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Research on Landscape Perception and Visual Attributes Based on Social Media Data—A Case Study on Wuhan University

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Abstract: With the rapid rise of social media, the photo-taking behavior of tourists and their uploaded photos provide a new perspective to explore landscape visual characters. In this study, we provide methodological advancements for assessing landscape visual quality based on content analysis of user-generated photographs. The purpose is to demonstrate an empirical method for evaluating visual indicators reflected in photographs through a case study application. This research takes the core cultural landscape area of Wuhan University as the research scope. The photographs shared on a famous Chinese social media platform Sina Weibo during the Cherry Blossom Festival, together with tourists' trajectory data, were used as data sources. Based on a fixed-point photography experiment, the spatial relationship between the scenic spot and the observation point was illustrated. Utilizing a semi-automatic photo content analysis founded on computer vision technology, landscape visual attributes of each attraction were studied thoroughly regarding complexity, visual scale, and color. The results indicate that the Old Dormitory is the most popular scenic spot with diverse viewing angles, strikingly vivid colors, and rich color combinations. Complexity and color play key roles in landscape visual quality, while the depth of view has a subtle impact, which suggests the depth-to-height ratio of less than 1 is the best distance for viewers to take photographs. In all, the mapping relationship between landscape visual attributes and viewers' perception was revealed in the present work.

Keywords: landscape visual characters; landscape perception; social media data; computer vision technology; content analysis; photographic behavior



Citation: Zhang, X.; Xu, D.; Zhang, N. Research on Landscape Perception and Visual Attributes Based on Social Media Data—A Case Study on Wuhan University. *Appl. Sci.* **2022**, *12*, 8346. <https://doi.org/10.3390/app12168346>

Academic Editor: Alexandros A. Lavdas

Received: 30 July 2022

Accepted: 19 August 2022

Published: 20 August 2022

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1. Introduction

According to the European Landscape Convention (ELC), “The landscape is part of the land, as perceived by local people or visitors, which evolves through time as a result of being acted upon by natural forces and human beings” [1]. This definition explicitly emphasizes the interaction between humans and landscape, highlighting landscape characters [2]. Landscape character can be described as “the presence, variety, and arrangement of landscape features, which give a landscape a specific identity” [3].

The fact that humans make vital visual connections with the environment is critical in landscape management and planning [4]. There is a large volume of published studies attempting to identify concepts for visual landscape characters. Through experiments, some researchers find that the relative degree of terrain undulation, the number of elements in the landscape, and the landform play important roles [5–8]. Litton [9,10] used Landscape Control Points to study landscape characters and visual impacts, concluding with basic design elements such as lines, form, color, and texture. Wohlwill [11] conducted a landscape viewing test on 45 people by varying the richness of the test photos, proposing that the human can see five to seven visual landscape elements. Coeterier [12] described the dominant attributes of the Dutch landscape as unity, its function, development in time, maintenance, spaciousness, naturalness, soil and water, and sensory qualities such as color and smell.

Based on research on landscape perception and evaluation, Tveit et al. [13] identified nine key visual concepts which are stewardship, historicity, coherence, disturbance, visual scale, complexity, imageability, naturalness, and ephemera. They proposed a framework of four levels relating to visual character assessment: concepts > dimensions > landscape attributes > indicators. Their identifications of visual characters are comprehensive and consistent with the ELC, which has been used in a few studies [3,14].

Landscape character assessment (LCA) is recognized as a tool for dynamic management concerning regional identity [15]. Since the 1970s, several methods for LCA have been applied, depending on the different aims of the assessment [16]. Briggs and France [17] found that there are two main methods for the evaluation of landscape: direct and indirect approaches. Direct methods are applied to compare public preferences for landscape [17,18], while indirect methods evaluate landscape by analyzing the presence or intensity of designated characters [19]. Similarly, Torres Sibille et al. [20] suggest that the aesthetic of landscape comprises both an objective part, which includes physical features, and a subjective part, which involves human perception. When the aim is to analyze the impact of human activities on a landscape, identifiable landscape attributes and physical elements are usually used in an assessment [21,22]. In visual landscape assessments, three models have been applied widely [23], which are scenic beauty estimation [24], landscape character assessment [25], and visual resource management [26]. For scenic beauty estimation, Cañas et al. [16] validated a model including 42 landscape attributes and explored which attributes are the most significant in their evaluations. As for landscape visual characters, landscape indicators provide a more objective basis for identifying features by dividing the totality of our visual perception into quantifiable characteristics [2]. Though visual landscape indicators are less developed than those for other functions of landscape [27], there has been increased emphasis on identifying visual indicators and evaluating landscape visual quality. Fry et al. [14] indicated that the visual and ecological landscape indicators share many common aspects relating to landscape structure. Badach and Raszeja [28] divided visual indicators into four categories: visual preferences landscape indicators, landscape visual character indicators, GIS-based landscape appreciation model indicators, and indicators based on the digital panoramic view analysis. Jessel [29] developed a method for registering the visual landscape on an element level, shape level, and space level, with the aim of describing changes in landscape structure and shape according to their intensity and character on different complexity levels. Built on the conceptual framework of four levels [13], Ode et al. [2] present an approach for capturing the visual character of a landscape, which is chosen as the method of this study. Based on previous studies on visual concepts, landscape preferences and landscape aesthetics, Ode et al.'s theoretical framework has represented the level at which the landscape could be quantified and measured, taking both empirically tested and suggested visual indicators into account. Furthermore, Ode et al. [2] have stated a filter approach that can help select an appropriate set of visual indicators for application within a specific landscape context. For all these reasons, the concept-indicator framework developed by Ode et al. is a suitable approach for describing visual indicators, identifying physical attributes, and laying the basis for landscape visual quality evaluation.

As the purpose of the study changes, the theoretical base and data source will vary depending on the information they can provide about a landscape. Ramírez et al. [30] state that the most exhaustive approach to assessment includes direct observation in the field. Some authors explore landscape preferences by evaluating cognitive aspects such as openness, coherence, harmony, and others [31,32]. Hence, for preference studies conducted through the perception of the evaluator, photographs are frequently used as representations of landscape [30,33,34]. In such studies, what is being rated is the character the photos represent. However, photographs may have limitations because it is difficult to capture the diversity of potential views and evaluate certain factors by using photographs [35]. In addition, the difficulty of offering a representative photo sample is stressed by several researchers [36]. Some authors suggest that a combined method using several data sources—

including field observations, landscape photographs, aerial photographs, and land cover data—will be the most appropriate [36–39].

Since the emergence of Web 2.0 technology [40], the rise of social media has opened up new paths for landscape visual character studies. The number of photos containing location-related information is increasing on social media platforms, leading to the fast development of crowdsourced geospatial data [40]. Uploading and sharing photographs on social networks such as Flickr, Panoramio, and Instagram have become prominent [41–43]. According to Zhang et al. [44], there are three main approaches for the application of online photo data in research: the study of text attached by photos, the study of metadata embedded by photos, and the study of the photos' visual content itself. As Albers and James argued [45], content analysis of landscape photographs is an observational approach to coding and analyzing the frequency of certain visual attributes and elements. To date, previous studies have analyzed crowdsourced geotagged photographs for assessing landscape features at different levels. At regional scales, Oteros-Rozas et al. [46] perform a content analysis of 1404 photos uploaded on Flickr and Panoramio platforms, and analyze the landscape features across five sites in Europe. At local scales, authors use content analysis of spatial photos to pinpoint what it is in a landscape to attract people [47,48]. However, based on computer vision technology related to deep learning, most research focuses on cultural ecosystem services and people's perception of landscape through the clustering of photo locations and recognition of different scenes [44,49,50]. Only a few researchers have explored the exact visual indicators in social media photos. For example, Tenerelli et al. [51] applied the geotagged photos uploaded on Flickr to analyze the characteristics of the landscape through a viewshed-based approach. Recent studies have not been able to precisely link the photo analysis of social media data to landscape visual quality theories as well as visual indicators.

Consequently, compared to traditional data collection, big data has advantages. It is an unstoppable tendency to use deep-going mining for applying user-generated photos to landscape visual quality research in the social network-occupied era [44]. At present, there are two main methods of research related to visual content analysis: one is the traditional way, which manually recognizes the visual contents of photographs, and the other is an emerging way based on computer vision technology. Though the research using the emerging approach has an advantage in the size of the sample and relatively precise analysis, most of the prior studies based on machine learning lack a mature theoretical and conceptual framework.

From this overview, it appears that the photo analysis of landscape visual indicators based on geotagged social data needs more evidence to understand the mapping of the observer's perception of the landscape. In the present study, the theoretical framework of Ode et al. [2] and the landscape attributes of Cañas et al. [16] served as bases to determine appropriate visual indicators reflected in social media photographs. This study aims to analyze user-generated digital photographs uploaded on a famous Chinese social platform Sina Weibo (hereinafter referred to as Weibo), to select the most popular scenic spot in a cultural landscape and characterize the content itself in terms of its landscape visual indicators. In the following, we present an attempt at our methodology, starting from its very first step in exploring the most popular scenic spots through online hotness data, up to (a) the density and diversity analysis of landscape attributes in each scenic spot, (b) the analysis of the depth of view in each scenic spot, and (c) the analysis of color in each scenic spot as reflected in the user-generated photographs. In the evolution of our work description, we shall also demonstrate some intermediate steps, such as defining a close-up view, medium view, and long-range view through a vision in the photograph and applying MATLAB to the analysis of color. The key contribution of this work is that the mapping relationship between landscape visual attributes reflected in photographs and public perception was reported. Moreover, we linked traditional landscape theories with computer vision technology related to social media data, combining both the theoretical base and emerging techniques. Another contribution is that we expanded the fixed-point

photography experiment into a more accurate way of measuring the visual scale, on the basis of the distance-to-height ratio.

In sum, the analysis focuses on the following questions:

1. Where are observers interacting with the cultural landscape?
2. What is it in a landscape that attracts people? Which landscape visual attributes are the most significant in observers' perception?

2. Materials and Methods

This chapter analyses the materials and the methodology applied in the study.

2.1. Study Area

The core cultural landscape area (Figure 1) is a typical tourist attraction in the center of Wuhan University. Wuhan University is located in Wuhan city, the capital of Hubei province, which is at the foot of Luoja Mountain and adjacent to East Lake. Known as one of the most beautiful universities in China, Wuhan University is characterized by its spectacular scenery and picturesque environment. Among all features, the elegant palatial historical buildings are the most attractive to people, which is a combination of Chinese and Western architectural styles. Especially in the core cultural landscape area, there are seven famous buildings acknowledged as must-visit scenic spots (Figure 1b): Wuhan University Library, the Old Dormitory, Neo-confucianism Building, Yifu Building, College of Engineering, Wanlin Art Museum, and Songqing Gymnasium. As Wanlin Art Museum was built in a different architectural style from the early buildings, this study shall only select 6 buildings in the core landscape area. Among these 6 buildings, Yifu Building was built in the 1990s, while the other five buildings were built in the 1930s with the same history. To maintain a unified style with the early architecture, Yifu Building used homogeneous elements such as green roof and geometric forms.

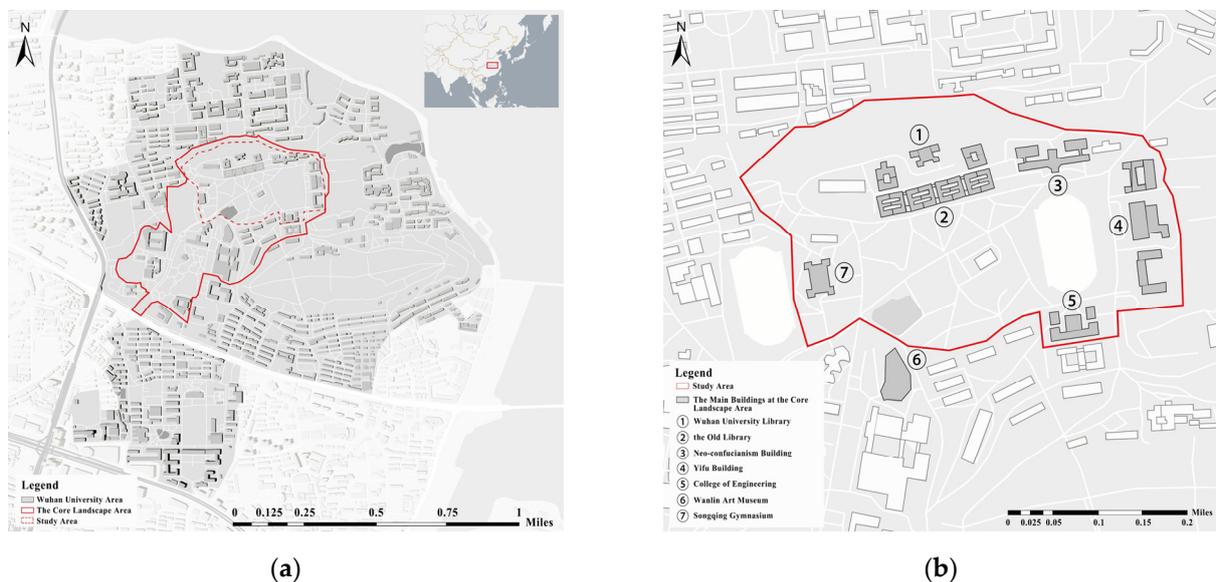


Figure 1. Location of the case study area. (a) The study area is located in Hubei province, China. The gray area represents the Wuhan University area, while the area within the red line represents the core cultural landscape area; (b) it shows 7 main buildings in the core landscape area.

Since the “Cherry Blossom Festival” at Wuhan University has become a countrywide social and cultural hotspot, the interaction between visitors and the landscape during the cherry viewing period is worthy of in-depth study [52]. Throughout the seasonal “Cherry Blossom Festival”, a large number of people visited Wuhan University. Visitors took photographs of the buildings from different viewpoints and uploaded them on Weibo. There is

a mapping relationship between photographs on social media and people's perception of the landscape. Based on visitors' photo-taking behavior and photographs with geographical location, the most popular view of the core cultural landscape area and most preferable landscape visual characters can be elucidated.

2.2. Data

As a proxy for people's opinions and perceptions, the research used content on the Weibo platform. In the era of information explosion, social media has satisfied people's constant interaction and instant access to information. Weibo, which has 528 million monthly active users, is one of the most influential social media platforms in China [53]. This study chose Weibo because other social media platforms such as WeChat and Douyin feature chatting or short videos. Weibo mainly aims to contain valuable text and photo contents with geographical information. Based on keywords and hashtags, trending topics on Weibo may capture timely hot spots and reflect users' attention and attitude to social events.

Considering the temporal efficiency of the Internet, this paper selected records on Weibo on 23 March 2019, which was during the mid-Cherry Blossom Festival, as a sample. Therefore, taking "Wuhan University Library", "the Old Dormitory", "Neo-confucianism Building", "Yifu Building", "College of Engineering", and "Songqing Gymnasium" as keywords separately, the search volume and the number of likes on Weibo were counted. Table 1 shows the statistics of each spot. It is clearly seen (Table 1) that the Old Dormitory, Wuhan University Library, and the College of Engineering are the most popular scenic spots among visitors.

Table 1. The search volume and the number of likes of each scenic spot on Weibo within one day.

Name of the Spot	Search Volume	The Number of Likes
Wuhan University Library	17,841	105,400
The Old Dormitory	21,521	125,000
Neo-confucianism Building	7581	37,500
Yifu Building	6576	27,500
College of Engineering	16,034	97,580
Songqing Gymnasium	8156	69,500

To figure out what landscape visual characters lying in these popular spots attract observers, further studies were conducted.

2.2.1. Weibo Dataset

Selecting "Wuhan University" as a keyword, we searched photos on Weibo related to the hashtag of Wuhan University on 23 March 2019. Using automated API requests with Python, the data were downloaded from the Weibo server. Both the actual photo and the meta-data (geo-tag, upload date and time, user name, and the number of likes, comments, and forwards) were downloaded. Only landscape photographs were preserved through manual recognition, while photographs of people, other buildings, or vehicles were excluded. Based on the text content embedded in the data, photographs were classified into 6 groups, which represented 6 scenic spots. Sorted by the number of likes, we chose the top 100 photographs of each spot as a dataset. The Weibo dataset contained 600 photos in total, which were used as research materials. According to the Sina Weibo certification list of the dataset, there were 385 personal users and 215 official accounts, which can show public preferences for the core landscape area. The ratio of male users to female users was about 1.5. Considering sex has no significant influence on landscape preference in prior studies, this paper did not explore the gender differences on landscape evaluation.

2.2.2. Trajectory Dataset

We developed a mini program on WeChat called Architectural Tour in Wuhan University, which supported users to record their spatial locations and behavioral trajectory. On 23 March 2019, the mini program was used about 6000 times, resulting in more than 100,000 observations. Downloaded from the back-end program, 124,210 trajectory points were saved as a dataset. The trajectory dataset can reflect observers' preference for landscape (Figure 2).

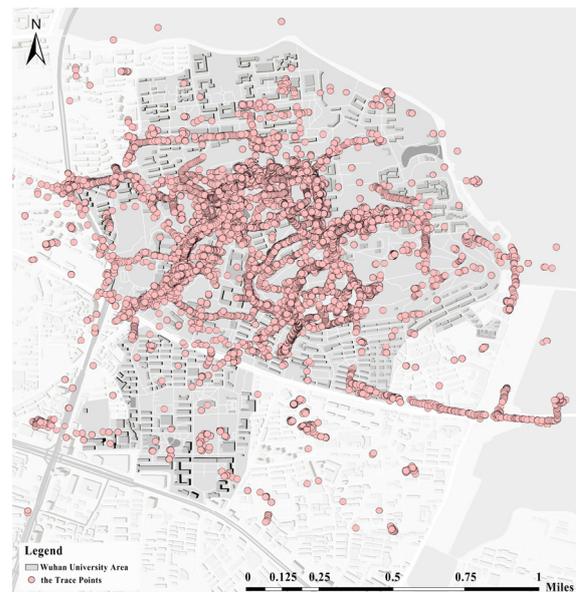


Figure 2. Trajectory points of observers.

2.3. Methodology

The method involved applying a visual method [16] and selecting indicators to quantify the character of the landscape, starting from fix-pointed photographs taken at some observation points in the field. Through the experiment of fixed-point photography, we explored the spatial relationship between the scenic spot and viewpoints.

Following the study of Ode et al. [2], their conceptual scheme enables the linking of visual indicators to landscape aesthetic theory based on four levels. These 9 concepts that characterize the landscape can be divided into two groups: those calculated for the observation points, and those calculated for the whole territory [3]. Given that this study aims at interpreting the visual characters reflected in photographs, only two visual concepts which are most relevant for landscape photographs were selected: the complexity and the visual scale. The indicators for complexity were calculated for the whole scenic spot, while the indicators for visual scale were obtained at the viewpoints. Additionally, in the assessment of the scenic beauty of the landscape, color plays a vital role in terms of aesthetic attributes [16]. Thus, the saturation and hue of color in photographs were chosen as visual indicators as well [54].

2.3.1. Fixed-Point Photography

According to the Weibo dataset, it is found that the photo content consists of the building and its environment. Observers perceive the landscape through senses from different dimensions. To interpret the photo-taking behavior, a visual experiment was conducted.

Yoshinobu Ashihara [55] defined the external modulus theory, in which he suggested every 20–25 m as a module to change the vision of the urban environment. According to Jan Gehl [56], 100 m and 25 m are two main thresholds for overview and detailed scale in the urban planning context. Hence, scale is influenced by the distance between the human body and the object. By setting the building height as H and the distance between adjacent

buildings as D , Yoshinobu pointed out that the distance-to-height (D/H) ratio reflects the interaction of two buildings. Taking the ratio of 1 to 1 as a threshold, if the ratio is less than 1, it brings a sense of oppression. Conversely, as the ratio is more than 1, it creates a sense of distance [55]. From the consideration of Yoshinobu's theory and human scale, this study sets the scenic building's height as H and the distance between the observation point and the building as D . We identify the close-up view at the ratio less than 1, from which the details of the building can be accurately recognized. When the D/H ratio is between 1 to 1 and 2 to 1, observers can catch the building's dominant elements from the mid-range view. As for the long-range view, observers can identify the outline and shape of the building when the ratio is between 2 to 1 and 3 to 1.

Resorting to the photographic method Jan Gehl used to explain a social field of vision [56], we took photos in the field (Figure 3). As the building from different levels of view is displayed at different ratios in a layout, we can identify the distance and dimension between viewpoints and building through photographs.

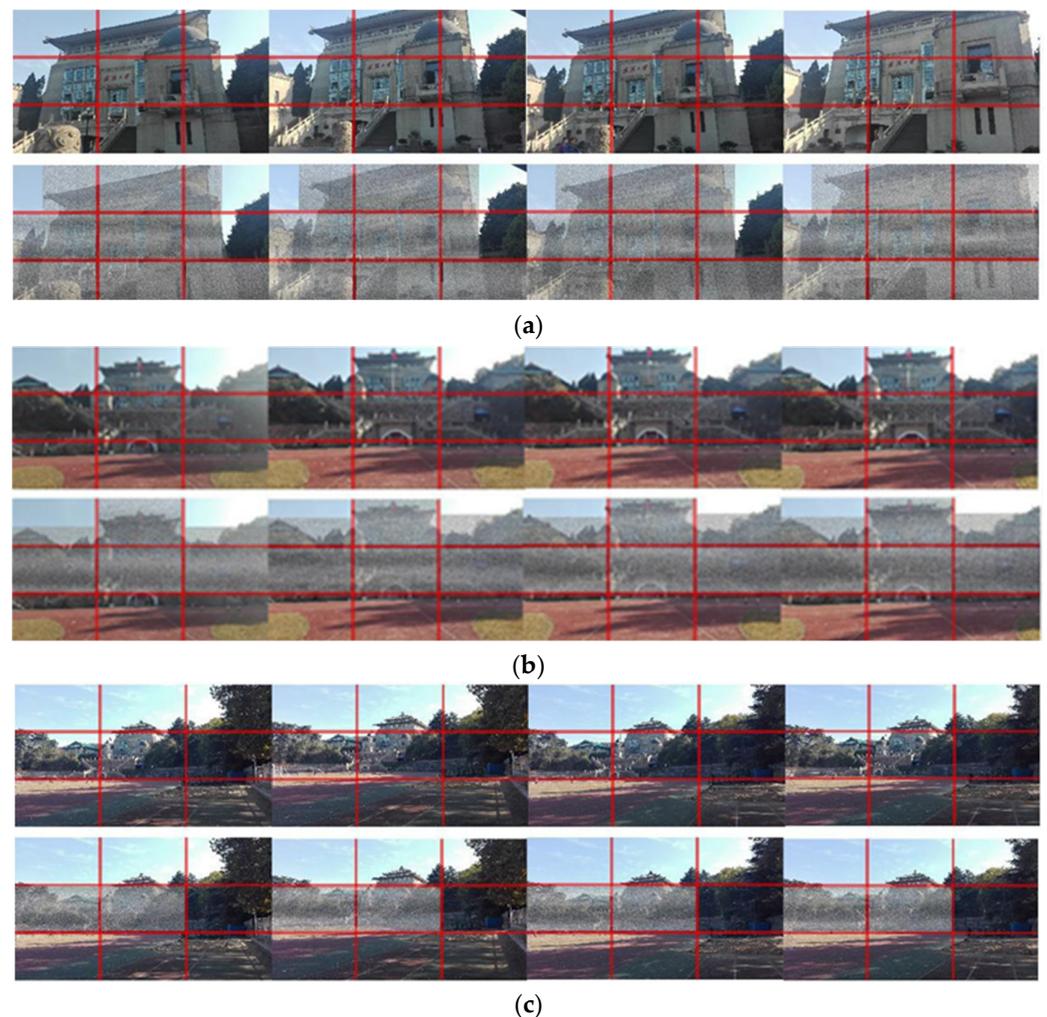


Figure 3. The fixed-point photography experiment. (a) Composition analysis of close-up photographs; (b) composition analysis of mid-range photographs; (c) composition analysis of long-range photographs.

After fixed-point photography, a grid overlay of 9 parts was used to quantify the proportions of the scenic spot in the photograph scenes [57]. The subject in close-up photos accounts for about 70% and above in a layout. The scenic building in mid-range landscape photos accounts for approximately 50% to 60% of a layout, while in long-range photos the subject covers almost 20% of the layout.

2.3.2. Complexity

The complexity concept is defined as the richness and diversity of landscape features and elements and the interspersed patterns in the landscape [13]. It is based on several theories. Presenting the Biophilia hypothesis, Kellert and Wilson [58] stress the importance of diversity regarding landscape types and species. Kaplan and Kaplan [59] mention that complexity is a component of information processing theories. Ode et al. [2] propose three dimensions to describe complexity: distribution of landscape attributes which focuses on the number of landscape elements, the spatial organization of patterns, as well as variation and contrast between landscape elements. As this study describes the number and range of landscape elements only, indicators of the spatial organization are not included.

To assess complexity, patch richness density PRD was chosen. As Urban et al. [60] point out, "A landscape is a mosaic of patches, the components of pattern". Several terms have been applied to identify the basic units or elements making up a landscape, such as landscape component, landscape unit, facies, and site [61]. Since environments are patchy in practice, patches may be defined as grain responses related to the distribution of activity among environmental units [62]. Moreover, patches must be explained considering the given situation. Camillo Sitte et al. [63] indicated that, from different perspectives, people would capture different views of the same object. Thus, in the context of visual units in landscape photographs, we defined photo angles of a scenic spot as patches. According to Mcgarigal et al. [64], PRD is defined as follows:

$$NP_i = N_i \quad PR_i = m_i \quad (1)$$

$$PRD_i = \frac{m_i}{A_i} (10,000) \quad (2)$$

where NP_i equals the number of patches of a particular type in the scenic spot i ; PR_i equals the number of different patch types corresponding to a scenic spot i ; and A_i equals the minimum area (m^2) of the scenic spot i covering all the photo angles, multiplied by 10,000.

As richness is one of the diversity metrics and partly a function of scale, PRD quantifies richness on a per area basis [64].

2.3.3. Visual Scale

The concept of visual scale defines the perceptual units with regard to their size, shape, diversity, and degree of openness in the landscape [2]. Visual scale can be mainly explained by Appleton's prospect-refuge theory [8], which indicates that humans have adapted to landscape offering both prospect and refuge. Two groups of indicators for assessing visual scale have been suggested by Ode et al. [2]: the indicators for measuring open area and obstruction of view.

The depth of view has been selected to assess the open area. Several studies have shown that depth has effects on the scale of landscape elements [65], which reveals that a moderate to a high level of depth can affect the observer's perception of involvement in the landscape [66,67]. Photographs are commonly used to assess the depth of view. Hull and Buhyoff [68] took photos of landscapes at various distances from the topographic features, and the average of the distance was 100 feet. In this research, we conducted a photographic experiment to define the close-up view, mid-range view, and long-range view corresponding to the concepts of foreground, middle ground, and background. The indicator is expressed as follows:

$$V_i = \text{the proportions of photos of the view } (1-3)^a \text{ related to a scenic spot} \quad (3)$$

^a e.g., 1 = close-up; 2 = mid-range; 3 = long-range.

The V_i indicator describes the distribution of different levels of view associated with each scenic spot. The standard deviation and extreme deviation of photos at different levels related to a scenic spot were selected as well.

2.3.4. Color

The concept of color plays the main role in the relationship between the building and its environment, which reflects the harmony and compatibility of the landscape [69]. According to the USA Bureau of Land Management, color is one of the factors for visual landscape quality assessment, which compares the variety, contrast, and harmony of the color [70]. Garcia et al. [54] indicate that color is defined by its hue, saturation, and lightness, and building colors can affect its integration into the landscape. Several studies have used the number of colors or the contrast of color as indicators to assess the visual quality [21,71,72].

The contrast between the colors of the building and environment, the arithmetic means of saturation, and the standard deviation of hue were selected to assess the color of each scenic spot. The indicators are defined as follows:

$$CC_i = \text{color contrast} \quad (4)$$

$$AMS_i = \text{the arithmetic means of saturation} \quad (5)$$

$$SDH_i = \text{the standard deviation of hue} \quad (6)$$

Based on the HSV color model, we used the Image Processing Toolbox in MATLAB to calculate the values of digital photographs in the Weibo dataset. These indicators suggest different aspects of color. Some contrasts may break the scene's unity and consequently its compatibility. Saturation refers to the purity of color. Perception of the scene changes when the hue values vary from the warmest color to the coldest [54].

3. Result

3.1. Complexity

In Figure 4, the number of different types of photo angles within each scenic spot is presented. With nine types of views, the Old Dormitory has the richest camera angles covering all facades. The shooting angles of Wuhan University Library, the College of Engineering, and Songqing Gymnasium focus on the main and secondary façade, while the photographs of the Neo-confucianism Building and Yifu Building are taken mostly from the main road.



Figure 4. Analysis of landscape visual complexity.

From the analysis of Table 2, it can be concluded that the PRD index represents the richness of the scenic spot views. With the maximum PRD value of 52.26, the Old Dormitory

provides the richest and most diverse visual elements to the landscape scene based on various architectural facades. Furthermore, there is a 100-step staircase throughout the Old Dormitory, which offers visitors space to observe different scenes. The scenic spot with the second highest PRD index is Wuhan University Library. With the minimum PRD index of 14.27, observers have limitations for visual perception of the Yifu Building. Due to the confined site of the Yifu Building, visitors can only take photographs from fewer angles compared to other attractions.

Table 2. Values of landscape visual indicators depicted in photographs in each study scenic spot.

Name of the Spot	Complexity			Visual Scale			Color		
	PR _i	A _i (m ²)	PRD _i	% Value of View1:View2:View3	The Standard Deviation of V _i	Extreme Deviation of V _i	CC _i	AMS _i	SDH _i
Wuhan University Library	7	1589	44.05	58:26:16	17.91	42	65.80	0.28	0.22
The Old Dormitory	9	1722	52.26	63:28:9	22.37	54	67.61	0.31	0.28
Neo-confucianism Building	6	3115	19.26	45:18:37	11.32	27	69.43	0.29	0.18
Yifu Building	5	3505	14.27	52:38:10	17.46	42	83.16	0.21	0.17
College of Engineering	6	2035	29.48	52:20:27	14.20	33	64.36	0.31	0.23
Songqing Gymnasium	6	1549	38.73	47:35:18	11.90	29	76.07	0.25	0.23

3.2. Visual Scale

As shown in Figure 5, the core landscape area has the largest number of photographs of close-up view, followed by the mid-range view and the least number of photos from long-range view. In particular, the proportion of long-range view photos of the Old Dormitory and Yifu Building is less than 10%, indicating that observers are inclined to take close-up photographs at these attractions. With regard to the Neo-confucianism Building and Songqing Gymnasium, the difference value between view 1 and view 2, as well as view 2 and view 3, is approximately 15%, implying that visitors can relatively easily observe different levels of landscape and have a broad view when taking photos in these two scenic spots.

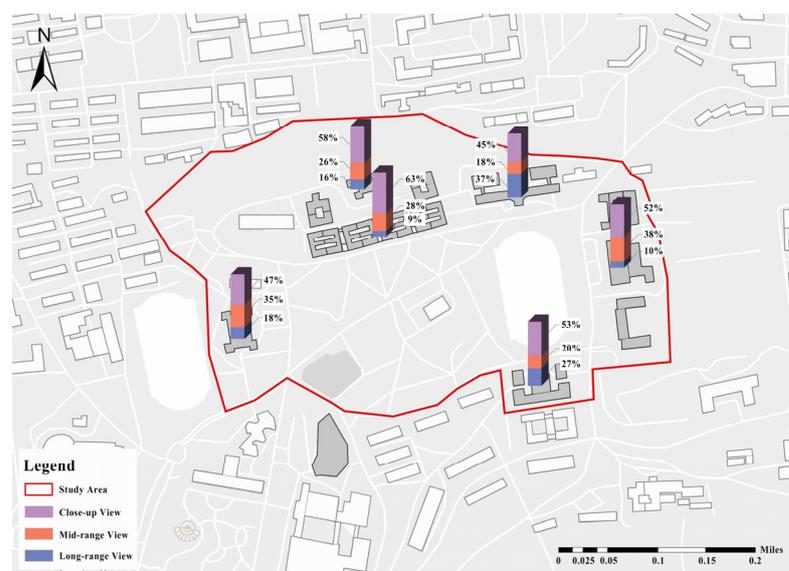


Figure 5. Analysis of landscape visual scale.

The standard deviation of photographs at each type of view suggests the extent of dispersion for the photograph data at each attraction, while the extreme deviation reflects the difference between the maximum and minimum values. Table 2 illustrates that both the standard deviation and extreme deviation of the Neo-confucianism Building and Songqing Gymnasium are two minimum values, showing that these two attractions have various depths of view. The difference between the maximum value (at the close-up view) and the

minimum value (at the long-range view) of the Old Dormitory, Wuhan University Library and Yifu Building are above 40%, indicating that the distribution of each type of photo is unbalanced. It is difficult for observers to appreciate different levels of landscape in such scenic spots, probably because they face the campus’s main road with undulating terrain.

3.3. Color

Color is a fundamental component of the landscape. To facilitate the comparison, the value of color contrast, saturation, and hue were normalized (see Figure 6). Taking two typical photographs shared on Weibo as samples, the impacts of three color dimensions can be illustrated distinctly (see Figure 7). The Image Processing Toolbox in MATLAB was applied to calculate the color values.

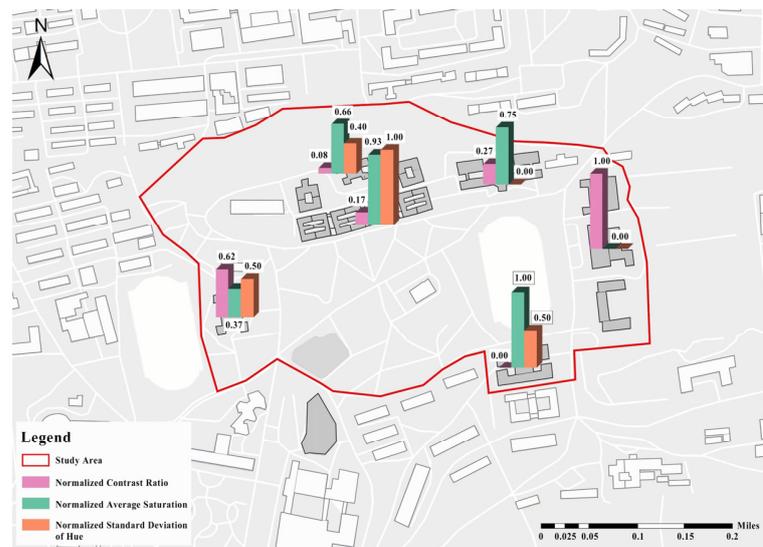


Figure 6. Analysis of landscape colors.

As can be seen in Figure 6, with the maximum contrast value of 83.16, Yifu Building stands out from the background, clearly highlighting its monumental image of the building. Conversely, the College of Engineering, Wuhan University Library and the Old Dormitory have low values of contrast, suggesting that these buildings have good integration into the environment. Comparing the CC_i values in Figure 7, the color contrast of the Yifu Building is about 1.5 times as much as the Old Dormitory, which shows that the difference in brightness between the colors of the Yifu Building is larger than that of the Old Dormitory.



(a) The Old Dormitory. One typical photograph of the Old Dormitory shared on Weibo.



(b) Yifu Building. One typical photograph of Yifu Building shared on Weibo.

Figure 7. Cont.



Figure 7. The analysis of the color of two typical photographs shared on Weibo based on MATLAB.

Using the mean saturation value (AMS_i), the dominance of the tones is represented, with higher saturation indicating more vivid colors and less gray. An object with high saturation values attracts the attention of the observer more [73]. Looking at Figure 6, with the AMS of 0.31, the College of Engineering and the Old Dormitory have the highest mean saturation values, which indicates that the colors of these landscapes and environments are the most vivid, leading to visitors taking photos of such attractions with striking colors. On the contrary, the mean saturation value of the Yifu Building is the lowest, which is only 0.21, revealing the dull scene of such an attraction. As shown in Figure 7, the AMS_i values of the Old Dormitory are twice as much as that of the Yifu Building.

The standard deviation of hue (SDH_i) measures the amount of variation of the hue values related to a certain attraction. The figure above (Figure 6) shows that the SDH of the Old Dormitory is significantly higher than other landscapes, which is 0.28, indicating that the color diversity of the Old Dormitory is the highest, and observers perceive various colors strongly when taking photos. With a minimum SDH of about 0.17, the Neo-confucianism

Building and Yifu Building have homogenous colors unappealing to observers. Looking at Figure 7g,h, the SDH_i value of the Old Dormitory is higher than that of the Yifu Building.

3.4. The Most Popular Scenic Spot

The results of the point density analysis based on ArcGIS are shown in Figure 8. It is clearly seen that the Old Dormitory is the most popular scenic spot. Observers interact with the landscape mostly on the main road in front of each scenic building, especially around the Old Dormitory.

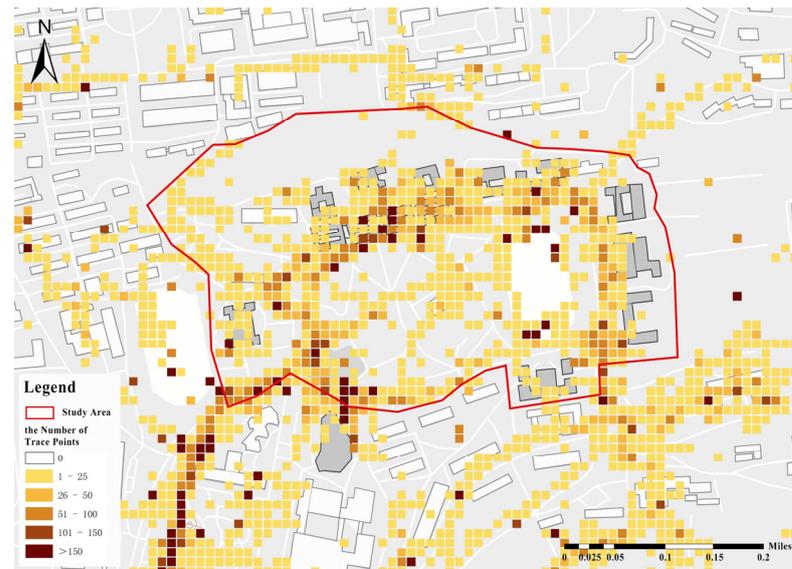


Figure 8. Point density analysis of trajectory data.

Looking at indicators of complexity, the visual scale, and the color of the Old Dormitory, it can be found that complexity and color play the main roles in the visual perception of the cultural landscape. Preference for a scenic spot is especially high when there is a high richness of viewing angles. In addition, color is a crucial concept in determining the visual quality with regards to color contrast, saturation, and hue. Observers tend to gather at the attractions with vivid colors and rich color combinations, where the man-made buildings harmonize with the environment. The visual scale is less dominant compared with the former two concepts. The distance between the direct stimulus and the viewer indicates different levels of involvement. For cultural landscapes, close-up views have the effect of increasing the viewer's perception of all the physical elements. Thus, mid-range and long-range views are relatively inconsequential.

4. Discussion and Conclusions

Social media data, especially photographs, has become a new form of evaluating landscape visual indicators [46]. This article highlights the considerable potential of uploaded photographs for public perception analysis and landscape visual quality assessment. Through photograph content analysis, a deep comprehension of what observers portray can be applied to exploring the landscape attributes which attract people.

The major discoveries of the present study are as follows:

- In line with prior studies on landscape preference and visual landscape assessment based on traditional data and social media data [47,74], which suggest a positive relation between landscape diversity and observer's perception, this article confirms that the complexity of landscape attributes is a determining factor related to landscape visual quality. However, as people tend to have different preferences towards different landscape types [75], this finding related to cultural landscapes is slightly inconsistent with previous studies on ecological landscapes. Complexity affects both

the effort required to perceive the object and the amount of information in a landscape scene. In terms of ecological landscapes, the inverted-U-shaped relation between complexity and landscape preference has been proved in many papers [65]. As for cultural landscapes, the elements for visual quality in urban settlements range from the whole of the city to its parts, such as a boulevard or a street [76]. Among the urban landscape indicators, building facades serve as a vital feature providing important information [77]. Thus, this research innovatively selects camera angles reflecting different facades of attractions as landscape patches, which could be a valuable application to assess the complexity of cultural landscapes. The Old Dormitory in the study area has the maximum value of PRD, which suggests that visitors can have the richest observation points around this attraction.

- The results about saturation and hue values corroborate the findings of a great deal of previous work in visual elements accounting for people's preferences [16,47,54,77]. With high AMS and SDH values, observers are willing to stay and obtain picturesque images at the Old Dormitory and College of Engineering. This finding is consistent with the results in the investigation by Huang and Lin [75], in which high color variation and chroma have positive correlations with preference and encourage visual fixation. Nonetheless, contrast can be perceived differently. According to Garcia et al. [54], incompatible contrasts might lead to poor integration into the environment, such as color contrast in urban signposting. Conversely, the preference for visual beauty has a positive correlation with color contrast in Arriaza et al.'s work [21]. This study supports the finding of Garcia et al., which indicates that the color contrast existing in the study area is incompatible. With low values of contrast, Wuhan University Library, the Old Dormitory and the College of Engineering provide a sense of wholeness in the landscape.
- As for the results about visual scale, depth of view has a relatively minor impact on perceived visual quality. With close-up photos accounting for about 50% of the total photos, the uploaded photographs contain mainly close-up views, which indicates that observers tend to appreciate these landscapes at a close distance. However, this outcome is contrary to that of Hull and Buhyoff [68], who found that distance to the back ridge was much more predictive of scenic beauty than the distance to the front ridge, and there was a concave upward relationship between distance and preference. A possible explanation for these results may be that cultural landscapes are perceived differently from natural landscapes. For cultural landscapes, as the distance of view decreases, the opportunity for involvement increases by increasing the sense of enclosure [67], leading to a close look at visual elements such as decorations and texture. As for natural landscapes, a far distance between the viewer and features tends to lower the complexity and increase the preference by making the viewer grasp notable patterns of an order [65]. Since the close-up view is the main factor for preference, a richness in different levels of view has not been able to demonstrate that cultural landscapes with balanced close-to-far depths of view are more popular.
- The presented results enabled us to answer the two main research questions. In accordance with the trajectory data analysis, viewers tend to interact with the cultural landscapes along the main roads, particularly at the Old Dormitory. Density and diversity of the camera angles, depth of view, and the color of each scenic spot were selected as indicators for exploring the visual quality. In reference to the findings, observers have preferences for cultural landscapes with diverse viewing angles, high values of saturation, and the standard deviation of hue. The distance-to-height ratio of less than 1 indicates the close distance which can most arouse the viewer's interest in taking photographs.

Based on these findings, government, urban planners, and landscape designers can manage cultural landscape and enhance the attractiveness of tourism destinations precisely. By increasing the complexity of buildings, integrating buildings into the environment, and maintaining a proper distance-to-height ratio, cultural landscapes such as historic designed

landscapes and traditional villages might draw observers' attention and attract them to stay for longer and take photographs.

The second contribution of this study refers to linking systematic theories to visual indicator analysis based on computer vision technology. The methodology demonstrated in this paper adds to a growing body of evidence for visual indicator application based on content analysis of social media photographs. The prior studies applying crowdsourced geodata on social media platforms in landscape perception analysis mainly focus on coding and scene recognition [46–48,50,78], which is highly efficient in evaluating public preferences and opinions by automatic computer programs. However, most of the prior studies have been unable to link mature landscape theories to emerging methodologies. Using Ode et al.'s theory-based framework, this research assesses the feasibility of semi-automatic photo content analysis combined with the MATLAB algorithm and manual recognition. The third contribution of this paper is that the fixed-point photography experiment provides an approach to measuring the depth of view related to the classical way. The planimetric and panoramic simulations are used widely to quantify the dimensions of views in recent times [79], while photographs and field observations are traditional ways [57,66,68]. We developed the photographic method into a more precise measurement with the concept of distance-to-height ratio, which is more appropriate to determine the visual scale at a local scale compared with the simulations, especially in relation to specific buildings' visual elements.

Though this essay has made contributions concerning big data, computational techniques and visual indicators, limitations exist in three aspects. First, as the present study had a quite experimental character, the findings might not be suitable for extrapolation to cultural landscapes at a large scale. Second, for different aims, certain social media platforms are used more than others in particular areas [80]. Oteros-Rozas et al. [46] suggest a similar finding that Flickr hosts more photographs representing CES compared to Panoramio. In China, other social media platforms with considerable shared photographs have emerged recently, such as the Douyin app, the Ctrip website, and other platforms. The differences between photos on certain platforms should be addressed in future studies. Third, another challenge that remains in big data application is that the potential for rigorous quality control and generalizability is required to be clarified [81]. As photographs on social media might have poor reliability in the location or image quality [4], more attention needs to be drawn to the synthesis process regarding a principle expressed as Linus's Law, which suggests overlapping observations for effective convergence. Our findings related to the landscape features depicted in photographs revealed public preferences for landscapes based on user-generated content and trajectory data. However, comparing the content analysis with the results from other data sources such as land cover data and orthophotos should be explored.

In the future, it will be important to explore the potential use of user-generated data on social media platforms from different cultural backgrounds, with the aim of comparing similarities and differences related to people's perception of landscape. Users located in different parts of the world might prefer disparate landscape visual features. What's more, users' information embedded in social media data remains to be studied. For each landscape attribute, factors such as age, gender, cultural backgrounds, and living environment (native vs. non-native) of the photographer might cause differences in landscape visual preferences. In addition, as this study focuses on complexity, visual scale, and color only, further research should be carried out to assess other concepts of landscape visual quality such as coherence, disturbance, historicity, and other indicators according to Ode et al.'s framework [2], which might use content analysis of photographs combined with other data sources.

Author Contributions: Conceptualization, X.Z. and D.X.; methodology, D.X. and N.Z.; software, D.X.; validation, X.Z., D.X. and N.Z.; formal analysis, D.X.; investigation, N.Z.; resources, X.Z.; data curation, N.Z.; writing—original draft preparation, D.X. and N.Z.; writing—review and editing, X.Z.; visualization, D.X.; supervision, X.Z.; project administration, D.X.; funding acquisition, X.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China [Grant No. 41671442]: Human Behavior Patterns Analysis and Space Optimization based on the Big Trace Space-time Data.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

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