain their desired appearance and to prevent safety hazards [31]. Similarly, the trees growing in urban environments need to be pruned regularly to improve views, reduce conflicts with buildings and infrastructure, and reduce wind resistance [32].

Maintaining urban green spaces in a static spatial form through extensive pruning and other high-intensity maintenance practices to meet people’s visual preferences is both costly and detrimental to the ecological services provided by vegetation, including trees [31]. We should try to design and maintain urban green spaces in a green and sustainable way that considers landscape preferences [33]. Therefore, conducting a comprehensive investigation

into the changes in the visual attributes of urban green spaces over time is essential to inform design and long-term maintenance strategies.

Although there are currently methods available for the study of landscape change at a large scale, approaches to the study of long-term changes in the visual attributes of urban green spaces are still limited. For example, previous studies on landscape changes mainly focused on the use of remote sensing, historical maps, and GIS to analyse long-term changes in urban green space patterns or urban vegetation [34]. Recording the landscape environment by taking photos repeatedly at the same location can intuitively reflect the changing characteristics of the landscape and is closer to the actual perception of the human eye [23,35]. Despite its suitability for judging the changes in landscape elements by using two-dimensional image analysis, it lacks the ability to analyse three-dimensional spatial attributes. Due to the limitation of factors such as the photo angle, it is currently only used in the study of the natural environment. Walz et al. [36] proposed a method for analysing landscape structure considering time and three-dimensional features and proposed some three-dimensional landscape metrics, such as average surface roughness, edge contrast index, proximity, etc. However, the method is aimed at the analysis of landscape structure, which is difficult to apply to the study of the visual attributes of urban green spaces. Thus, we need to develop a method that can accurately record the spatial changes in urban green space, simulate the visual perception of the people, and analyse the visual attributes of the urban green space.

The development of digital technology presents an opportunity for the precise quantification of visual attributes and the accurate documentation of morphological changes in urban green spaces. Utilising two-dimensional images such as photographs, street view images, and panoramas allows for the convenient analysis of the elemental composition of the visual interface [22,37]. Yang et al. employed machine learning techniques to semantically segment images and then calculated indicators such as the green view ratio of landscape spaces [38]. Additionally, point cloud models can be processed to generate visual interfaces corresponding to viewpoints, facilitating the analysis of visual attribute indicators [39]. Point cloud models, capable of recording 3D shape information with high accuracy, offer invaluable support for documenting spatial form differences in green spaces over time and comparing visual features across different periods [40,41].

The aim of this study is to investigate whether visual attributes change dynamically in urban green spaces and to what extent. Based on this, we asked the following research questions:

1. How can we identify long-term changes in the visual attributes of urban green spaces?
2. What trends do the visual attributes of urban green spaces have?
3. What is the relationship between the change in the visual attributes of urban green spaces and their initial attributes?

This study attempted to explore the long-term changes in visual attributes by collecting the spatial data of the same urban green space at five-year intervals. We selected Qinglv Yuan Park in Nanjing, China, as the study area and obtained point cloud models using unmanned aerial five-axis tilt photography in 2018 and 2023. After processing the point cloud model, we used a virtual camera to simulate the human visual interface in the green space and then quantitatively analysed the five visual attribute indicators. We compared the differences in indicator values before and after the five-year period and conducted correlation analyses between the changed values and the initial values of the indicators. This study not only explores the dynamic change characteristics of visual attributes within urban green spaces but also aims to provide support for their dynamic maintenance and long-term design.

2. Materials and Methods

2.1. Workflow

We proposed a three-step workflow to quantify the long-term changes in the visual attributes of green spaces (Figure 1). These steps include (1) spatial data acquisition and

processing, (2) visual attribute quantification, and (3) visual attribute change analysis. We utilised unmanned aerial vehicles (UAVs) with five-axis tilt photography to obtain the point cloud models of urban green spaces during the summers of 2018 and 2023. By setting up viewpoints to generate panoramic images, we analysed the changes in multiple visual attribute indicators of 15 spatial samples over five years.

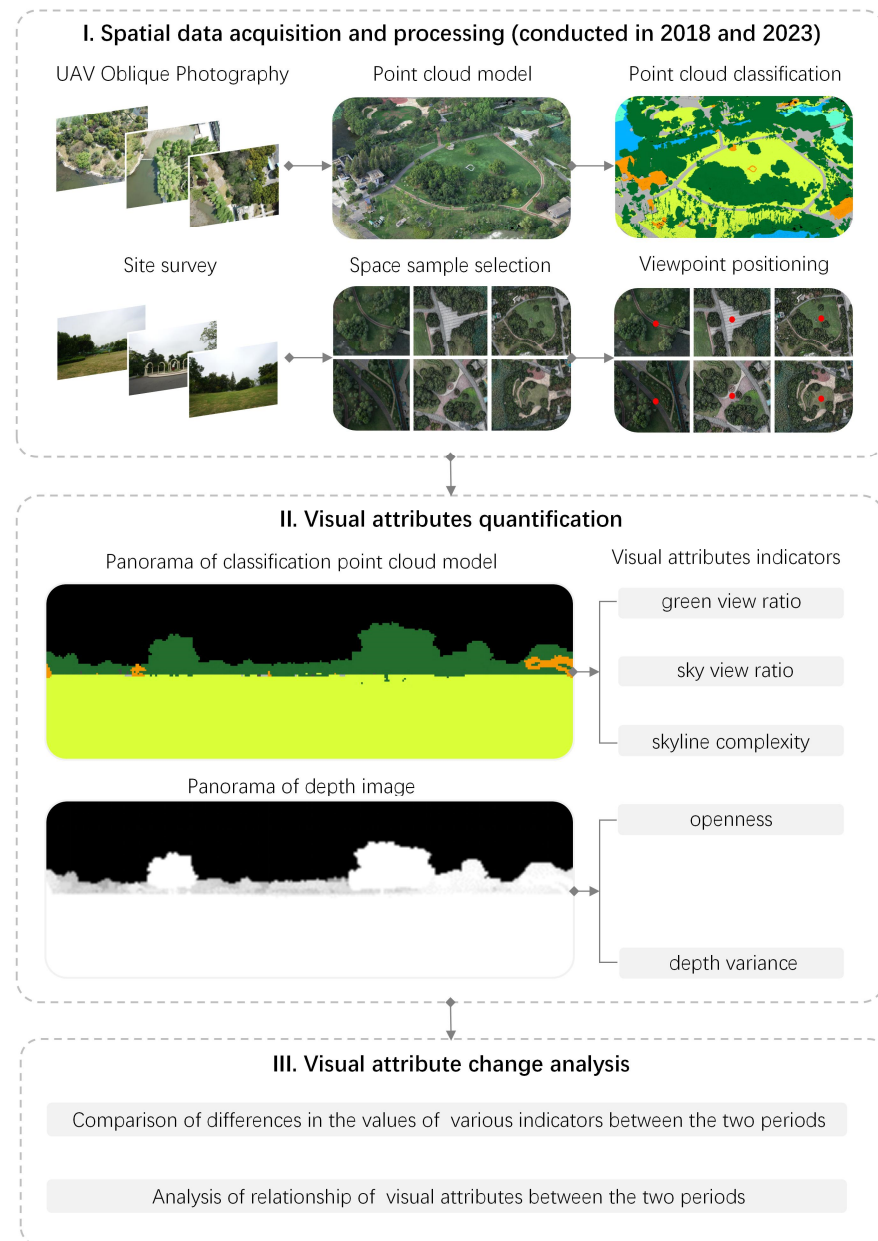


Figure 1. A workflow to analyse long-term changes in the visual attributes of urban green spaces. The red dots represent the location of the viewpoints of the spatial samples.

2.2. Study Area

The study of long-term changes in the visual attributes of urban green spaces requires the continuous tracking of these spaces over a long period. It also necessitates that the study area remains in a maintained state without massive spatial layout changes. Qinglv Yuan Park (QLY) in Nanjing, China, was selected as our study area (Figure 2).



Figure 2. Spatial sample selection of Qinglv Yuan Park.

Nanjing is in the southeast coastal area of China, with a subtropical monsoon climate situation. QLY, a comprehensive urban park in the main city of Nanjing, was constructed in the 1960s and covers a total area of 30 hectares. It boasts diverse vegetation species and spatial patterns, making it a popular urban green space among residents who frequently utilise it for fitness and recreational activities.

We selected three types of landscape spatial samples, including lawns, paths, and plazas. Following a thorough site survey, we carefully selected 15 spatial samples for the study based on their representation of the typical characteristics of urban green spaces in China, with no drastic changes observed over the five years, and their status as active nodes frequented by people.

2.3. Data Collection and Processing

The use of UAV five-axis tilt photography to acquire the three-dimensional spatial data of urban green spaces has been applied in various quantitative spatial morphology studies of urban spaces, offering distinct advantages in terms of data collection efficiency [42]. We conducted the aerial five-axis tilt photography of QLY in August 2018 and September 2023. Subsequently, the captured photos were imported into the DJI Terra 3.9.0 software to generate comprehensive 3D models, which were exported in a point cloud format.

To fulfil the requirements for analysing multiple visual indicators, we employed the outdoor point cloud classification tool within the Trimble Realworks 12.0 software to automatically classify the point cloud model. Following this automated classification, manual correction and secondary editing were conducted to refine the classification process. As a result, the point cloud model was classified into six distinct categories, namely vegetation (trees and shrubs), lawn areas, hard surfaces, water bodies, buildings, and facilities. Each category was assigned a different colour, and the point cloud models were finally assembled as the basis for subsequent analysis.

2.4. Visual Indicator Calculation

We selected five indicators for analysis, including openness (OP), depth variance (DV), green view ratio (GVR), sky view ratio (SVR), and skyline complexity (SC), which are related to the three-dimensional and two-dimensional visual attributes of the urban green spaces. Referring to the method used by Tang et al. [39], we employed parameterised virtual cameras in the classified point cloud models to generate panoramic images integrated with spatial information. Additionally, we utilised depth images, which encode the visual distance between elements and the human eye through pixel colour information, as an effective means to study the 3D visual attributes of landscape space, such as openness and depth variance [22,43].

Firstly, we set the viewpoint positions and parameters in the classified point cloud models. A virtual viewpoint was placed in the centre of each spatial sample at a height of 1.6 m above the ground. The field of view for each viewpoint was set to 360° horizontally and 120° vertically. Secondly, using the visualisation function in the open-source C++ library PCL (point cloud library), we simulated the visual interfaces corresponding to each viewpoint to obtain panoramic images containing element classification information and panoramic depth images. Finally, by processing and analysing the resulting images, we could calculate the relevant visual attribute indicators (Table 1).

Table 1. Description and calculation of visual attribute indicators.

Indicator	Reference	Description of Indicators	Equation	Note
Openness (OP)	[18]	OP is the average distance of elements within a person's visual field, indicating the person's perception of the visual scale.	$OP = \sum_{i=1}^n \frac{d_i}{n}$	n is the number of pixels in the panorama, and d_i is the depth value of each pixel.
Depth variance (DV)	[22]	DV is the variance of the depth values of the elements within a person's visual field, describing the complexity of the space in the longitudinal direction.	$DV = \sum_{i=1}^n \frac{(d_i - OP)^2}{n}$	OP is the openness, n is the number of pixels in the panorama, and d_i is the depth value of each pixel.
Green view ratio (GVR)	[21]	GVR is the proportion of vegetation in a person's visual field, describing the degree of naturalness of the space.	$GVR = \frac{S_v}{S_w}$	S_v is the area of vegetation in the panoramic image, and S_w is the area in the panoramic image.
Sky view ratio (SVR)	[44]	SVR is the proportion of the area of the sky in a person's visual field, describing the visual scale of the space.	$SVR = \frac{S_s}{S_w}$	S_s is the area of the sky in the panoramic image, and S_w is the area of the panoramic image.
Skyline complexity (SC)	[45]	SC is the ratio of the length of the skyline to the width of the visual interface, indicating the vertical complexity of spatial elements.	$SC = \frac{L_s}{L_w}$	L_s is the length of the skyline, and L_w is the width of the panoramic image the panoramic image.

2.5. Statistical Analysis

Excel and SPSS were employed to analyse long-term changes in the five visual indicators across the fifteen spatial samples, as well as to explore differences in indicator values and the extent of change. The quantitative results of the visual attribute indicators were input into Excel, where they were visually analysed through the creation of bar charts. Furthermore, to investigate the potential for predicting future changes in the visual attributes of landscape spaces, we analysed the correlation between the change values of the visual indicators and their initial values. We derived the difference values of various indicators before and after five years (d_{OP} , d_{DV} , d_{GVR} , d_{SVR} and d_{SC}). Subsequently, the Spearman correlation analysis tool within SPSS was utilised to examine the correlation between these difference values and the respective indicator values as of 2018.

3. Results

3.1. Comparison of Point Cloud Models before and after Five Years

Given that changes in the physical form of the landscape space are prerequisites to alterations in visual attributes, we initially investigated differences in the point cloud model of QLY before and after the five years (Figure 3). Upon the examination of the classified point cloud models, it became apparent that the overall spatial pattern of the park remained relatively stable. The main changes were the new buildings inside the park and the increase in some vegetation. Notable changes include the conversion of a densely wooded area in the central part of the park into a landscaped building and the establishment of a new shopping street in the southeast corner of the park. Additionally, shrubs were planted on some open lawns.

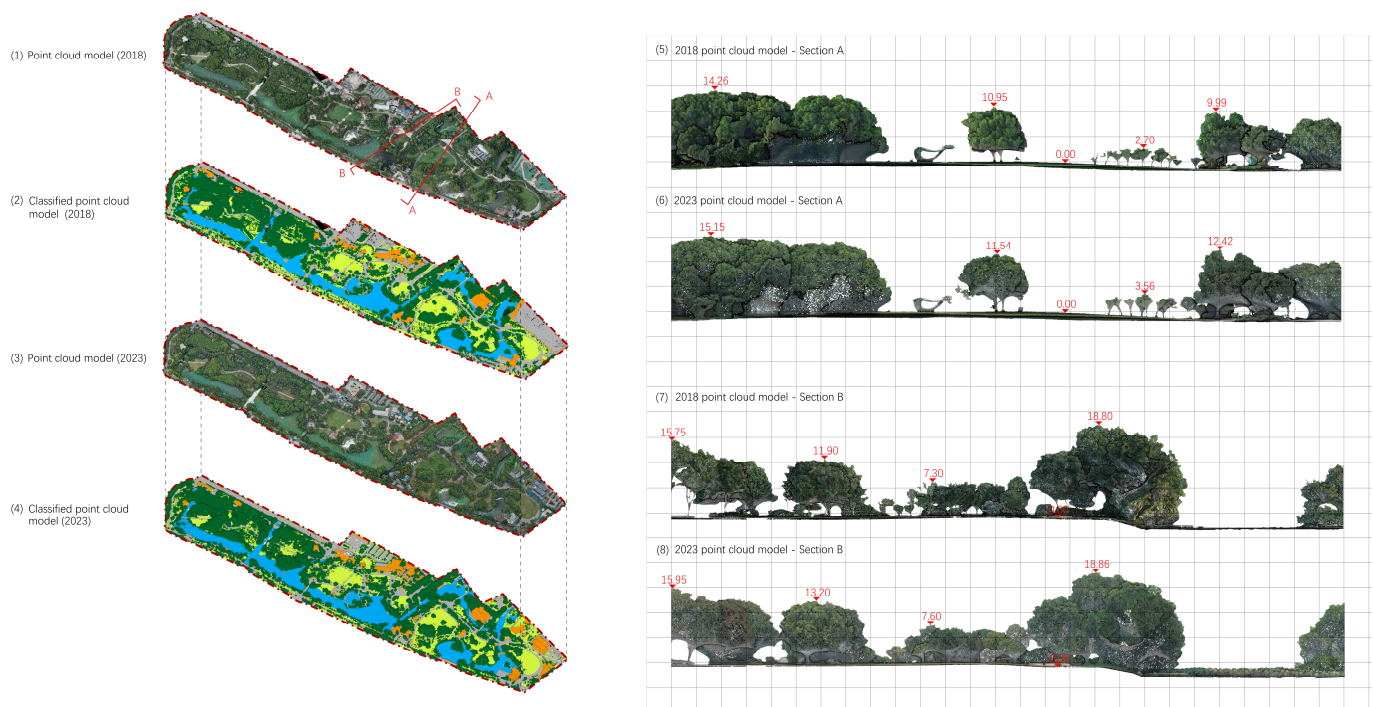


Figure 3. Differences between the point cloud models of the two periods.

In addition to these artificial renovations, changes in vegetation form over the five-year period also influence the visual characteristics of green spaces. We delved into the subtle changes in vegetation form by investigating two sections of the central area of QLY. Overall, the trees experienced an increase in height over the five years, with the highest increase recorded at 2.43 m. There was considerable variation in the extent of height growth among individual trees. For instance, in Section A, which encompasses the lawn area in the park centre, the trees exhibited a height increase from 10.95 m in 2018 to 11.55 m in 2023, marking a growth of 0.6 m. However, there was a notable disparity in the growth rate of trees on either side of the lawn. Specifically, the taller trees on the left side experienced a height increase of 0.89 m, while the shorter trees on the right side saw a height increase of 2.43 m. Similar disparities in tree height growth were observed in Section B. While the trees in the middle of Section B increased in height from 11.9 to 13.2 m, the taller trees on either side experienced marginal height increases of 0.2 and 0.06 m.

3.2. Changes in Visual Attributes before and after Five Years

Figure 4 illustrates the results of the analysis of the five visual attribute indicators across the 15 samples. In general, all the indicators exhibited some degree of change after five years. Although there are variations in the extent of changes between the indicators,

there are some similarities in the changes in the visual features across the samples. For example, OP, DV, and SVR generally decreased, while GVR increased after five years.



Figure 4. Comparison of visual attribute indicators before and after five years.

(1) Changes in openness (OP)

The openness of all the samples decreased over the five-year period except for sample A1 (Figure 4a–c). This exception may be attributed to the construction of its eastern bare side as a commercial street area. Notably, the lawn samples exhibited higher openness values compared to the path and plaza samples in 2018. For example, in 2018, the openness of the lawn samples was [82.4, 97.3] (Figure 4a), while the distribution interval of openness values for the path and plaza samples was [60.9, 86.6] (Figure 4b,c). However, after five years, the lawn samples experienced the lowest reduction in openness. The path and plaza samples, on the other hand, demonstrated greater reductions in openness values, with

sample B4 exhibiting the most significant reduction, from 68.8 to 59.9, indicating a decrease of 12.8% (Figure 4b).

(2) Changes in depth variance (DV)

Similar to openness, changes in depth variance exhibited an overall declining trend (Figure 4d–f). Individual samples showed notable changes, such as a 10% decrease in sample B4 (Figure 4e). The rest of the samples showed decreases of less than 6%. The changes in DV values for the lawn samples were minor compared to the path and plaza samples.

(3) Changes in green view ratio (GVR)

All the samples demonstrated an increase in GVR after five years except for sample A1 (Figure 4g–i). The decrease in vegetation and increase in architectural elements in sample A1 were attributed to the removal of some trees at the edge of the lawn. The magnitude of changes in GVR did not significantly differ among the three types of spatial samples. The largest increases were observed in samples A3 (16.1%), B5 (26.6%), and C3 (23.1%). These changes were primarily driven by alterations in vegetation. Samples A3 (Figure 4g) and B5 (Figure 4h) experienced an increase in shrub planting on the lawn in 2023, while sample C (Figure 4i) witnessed an increase in the canopy width of trees around the plaza.

(4) Changes in sky view ratio (SVR)

The changes in SVR exhibited a trend nearly opposite to that of GVR, with sky coverage decreasing after five years for all the samples except A1 (Figure 4j–l). However, compared to the changes in GVR, the decrease in SVR was relatively smaller. For instance, sample B4 experienced the largest decrease of 14.6% (Figure 4k). The lawn and plaza samples showed reductions in SVR values of less than 4% and 10%. It is notable that the distribution of SVR values and the changes in SVR for each sample mirrored those of OP, but the decrease in OP values was more pronounced. This discrepancy could be attributed to the growth of tree canopies in both vertical and horizontal dimensions over the five-year period, which reduced the distance between the canopy surface and observers, consequently reducing the area of sky visible in people's field of view.

(5) Changes in skyline complexity (SC)

The changes in SC presented significant differences from the other indicators, as the samples did not exhibit a uniform increase or decrease trend in values (Figure 4m–o). Variations in changes were observed among different types of samples. For instance, the SC of the plaza samples uniformly decreased, while the path samples demonstrated an increase in value for all the samples except B1, and the lawn samples displayed both increases and decreases in value. Regarding the magnitude of change, samples A1 (Figure 4m) and B1 (Figure 4n) exhibited the largest changes of 21.4% and 21.6%. The decrease in SC for sample A1 was primarily due to the replacement of trees on the fringe of the lawn with new buildings. In contrast, the trees on the border of sample B1 experienced growth over the five-year period, resulting in canopy connectivity and a decrease in SC.

3.3. Correlation of the Changed and Initial Values of Indicators

Table 2 depicts the results of a Spearman correlation analysis of the changes in visual characteristic indicators compared to their initial values from five years ago. A negative correlation is observed between SC and d_SC, with a correlation coefficient of -0.545 . However, correlations between SC and d_SC and the other indicators are notably weak. Additionally, correlations are observed between GVR and d_GVR, and SVR and d_GVR, with the correlation coefficients of 0.518 and -0.611 , respectively. d_GVR and GRV show a positive correlation, while d_GVR and SVR show a negative correlation. This suggests that when there are more green plants in the landscape space, the growth rate of GVR may also be higher.

Table 2. Spearman correlation analysis of the changes in visual indicators compared to their initial values.

	OP	DV	GVR	SVR	SC
d_OP	0.489 (0.064 *)	0.371 (0.173)	−0.282 (0.308)	0.329 (0.232)	−0.275 (0.321)
d_DV	0.496 (0.060 *)	0.382 (0.160)	−0.286 (0.302)	0.332 (0.226)	−0.3 (0.277)
d_GVR	−0.389 (0.152)	−0.225 (0.420)	0.518 (0.048 **)	−0.611 (0.016 **)	0.025 (0.930)
d_SVR	0.229 (0.413)	0.086 (0.761)	−0.279 (0.315)	0.421 (0.118)	0.000 (1.000)
d_SC	−0.013 (0.965)	0.009 (0.975)	0.036 (0.899)	0.084 (0.766)	−0.545 (0.036 **)

Notes: ** $p \leq 0.05$, * $p \leq 0.1$.

4. Discussion

4.1. Confirming the Long-Term Changes in Visual Attributes of Urban Green Spaces

Quantitatively describing the visual attributes of landscape space through visual indicators plays a role in assessing the quality of landscape space and supporting landscape design [13,22,46]. For example, previous studies have experimentally confirmed people's preference for landscape spaces with a high level of openness or complexity [19,47]. Although these thresholds on landscape visual indicators provide a reference for designers in urban green space design, achieving landscape spaces that align precisely with these findings is not always straightforward. As illustrated by Ode et al. [26] and demonstrated in this paper, the visual attributes of landscape spaces can change over a long period. Factors such as the growth and death of plants, as well as artificial pruning and renovation, all contribute to the change in visual attributes.

The findings of this study confirm that the visual attributes of urban green spaces undergo changes over a five-year period, with certain indicators experiencing notable fluctuations. Among all the samples, the maximum decrease in OP is 12.8%, and the maximum increase in GVR is 26.6%. This means that the same landscaped space may have deteriorated in spatial quality over a five-year period, which in turn may affect the vitality of the space and the activities of people [48]. For instance, Jiang et al. found that green spaces provide the highest degree of stress-relieving benefits to men when the percentage of trees in the field of view is 24–34% [49]. Sample B5 had a GVR of 28% in 2018 and 35.4% in 2023, exceeding the threshold range proposed by Jiang et al. This suggests that the monitoring of dynamic changes in the visual attributes of urban green spaces can provide some decision-making support for the management of green spaces. However, we do not know whether changes in the visual character of the same landscape space can lead to a significant reduction in landscape preference for residents who regularly spend time in the green space since factors such as familiarity with the landscape environment can also influence landscape preference [50].

The use of photographs in the studies of landscape change allows the rapid documentation of spatial change, but in addition to the requirements for the angle and position of the photographs, it is difficult to analyse the spatial depth and other three-dimensional visual features. For example, Hammond et al. found that the similarity of the photographs before and after two years was around 90% by calculating the similarity of the pictures after repeating the photographs at the same location in 2015, 2016, and 2017 [51]. Li showed by analysing the Google Street View images of New York City that the mean Green View Index of the study area increased from 19.33 to 19.77 from 2008–2013 to 2014–2018 [52]. Point clouds can not only accurately and intuitively show the changes in the spatial form of green spaces but also help in analysing 2D and 3D visual attributes [17]. In our analyses of multiple spatial samples in QLY, we not only analysed the changes in the visual attributes of each sample but also found that different types of spatial samples exhibit variations in the changes in various indicators. For instance, for OP and DV, the lawn samples showed a lower magnitude of change than the path and plaza samples. This could be difficult to achieve with the use of 2D images.

Similar to recording and understanding landscape changes through photographs taken over time [53,54], we can record spatial information of urban green spaces through

a repeated collection of point clouds in order to understand the changes in their visual attributes. In response to these changes, appropriate management strategies such as tree pruning can be developed to meet the needs of sustainability and conform to people's preferences.

4.2. Potential for Predicting Long-Term Changes in Visual Attributes of Urban Green Spaces

Grêt-Regamey and Fagerholm proposed that we need to use 3D digital environments to support an adaptive process between people's perceptions and planning proposals [55]. When our tools are unable to consider short- and long-term spatial and temporal dynamics, it will be difficult to propose effective novel governance strategies. By constructing a 3D visualisation platform, some studies developed a more realistic vision of the landscape design scheme and how the vision may change over time [56,57]. However, the dynamics of these platforms are often realised by applying a single rule of shape change to the same species of tree. The results of this study suggest that the spatial form and visual attributes of urban green spaces may show a more complex variation.

We hope to explore the potential for predicting changes in the visual attributes of urban green spaces. As shown in the results, certain correlations exist between some of the indicators. For example, the change in GVR may be related to the initial GVR and SVR. Notably, a strong negative correlation exists between changes in SC and the initial value, while correlations with other visual characteristic indicators are weak. However, we found that the variety of changes in the form of individual trees posed challenges in accurately discerning the mechanism of correlation between indicators. For instance, considering SC, its value was higher when trees had smaller crowns and gaps between each other in the early stages. As trees grew and canopies expanded, multiple canopies may eventually connect, leading to a decrease in SC. Additionally, differences in the growth rates of different trees further influenced changes in SC.

Studies have demonstrated that tree growth rates are influenced by various factors, including tree size, age, competition with neighbouring trees, and environmental conditions [58]. With advancements in fields such as forestry, growth simulation and shape prediction of trees have become possible [28,29,59]. The realisation of tree growth prediction will contribute to the exploration of the dynamics of the visual attributes of urban green spaces. Furthermore, when viewed over a long period of time, elemental changes in landscape space tend to receive the influence of more complex factors. For example, Roman et al. [60] analysed changes in tree canopy cover on a university campus through a combination of archival records and aerial imagery and found that the trees on campus were influenced by a combination of planting actions and management approaches, urban greening and city planning movements, and university faculty. Therefore, future studies on predicting long-term changes in the visual attributes of urban green spaces need to focus on the links between the properties of trees and their environmental conditions. Additionally, they should investigate the mechanisms of changes in visual attributes over longer time spans and with multiple recorded sources.

4.3. Limitations

This study utilised UAV 5-axis photography for collecting spatial data on urban green spaces. This method lacks data acquisition for the bottom layer of the canopy, which is often too dense to capture from aerial perspectives, resulting in difficulties in obtaining accurate information about tree trunks and branches. Future studies could consider obtaining more precise and complete point cloud models using ground-based or mobile LiDAR scanning, potentially aiding in predicting tree growth.

Additionally, our choice of QLY, established in the 1960s, as our study area means that most trees in the park are relatively old. As the growth rate of trees correlates with their age, the results of our study may not be directly applicable to parks with more recent construction dates. Moreover, the on-site pruning and maintenance of vegetation conducted by gardeners posed challenges in obtaining the records of manual maintenance

over the five-year period. Although we could infer changes in vegetation volume through point cloud modelling, we lacked information regarding whether these changes resulted from manual pruning. In the future, conducting long-term tracking surveys of urban green spaces and recording more comprehensive maintenance information could support the in-depth studies of changes in the visual attributes of urban green spaces.

5. Conclusions

The visual attribute of urban green space is one of the most important factors in shaping the quality of landscape space and influencing people's landscape preferences. However, previous studies often overlook the dynamic changes in landscape spaces, potentially hindering the applicability of their findings to design and maintenance practices.

This study proposed a novel approach using point clouds to examine the long-term changes in the visual attributes of urban green spaces, with a focus on a comprehensive urban park in Nanjing, China. Our investigation reveals that there could be considerable changes in visual indicators such as the green visual ratio (GVR) and the openness (OP) of urban green spaces. Although there is a correlation between indicators, such as skyline complexity (SC) and its change (d_SC), and between GVR and its change (d_GVR), it is still difficult to accurately describe the changing patterns and influencing factors. It is concluded that monitoring and analysing the long-term changes in the visual attributes of urban green spaces can support sustainable maintenance and design strategies. Future research could explore the evolving patterns of these visual attributes over extended timeframes and incorporate more diverse data sources based on the accurate simulation of the dynamic changes in trees and other environmental elements.

Despite some limitations, this study demonstrates the feasibility of exploring long-term changes in the visual attributes of urban green spaces using point clouds. This approach may be useful for exploring the dynamic changes in landscape space in the future.

Author Contributions: Conceptualisation, X.Z.; methodology, X.Z.; software, S.C.; formal analysis, X.Z. and Y.F.; investigation, X.Z.; resources, S.C. and X.Z.; data curation, X.Z. and Y.F.; writing—original draft preparation, X.Z. and Y.F.; writing—review and editing, S.C. and G.Z.; visualisation, X.Z. and Y.F.; funding acquisition, S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Fundamental Research Funds for the Central Universities, grant number 2242021R20016; Jiangsu Planned Projects for Postdoctoral Research Funds, grant number 2021K024A; China Postdoctoral Science Foundation, grant number 2021M700767; China Postdoctoral Science Foundation, grant number 2022T150115; National Natural Science Foundation of China, grant number 52108045; The Scholarship for Visiting Scholars of Key Laboratory of New Technology for Construction of Cities in Mountain Area, grant number LNTCCMA-20240106 and China Scholarship Council, grant number 202206090038.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the corresponding author.

Acknowledgments: We would like to thank Yuanfei Ma for his support in software and equipment, Chaoming Li and Yijing Wang for their technical assistance in the point cloud data acquisition and processing and Yuning Cheng for his support throughout this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lam, W.W.Y.; Loo, B.P.Y.; Mahendran, R. Neighbourhood environment and depressive symptoms among the elderly in Hong Kong and Singapore. *Int. J. Health Geogr.* **2020**, *19*, 48. [[CrossRef](#)] [[PubMed](#)]
2. Reuben, A.; Rutherford, G.W.; James, J.; Razani, N. Association of neighborhood parks with child health in the United States. *Prev. Med.* **2020**, *141*, 106265. [[CrossRef](#)] [[PubMed](#)]
3. Vassos, E.; Agerbo, E.; Mors, O.; Pedersen, C.B. Urban–rural differences in incidence rates of psychiatric disorders in Denmark. *Br. J. Psychiatry* **2016**, *208*, 435–440. [[CrossRef](#)] [[PubMed](#)]

4. Chen, T.; Lang, W.; Li, X. Exploring the impact of urban green space on residents' health in Guangzhou, China. *J. Urban Plan. Dev.* **2020**, *146*, 05019022. [\[CrossRef\]](#)
5. Duan, J.; Wang, Y.; Fan, C.; Xia, B.; de Groot, R. Perception of urban environmental risks and the effects of urban green infrastructures (UGIs) on human well-being in four public green spaces of Guangzhou, China. *Environ. Manag.* **2018**, *62*, 500–517. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Madureira, H.; Nunes, F.; Oliveira, J.V.; Cormier, L.; Madureira, T. Urban residents' beliefs concerning green space benefits in four cities in France and Portugal. *Urban For. Urban Green.* **2015**, *14*, 56–64. [\[CrossRef\]](#)
7. Alcock, I.; White, M.P.; Wheeler, B.W.; Fleming, L.E.; Depledge, M.H. Longitudinal Effects on Mental Health of Moving to Greener and Less Green Urban Areas. *Environ. Sci. Technol.* **2014**, *48*, 1247–1255. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Chen, Y.; Liu, T.; Xie, X.; Marusic, B.G. What Attracts People to Visit Community Open Spaces? A Case Study of the Overseas Chinese Town Community in Shenzhen, China. *Int. J. Environ. Res. Public Health* **2016**, *13*, 644. [\[CrossRef\]](#)
9. Polat, A.T.; Akay, A. Relationships between the visual preferences of urban recreation area users and various landscape design elements. *Urban For. Urban Green.* **2015**, *14*, 573–582. [\[CrossRef\]](#)
10. Appleton, J. *The Experience of Landscape*; Wiley: Hoboken, NJ, USA, 1996.
11. Kaplan, R.; Kaplan, S. *The Experience of Nature: A Psychological Perspective*; Cambridge University Press: Cambridge, UK, 1989.
12. Grahn, P.; Stigsdotter, U.K. The relation between perceived sensory dimensions of urban green space and stress restoration. *Landsc. Urban Plan.* **2010**, *94*, 264–275. [\[CrossRef\]](#)
13. Tveit, M.; Ode, Å.; Fry, G. Key concepts in a framework for analysing visual landscape character. *Landsc. Res.* **2006**, *31*, 229–255. [\[CrossRef\]](#)
14. Purcell, A.T.; Lamb, R.J. Preference and naturalness: An ecological approach. *Landsc. Urban Plan.* **1998**, *42*, 57–66. [\[CrossRef\]](#)
15. Susaki, J.; Kubota, S. Automatic Assessment of Green Space Ratio in Urban Areas from Mobile Scanning Data. *Remote Sens.* **2017**, *9*, 215. [\[CrossRef\]](#)
16. Wu, J.; Lu, J. Spatial scale effects of landscape metrics on stream water quality and their seasonal changes. *Water Res.* **2021**, *191*, 116811. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Qi, J.; Lin, E.S.; Yok Tan, P.; Chun Man Ho, R.; Sia, A.; Olszewska-Guizzo, A.; Zhang, X.; Waykool, R. Development and application of 3D spatial metrics using point clouds for landscape visual quality assessment. *Landsc. Urban Plan.* **2022**, *228*, 104585. [\[CrossRef\]](#)
18. Zhao, Y.; Wu, B.; Wu, J.; Shu, S.; Liang, H.; Liu, M.; Badenko, V.; Fedotov, A.; Yao, S.; Yu, B. Mapping 3D visibility in an urban street environment from mobile LiDAR point clouds. *GIScience Remote. Sens.* **2020**, *57*, 797–812. [\[CrossRef\]](#)
19. Zhang, G.; Yang, J.; Wu, G.; Hu, X. Exploring the interactive influence on landscape preference from multiple visual attributes: Openness, richness, order, and depth. *Urban For. Urban Green.* **2021**, *65*, 127363. [\[CrossRef\]](#)
20. Sugiyama, T.; Thompson, C.W. Older people's health, outdoor activity and supportiveness of neighbourhood environments. *Landsc. Urban Plan.* **2007**, *83*, 168–175. [\[CrossRef\]](#)
21. Zhu, H.; Yang, F.; Bao, Z.; Nan, X. A study on the impact of Visible Green Index and vegetation structures on brain wave change in residential landscape. *Urban For. Urban Green.* **2021**, *64*, 127299. [\[CrossRef\]](#)
22. Zhang, X.; Lin, E.S.; Tan, P.Y.; Qi, J.; Waykool, R. Assessment of visual landscape quality of urban green spaces using image-based metrics derived from perceived sensory dimensions. *Environ. Impact Assess. Rev.* **2023**, *102*, 107200. [\[CrossRef\]](#)
23. Clark, P.E.; Hardegree, S.P. Quantifying Vegetation Change by Point Sampling Landscape Photography Time Series. *Rangel. Ecol. Manag.* **2005**, *58*, 588–597. [\[CrossRef\]](#)
24. Kienast, F.; Frick, J.; van Strien, M.J.; Hunziker, M. The Swiss Landscape Monitoring Program—A comprehensive indicator set to measure landscape change. *Ecol. Model.* **2015**, *295*, 136–150. [\[CrossRef\]](#)
25. Liu, T.; Yang, X. Monitoring land changes in an urban area using satellite imagery, GIS and landscape metrics. *Appl. Geogr.* **2015**, *56*, 42–54. [\[CrossRef\]](#)
26. Ode, Å.; Tveit, M.S.; Fry, G. Advantages of using different data sources in assessment of landscape change and its effect on visual scale. *Ecol. Indic.* **2010**, *10*, 24–31. [\[CrossRef\]](#)
27. Smardon, R.C. Perception and aesthetics of the urban environment: Review of the role of vegetation. *Landsc. Urban Plan.* **1988**, *15*, 85–106. [\[CrossRef\]](#)
28. Rotzer, T.; Rahman, M.A.; Moser-Reischl, A.; Pauleit, S.; Pretzsch, H. Process based simulation of tree growth and ecosystem services of urban trees under present and future climate conditions. *Sci. Total. Environ.* **2019**, *676*, 651–664. [\[CrossRef\]](#)
29. Vaz Monteiro, M.; Levanič, T.; Doick, K.J. Growth rates of common urban trees in five cities in Great Britain: A dendrochronological evaluation with an emphasis on the impact of climate. *Urban For. Urban Green.* **2017**, *22*, 11–23. [\[CrossRef\]](#)
30. Yang, J.; Zhang, M.; Zhang, J.; Lu, H.; Hauer, R.J. Allometric Growth of Common Urban Tree Species in Qingdao City of Eastern China. *Forests* **2023**, *14*, 472. [\[CrossRef\]](#)
31. Speak, A.F.; Salbitano, F. The impact of pruning and mortality on urban tree canopy volume. *Urban For. Urban Green.* **2023**, *79*, 127810. [\[CrossRef\]](#)
32. Duryea, M.L.; Blakeslee, G.M.; Hubbard, W.G.; Vasquez, R.A. Wind and trees: A survey of homeowners after Hurricane Andrew. *J. Arboric.* **1996**, *22*, 44–50. [\[CrossRef\]](#)
33. Zhao, W.; Zhang, L.; Li, X.; Peng, L.; Wang, P.; Wang, Z.; Jiao, L.; Wang, H. Residents' Preference for Urban Green Space Types and Their Ecological-Social Services in China. *Land* **2022**, *11*, 2239. [\[CrossRef\]](#)

34. Walz, U. Monitoring of landscape change and functions in Saxony (Eastern Germany)—Methods and indicators. *Ecol. Indic.* **2008**, *8*, 807–817. [\[CrossRef\]](#)
35. Bayr, U. Quantifying historical landscape change with repeat photography: An accuracy assessment of geospatial data obtained through monoplottting. *Int. J. Geogr. Inf. Sci.* **2021**, *35*, 2026–2046. [\[CrossRef\]](#)
36. Walz, U.; Hoechstetter, S.; Dräguţ, L.; Blaschke, T. Integrating time and the third spatial dimension in landscape structure analysis. *Landsc. Res.* **2015**, *41*, 279–293. [\[CrossRef\]](#)
37. Larkin, A.; Hystad, P. Evaluating street view exposure measures of visible green space for health research. *J. Expo. Sci. Environ. Epidemiol.* **2019**, *29*, 447–456. [\[CrossRef\]](#)
38. Yang, Y.; Lu, Y.; Yang, H.; Yang, L.; Gou, Z. Impact of the quality and quantity of eye-level greenery on park usage. *Urban For. Urban Green.* **2021**, *60*, 127061. [\[CrossRef\]](#)
39. Tang, L.; He, J.; Peng, W.; Huang, H.; Chen, C.; Yu, C. Assessing the visibility of urban greenery using MLS LiDAR data. *Landsc. Urban Plan.* **2023**, *232*, 104662. [\[CrossRef\]](#)
40. Urech PR, W.; Dissegna, M.A.; Girot, C.; Grêt-Regamey, A. Point cloud modeling as a bridge between landscape design and planning. *Landsc. Urban Plan.* **2020**, *203*, 103903. [\[CrossRef\]](#)
41. Xiao, W.; Cao, H.; Tang, M.; Zhang, Z.; Chen, N. 3D urban object change detection from aerial and terrestrial point clouds: A review. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *118*, 103258. [\[CrossRef\]](#)
42. Yijing, W.; Yuning, C. Construction and analysis of 3D scene model of landscape space based on UAV oblique photography and 3D laser scanner. *J. Digit. Landsc. Archit.* **2018**, *3*, 283–290.
43. Yokoya, N.; Nakazawa, S.; Matsuki, T.; Iwasaki, A. Fusion of hyperspectral and LiDAR data for landscape visual quality assessment. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 2419–2425. [\[CrossRef\]](#)
44. Wang, R.; Jiang, W.; Lu, T. Landscape characteristics of university campus in relation to aesthetic quality and recreational preference. *Urban For. Urban Green.* **2021**, *66*, 127389. [\[CrossRef\]](#)
45. Hu, T.; Wei, D.; Su, Y.; Wang, X.; Zhang, J.; Sun, X.; Liu, Y.; Guo, Q. Quantifying the shape of urban street trees and evaluating its influence on their aesthetic functions based on mobile lidar data. *ISPRS J. Photogramm. Remote. Sens.* **2022**, *184*, 203–214. [\[CrossRef\]](#)
46. Huang, J.; Liang, J.; Yang, M.; Li, Y. Visual Preference Analysis and Planning Responses Based on Street View Images: A Case Study of Gulangyu Island, China. *Land* **2022**, *12*, 129. [\[CrossRef\]](#)
47. Liu, Q.; Zhu, Z.; Zeng, X.; Zhuo, Z.; Ye, B.; Fang, L.; Huang, Q.; Lai, P. The impact of landscape complexity on preference ratings and eye fixation of various urban green space settings. *Urban For. Urban Green.* **2021**, *66*, 127411. [\[CrossRef\]](#)
48. Wang, M.; Qiu, M.; Chen, M.; Zhang, Y.; Zhang, S.; Wang, L. How does urban green space feature influence physical activity diversity in high-density built environment? An on-site observational study. *Urban For. Urban Green.* **2021**, *62*, 127129. [\[CrossRef\]](#)
49. Jiang, B.; Chang, C.-Y.; Sullivan, W.C. A dose of nature: Tree cover, stress reduction, and gender differences. *Landsc. Urban Plan.* **2014**, *132*, 26–36. [\[CrossRef\]](#)
50. Mangone, G.; Dopko, R.L.; Zelenski, J.M. Deciphering landscape preferences: Investigating the roles of familiarity and biome types. *Landsc. Urban Plan.* **2021**, *214*, 104189. [\[CrossRef\]](#)
51. Hammond, W.M.; Stone ME, B.; Stone, P.A. Picture worth a thousand words: Updating repeat photography for 21st century ecologists. *Ecol. Evol.* **2020**, *10*, 14113–14121. [\[CrossRef\]](#)
52. Li, X. Examining the spatial distribution and temporal change of the green view index in New York City using Google Street View images and deep learning. *Environ. Plan. B Urban Anal. City Sci.* **2020**, *48*, 2039–2054. [\[CrossRef\]](#)
53. Cerney, D.L. The use of repeat photography in contemporary geomorphic studies: An evolving approach to understanding landscape change. *Geogr. Compass* **2010**, *4*, 1339–1357. [\[CrossRef\]](#)
54. Millington, J.A.; Booth, C.A.; Fullen, M.A.; Moore, G.M.; Trueman, I.C.; Worsley, A.T.; Richardson, N.; Baltreinaite, E. The role of long-term landscape photography as a tool in dune management. *J. Environ. Eng. Landsc. Manag.* **2009**, *17*, 253–260. [\[CrossRef\]](#)
55. Grêt-Regamey, A.; Fagerholm, N. Key factors to enhance efficacy of 3D digital environments for transformative landscape and urban planning. *Landsc. Urban Plan.* **2024**, *244*, 104978. [\[CrossRef\]](#)
56. Lange, E.; Hehl-Lange, S. Making visions visible for long-term landscape management. *Futures* **2010**, *42*, 693–699. [\[CrossRef\]](#)
57. Yu, H.; Wu, M.M.; He, H.S. Developing platform of 3-D visualization of forest landscape. *Environ. Model. Softw.* **2022**, *157*, 105524. [\[CrossRef\]](#)
58. Zhang, Z.; Papaik, M.J.; Wang, X.; Hao, Z.; Ye, J.; Lin, F.; Yuan, Z. The effect of tree size, neighborhood competition and environment on tree growth in an old-growth temperate forest. *J. Plant Ecol.* **2017**, *10*, 970–980. [\[CrossRef\]](#)
59. Hu, X.; Zhang, H.; Yang, G.; Qiu, H.; Lei, K.; Yang, T.; Liu, Y.; Zuo, Y.; Wang, J.; Cui, Z. Visual Simulation Research on Growth Polymorphism of Chinese Fir Stand Based on Different Comprehensive Grade Models of Spatial Structure Parameters. *Forests* **2023**, *14*, 617. [\[CrossRef\]](#)
60. Roman, L.A.; Fristensky, J.P.; Eisenman, T.S.; Greenfield, E.J.; Lundgren, R.E.; Cerwinka, C.E.; Hewitt, D.A.; Welsh, C.C. Growing Canopy on a College Campus: Understanding Urban Forest Change through Archival Records and Aerial Photography. *Environ. Manag.* **2017**, *60*, 1042–1061. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.