Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 4662818, 18 pages
https://doi.org/10.1155/2022/4662818

Research Article

Tourists' Landscape Preferences of Luoxiao Mountain National Forest Trail Based on Deep Learning

Ying Ding,[1] Zhiyong Bai,[2] Hongling Xia,[3] and Hui Tang[2]

[1]*Forestry College, Central South University of Forestry and Technology, Changsha, 410004 Hunan, China*
[2]*Tourism College, Central South University of Forestry and Technology, Changsha, 410004 Hunan, China*
[3]*Department of Architecture, Hunan Urban Construction College, Xiangtan, 411100 Hunan, China*

Correspondence should be addressed to Hongling Xia; 20191100083@csuft.edu.cn

Received 9 March 2022; Revised 17 May 2022; Accepted 26 May 2022; Published 16 July 2022

Academic Editor: Chia-Huei Wu

Assessing visitor usage and understanding visitor experiences are key components of the sustainable management of the natural environment. In the study of the relationship between people and landscapes, the combination of deep learning and traditional classification is rarely used to study the landscape preferences in the natural environment, and the research perspective of vertical space at altitude is lacking. This article is based on photo data voluntarily uploaded by tourists on the 2bulu outdoor assistant platform. A combination of deep learning and traditional manual classification was used to divide the collected 43234 landscape photos into 9 categories. Then, the time stamp, latitude, longitude, altitude, and other attribute information about the geotagged photos were used to study the specific landscape preferences of the main nature reserves along the Luoxiao Mountain National Forest Trail at different time scales, protected areas, and altitudes. The research results showed that the capture ability of the landscape reduced the representativeness of social media in terms of the preferences of tourists. Roads and identification facilities were particularly preferred by tourists in this subcategory. The preferences for various landscape types exhibited an obvious festival effect, which was affected by the peculiarities of the landscape in a particular season. Spatially, it exhibited an agglomeration pattern characterized by the concentration in the central area and scattering in the northern and southern regions. The preference for landscape types in the southern section was more abundant than that in the northern section, and there were significant differences at different altitudes. Tourism facilities and characters were the most preferred by tourists in each altitude range.

1. Introduction

In recent years, with improvements in people's living standards, the demand for outdoor recreation has become increasingly diversified, and the demand for long-distance hikes through natural areas has grown rapidly. The crossing areas of China's National Forest Trails are mainly connected to or adjacent to various natural reserves such as forest parks, nature reserves, and scenic spots at all levels. The construction of national forest trails is not only beneficial to human physical and mental health but also can bring huge economic benefits to the natural protected areas and their protected objects by playing their role as tourist attractions [1]. According to the Guiding Opinions on Establishing a Nature Reserve System with National Parks as the Main Body, the main body of China's nature reserves will be transformed from nature reserves to national parks, which will have a huge impact on the protection and utilization of tourism resources in nature reserves [2]. Tourism resources are the premise and conditions of the tourism landscape, and they are transformed into tourism landscape through human tourism development activities [3]. Under the guidance of economic benefits, there have been many cases of extensive development and blind use of tourism resources. Previous studies have shown that the spatial distribution of the landscape attributes in nature reserves has an impact on the visitor rate [4], and the value of the landscape depends on the group characteristics of tourists and their needs and preferences for different recreational activities [5]. Therefore, studying the landscape preference characteristics of tourists

is not only conducive to the sustainable management of protected areas but also conducive to the construction and planning of national forest trails.

The term landscape has a rich connotation, which includes not only natural and artificial elements that can be visually recognized but also nonvisual ecological functions, historical and cultural values, entertainment functions, smell, and taste [6]. The landscape mentioned in this article mainly refers to the visual aesthetics, and it is people's visual perception of the environment. Anthropologist John Collier (1967) was the first to use photography as a tool to study human perception [7]. Shafer and Meitz's quantitative study of landscape beauty using photographs was the beginning of the study of landscapes from the perspective of vision [8]. In the 1980s, photography-based methods became more and more popular in landscape perception and preference research [9], and visitor-supplied photography and photography questionnaires became common research tools [10]. This self-directed approach to photography, however, is limited due to its cost (acquiring participants and providing cameras), and the method of obtaining observer ratings from photographs has been criticized by environmental behavior researchers and psychologists in terms of its limited applicability to assess situational behavior, interactions, and landscape meaning [11]. In recent years, mobile phone photography and mobile applications have resulted in the appearance of a large number of public environmental impression evaluations on the Internet. Obtaining perception and preference data through social media user-generated content (UGC) image metadata has gradually become a trend. The sharing of photos by tourists during their travels is a double filtering process. They first choose limited elements of the journey to take pictures of and then they upload some of the pictures taken [12]. Therefore, we can explore their perceptions and experiences through the photos they share, especially geotagged photos, and the results of such studies can help answer questions about the preferences and behaviors of tourists [13].

The current research on landscape preferences has mainly focused on the influencing factors, evaluation methods, and techniques. The research on the influencing factors mainly included two aspects: (1) the attributes of the subject of the landscape experiencer such as his/her professional background [14], educational level [15], and gender [16] and (2) the characteristics of the object of the landscape, such as the landscape quality [17], landscape type [18], and visual space attributes [19]. The methods and techniques for evaluating landscape preferences are diverse, but they basically follow the same principle; that is, landscape preferences should be judged by the viewer themselves [20]. At present, most of the studies using photos on social media platforms to explore tourist behavior and preferences focus on spatial feature analysis using the geotagged information of photos [21, 22], and a few have used the time stamps of photos to conduct spatiotemporal analysis [23]. Few studies, however, have combined photo metadata with its contents to study landscape preferences in nature reserves [24, 25], and the study of integrating altitude into space-time scale is even rarer.

Visual content analysis is a systematic, observational method used for exploring how the studied phenomenon is represented [26]. When analyzing the visual content of pictures, the method of manually encoding the pictures' content is the most widely used analysis method [27, 28], because it has a relatively mature concept and theoretical framework and a high classification accuracy, but the number of samples analyzed is limited. In recent years, with the development of computer deep learning technology, convolutional neural networks (CNNs) have been widely used for image classification, object retrieval, face recognition, and other analyses [29]. Computer image recognition technology is a process of processing pictures, which is mainly divided into two steps: image feature extraction and image classification prediction. Convolution can enhance the continuity of image information, so as to deepen the neural network's understanding of the image. At present, the research on the recognition and classification of photos using deep learning mainly focuses on the images of tourist cities [30–32] and tourists' perceptions and their behavior [33], and there are few researches on tourists' perceptions and preferences in natural environment. Although it can recognize and classify massive data, it will also spend a lot of time and energy in the process of coding and machine training in order to improve its accuracy, and the threshold of computer vision technology is too high, which is not conducive to the use of nonprofessionals.

Therefore, through sorting out previous studies, this paper identifies and classifies the photo content based on deep learning and artificial classification and then studies the landscape preference characteristics of various natural protected areas in series along the Luoxiao Mountain National Forest Trail at different times, different protected areas, and different altitudes. The contribution of this paper lies in not only using the method of combining deep learning with traditional manual classification to make up for the shortcomings of these two methods and improve the accuracy of classification but also innovatively introducing the vertical attribute of altitude in the research of the combination of photo content and temporal and spatial attributes, which provides a new perspective for the study of tourists' landscape preferences by using social media photos.

2. Materials and Methods

2.1. Study Region. The Luoxiao Mountain National Forest Trail is one of the first national forest trails designated by the China Forestry Administration (now the National Forestry and Grassland Administration) in 2017. It is located at the junction of Hunan and Jiangxi provinces, has a north-south trend, and is still under construction. It starts in Chongyi County, Jiangxi Province, in the south and ends in Linxiang City, Hunan Province, in the north. Its total length is 1400 km, including 942 km in Jiangxi and 458 km in Hunan. The forest accounts for more than 90% of the entire length. It is a typical midsubtropical evergreen broad-leaved forest and northern subtropical evergreen broad-leaved forest. The trail passes through many forest tourist destinations, red historical and cultural relics,

Buddhist and Taoist holy places, and ancient villages. It also connects many historical roads, such as the Tea Salt Valley Road and the Millennium Bird Road (i.e., the Suichuan Bird Road). As shown in Table 1, in this study, 13 nature reserves along the Luoxiao Mountain National Forest Trail were selected to analyze the landscape preference characteristics of tourists. Figure 1 shows the distribution of these 13 nature reserves along the trail.

2.2. Data Collection. Photos provided by many crowdsourcing platforms can be used as data sources for the description of landscape features. Among them, websites such as Panoramio, Flickr, and Instagram have been widely used [24], but most of the data on these websites are uploaded by foreign users and are difficult to obtain in China. Therefore, considering the simplicity and representativeness of the data acquisition, we mainly used the 2bulu outdoor assistant as the source of the research data. The 2bulu outdoor assistant began operation in May 2013. It is one of the most popular outdoor software packages on the Chinese market, is a Global Positioning System (GPS) software package, and can record tracks and mark points of interest.

The data acquisition was conducted using the Python Scrapy framework and using the 2bulu outdoor assistant application programming interface (API) to request the connection, and the name of the protected area was used as a keyword in the data search. Some protected areas with few pictures were supplemented using the names of their internal scenic spots as the keyword. As of May 31, 2021, 54,247 photos on 2208 trajectories voluntarily shared by tourists were obtained as the original data for this study. The attribute information of the picture metadata mainly included the track name, picture ID, shooting time, longitude, latitude, altitude, and user ID (Table 2).

Users may be affected by outdoor weather, terrain, and other confounding factors in the process of data uploading, which leads to unstable signals and thus repeated data collection or missing field attributes. Thus, it was necessary to further filter and clean the collected picture data. The screening and cleaning principles used are as follows: (1) the pictures with missing attribute information were deleted to ensure the integrity of the data. (2) The pictures with repeated, fuzzy, and unrecognizable content were removed. (3) Since the specific boundary map of the reserve cannot be obtained, the county (county-level city and district) where the reserve is located was taken as the scope (Figure 2), and the pictures that were not within this range were removed. Finally, a total of 43,234 photos on 2,142 trajectories voluntarily uploaded by tourists were obtained as the final data for this study; the distribution of the points of all of the photos is shown in Figure 3.

3. Methods

3.1. Recognition and Classification of Photos. First, we used the Inception v3 deep learning model in the Orange Data Mining 3.29 software to perform the preliminary image recognition and classification of the collected pictures. Then, based on previous studies, a set of manual classification standards was developed, and the preliminarily classified pictures were distributed to 10 people with relevant backgrounds for reclassification. Another person checked the reclassification results according to the standard. Although such repeated classification takes a certain amount of time and energy, it can effectively reduce the subjectivity and error rate of the classification.

Orange 3.29 is a software package that was jointly developed by the Bioinformatics Laboratory of the University of Ljubljana in Slovenia and the open-source community. Its image analytics component contains a variety of deep learning models, which can be used for image recognition and classification. We used the Inception v3 training model, which is a module in the GoogLeNet deep learning framework. It was developed based on Inception v1 and Inception v2. Its top-five error rate is 3.5%, making it one of the most accurate models in the field of image classification. At present, the classification system standards for tourism photos are all formed with tourism resources as the center [34]. We referred to the Classification, Investigation and Evaluation of Tourism Resources (GB/T 18972-2017), China Forest Park Landscape Resources Grade Evaluation (GB/T 18005-1999), and the classification of picture contents by Stepchenkova and Zhan [28] and Wang et al. [35], and based on the opinions of experts and repeated modifications, 9 categories were finally determined (Table 3). When classifying pictures, each picture can be regarded as a single content unit [36, 37]. According to the principle of whether it was located in the center of the picture or was the focus of the picture and whether it occupied the highest proportion, a picture was classified into a landscape category, and it was no longer decomposed into smaller content units for classification.

3.2. Research Methods at Different Time Scales. Time-stratification is a method used to analyze research data from a temporal perspective according to the time range of the data collection and at different time scales [38]. Based on previous research, we used the time-stratification method to extract the longitudinal temporal attributes of the data, and we obtained the number of landscape categories from 2015 to 2021. The horizontal time attributes were extracted according to the division of seasons defined by the China Meteorological Administration: spring from March to May, summer from June to August, autumn from September to November, and winter from December to February, and the number of landscape categories in each season was obtained. The seasonal index method was used to calculate and analyze the seasonal index at each time scale and to explore the temporal fluctuation characteristics of tourists' preferences for various landscape categories in the main nature reserves along the Luoxiao Mountain National Forest Trail. And the calculation formula of seasonal index is as follows:

$$C = \frac{A}{B}, \tag{1}$$

where C is the seasonal index, A is the average of the

Table 1: Main nature reserves along the Luoxiao Mountain National Forest Trail.

Serial number	Name of nature reserve	Area covered (hm)	Forest coverage rate (%)
1	Yangling National Forest Park	6889.8	96.80
2	Yangming Lake (Duoshui Lake) National Forest Park	22666.67	85
3	Wuzhifeng National Forest Park	24533.00	88
4	Sanwan National Forest Park	15333.33	90.50
5	Jinggang Mountain National Nature Reserve	15873	81.20
6	Bamian Mountain National Nature Reserve	10974	85.20
7	Wugong Mountain National Scenic Area	About 380	88.10
8	Mingyue Mountain National Forest Park	7842	73
9	Bihutan National Forest Park	6838.70	88.50
10	Dawei Mountain National Forest Park	About 4666.67	99
11	Mufu Mountain National Forest Park	1701	94
12	Dayun Mountain National Forest Park	1180.6	84.60
13	Wujian Mountain National Forest Park	2879.89	98.20

same quarters (months), and B is the total quarterly (monthly) average.

3.3. Research Methods of Landscape Preference in Different Protected Areas. We mainly used the fishnet and kernel density estimation in ArcGIS 10.2 to study the landscape preferences in 13 nature reserves along the Luoxiao Mountain National Forest Trail. The 21 counties (county-level cities and districts) involved in the main nature reserves along the trail were divided into 10 km × 10 km grids, combined with the latitude and longitude attributes of photos, and the number of photos in each grid was counted. We used the fishing net tools to visualize the spatial characteristics of the four seasons in the main nature reserves along the trail. Kernel density estimation is a popular spatiotemporal research method, which mainly analyzes the occurrence probability of point elements in different geographic spatial locations and can reflect the spatial distribution and characteristics of point elements. The higher the kernel density value, the higher the probability of event occurrence and the denser the points, and vice versa [39]. This method can be used to calculate the density of point elements around each output raster pixel, and it is the best method for visualizing the spatial aggregation characteristics of landscape categories.

3.4. Methods of Researching Landscape Preferences at Different Altitudes. To explore whether tourists have different landscape preferences at different altitudes, first, according to the altitude gradient (about 2060.27 m) of the main nature reserves along the Luoxiao Mountain National Forest Trail and an altitude interval of 200 m, the image data collected along the trail were evenly divided into 10 segments from low altitude to high altitude. Then, we performed the normality test on the number of pictures of each landscape type at different altitudes. The results showed that the P value was less than 0.05, and the overall sample did not exhibit a normal distribution. Therefore, we used the nonparametric test to explore the differences, mainly the Kruskal-Wallis test of K independent samples, because this test has a wider range of use and can be used to analyze data with any distribution [40].

4. Results

4.1. Descriptive Analysis. According to the statistics, we collected 43,234 photos on 2142 tracks uploaded by 1949 tourists in 13 nature reserves along the route. Among them, Wugong Mountain had the highest number of pictures and users, accounting for 64.22% of the photos, followed by Mingyue Mountain, Bamian Mountain, Dawei Mountain, and Wuzhifeng; in contrast, the other nature reserves had less than 1,000 pictures (Figure 4). When counting the number of photos attached to a single track of tourists, it is found that the track with the largest number of photos is attached to 591 photos, with a total track length of 28.6 km and an average of 20 photos/km. In addition, by calculating the proportion of each type of picture in each nature reserve, we concluded that in five nature reserves (i.e., Yangling, Bamianshan, Bihutan, Mingyue Mountain, and Dawei Mountain), the tourists were most concerned with the tourism facilities. In four nature reserves (i.e., Wuzhifeng, Jinggang Mountain, Wugong Mountain, and Wujian Mountain), the tourists paid more attention to their own emotions and experiences during their travels. In the Yangming Lake and Mufu Mountain nature reserves, tourists were more concerned with the biological landscape. In the Sanwan and Dayunshan nature reserves, the tourists paid more attention to the architecture and cultural relics. Finally, from the perspective of the entire Luoxiao Mountain National Forest Trail, the tourism facilities, biological landscape, people, architecture, and cultural relics were of the most concern and were the landscape types preferred by the tourists (Figure 5). We obtained further statistics on the biological landscape and part of the basic content of the tourism facilities and found that in the biological landscape, the attention given to animals was far lower than that given to plants, accounting for 2.83% of the entire biological landscape. Among tourism facilities, the tourists particularly preferred the various roads in the category of recreational

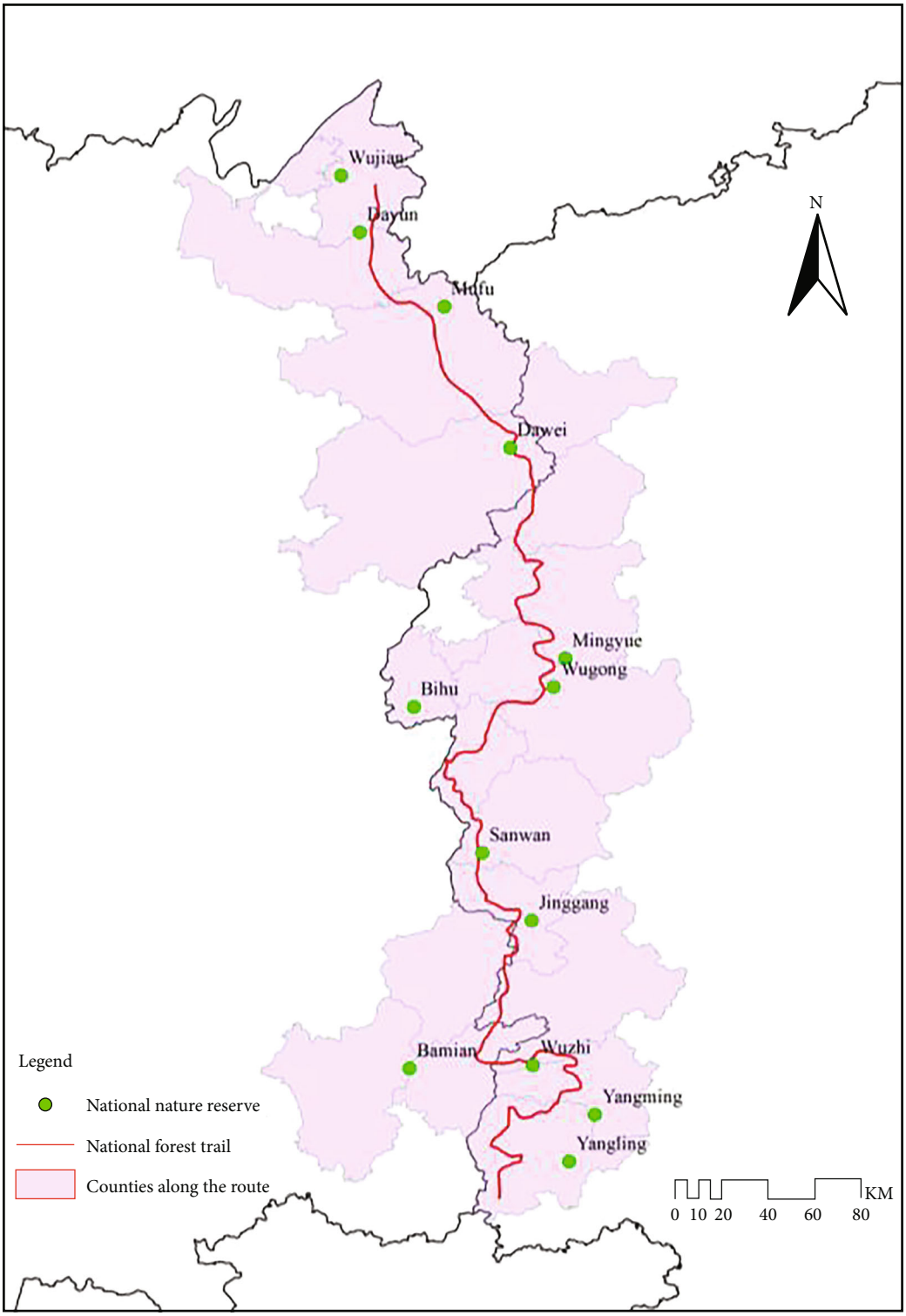


Figure 1: Distribution of nature reserves along the route.

service facilities and identification facilities, accounting for 50.07% and 41.73% of the total tourism facilities, respectively (Table 4).

4.2. Temporal Characteristics of Tourists' Landscape Preferences. The seasonal indexes (season and month) were counted and plotted as line charts, which illustrated the changes in the landscape types, and a thermal map was drawn for analysis, in which the colors, from blue to red, represented the degree of preference from low to high. The tourists' preference for various landscapes along the entire trail was a multiridge type, reaching the highest peak of landscape concern in May, forming two small peaks in August and October, and forming a very low trough in

Table 2: Image attribute information example.

Track name	Image ID	Shooting time	Latitude	Longitude	Altitude (m)	User ID
2021-01-11 15_21 Chongyi County, Ganzhou	944277428	2021/1/11 17 : 20	25.6318	114.3231	608.28	489502
2021-02-23 09_33 Chongyi County, Ganzhou	702199414	2021/2/23 9 : 44	25.6441	114.3233	546.83	19482348
2021-02-23 09_34 Chongyi County, Ganzhou	689518245	2021/2/23 9 : 42	25.6441	114.3234	548.68	22110916
2021-04-24 08_43 Chongyi County, Ganzhou	1030889391	2021/4/24 9 : 22	25.6097	114.2931	509.56	10417246

February (Figure 6). In May, June, August, October, and November, the monthly seasonal index was >1, and it was even >2 in May, indicating that the tourists' preferences and attention to various landscapes were relatively high in these months. February and March had low attention values for the various landscape types, and the tourists were paid little attention to the various landscapes in these two months (Figure 7).

The tourists' preferences for the various landscapes in the nature reserves along the trail did not fluctuate much in spring, summer, and autumn, and it fluctuated up and down around the seasonal index of 1. In winter, the attention to the various landscape types begins to decline (Figure 8). In winter, most of the landscape types were of low concern, and only the seasonal indexes of the celestial phenomena and climatic landscape were >1. In spring, the biological landscape was the landscape most preferred by tourists, and its seasonal index reached 1.6086, which not only was the highest in spring but also was the highest in all four seasons. In summer, water landscape, food, and outdoor equipment were the three landscape types of most concern to the tourists. In autumn, in addition to the biological landscape, the tourists paid the most attention to tourism facilities and outdoor equipment (Figure 9).

4.3. Spatial Characteristics of Tourist Landscape Preferences. As can be seen from Figure 10, the footprints of tourists were most widely distributed in spring, and according to the number of grids, the footprint distribution of the visitors along the trail in all seasons was ranked as follows: spring > autumn > winter > summer. Regardless of the season, Wugong Mountain was the most densely populated area, followed by Mingyue Mountain. Wujian Mountain and Dayun Mountain were the most visited by tourists in spring. Mufu Mountain was more visited in spring and autumn. Although Dawei Mountain had a higher hotspot in spring, it had a wider radiation range in autumn. Jinggang Mountain and Sanwan were of more concern to tourists in summer. Bamian Mountain had a small peak in spring. In winter, the Qiyun mountain scenic spot in Wuzhifeng reached its second hot spot, whereas Yangling and Yangming Lakes received the most attention in spring.

The other categories were removed from the 9 major categories, and kernel density maps for the remaining eight landscape categories were drawn. The tourists' preferences for the main nature reserves along the Luoxiao Mountain National Forest Trail were spatially concentrated in the middle and scattered in the northern and southern regions (Figure 11). Regardless of the type of landscape, Wugong Mountain and Mingyue Mountain in the middle of the region were the high kernel density areas along the entire national forest trail in Luoxiao Mountain, whereas the nature reserves in the northern and southern regions of the trail were high-sub-kernel density areas according to the different landscape types. The geographical landscape, celestial phenomena, climate landscape, and people formed high-kernel-density areas in Wugong Mountain and Mingyue Mountain and secondary-kernel-density areas in Dawei Mountain, Bamian Mountain, and Wuzhifeng. The water landscape and biological landscape were widely distributed and were basically high-heat-value areas in each protected area. The architecture, cultural relics, and tourism facilities were scattered in places other than Wugong Mountain and Mingyue Mountain, and the next highest value areas were not obvious. Outdoor equipment exhibited density clustering only in Wugong Mountain, Mingyue Mountain, Bamian Mountain, and Wuzhifeng, whereas it was low in other places. For the entire trail, we concluded that in addition to the high concentration in the middle section of the trail, the degree of concentration in the southern section was higher than that in the northern section, and the series of nature reserves in the southern section was closer than that in the northern section. On the basis of the existing data, tourists paid more attention to the landscape types along the trail, and the southern section was richer than the northern section.

4.4. Altitude Characteristics of Tourist Landscape Preferences. According to the results of the Kruskal-Wallis test, the significance was 0.000 less than 0.05, which indicated that there was a significant difference in the landscape categories at different altitudes. By comparing the proportions of the various landscape types in the tourist photos, we investigated the differences in the various landscape types at different altitudes. As can be seen from Figure 12, regardless of the altitude, tourist facilities and people were the landscape types of most concern to the tourists. The tourists' attention to the physiographic landscape increased continuously with increasing altitude, and in the interval of 1600–1800 m above sea level, the tourists' attention to the physiographic landscape reached the highest level. Most of the tourists focused on the biological landscape at elevations of 0–400 m and 600–1400 m, but the attention to the biological landscape at other elevations was relatively low. The attention the tourists paid to the astronomical phenomena and climate landscape was constant, and it increased rapidly above 1400 m and reached the highest value in the altitude range of 1800–2100 m. Most of the tourists' attention to the water landscape was concentrated in low-altitude areas, and it was strongly preferred by tourists in the range of 600–800 m. The attention of the

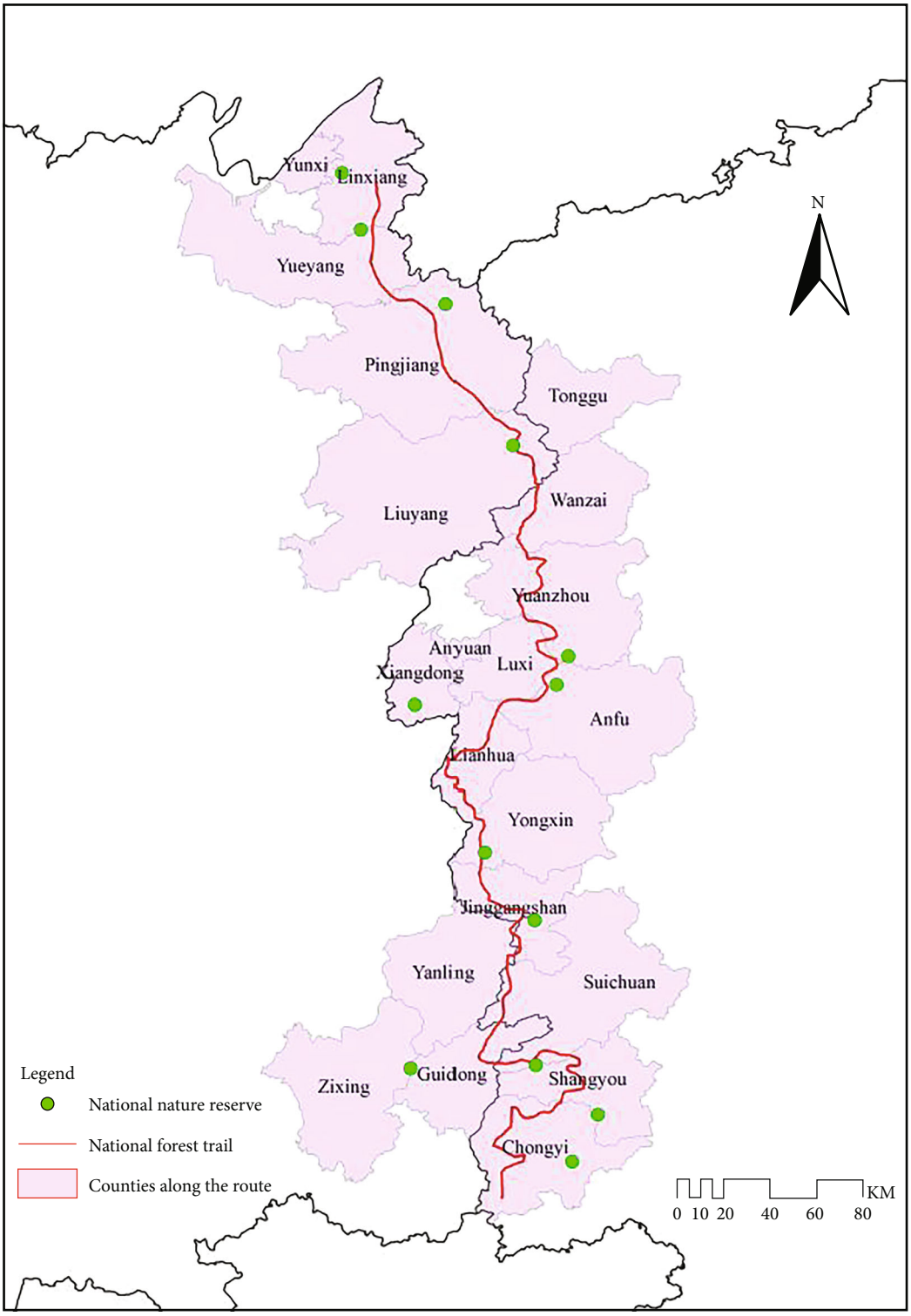


Figure 2: Counties along the route (county-level cities, districts).

tourists to the water landscape, however, became extremely low above 1400 m. Regardless of the altitude interval, the tourists paid more attention to the architecture and cultural relics, with a strong preference in the low-altitude areas. In the high-altitude areas, especially in the 1400–1600 m interval, the tourists did not pay less attention to the architecture and cultural relics than in the low-altitude areas. Outdoor equipment was always the least perceived by tourists along

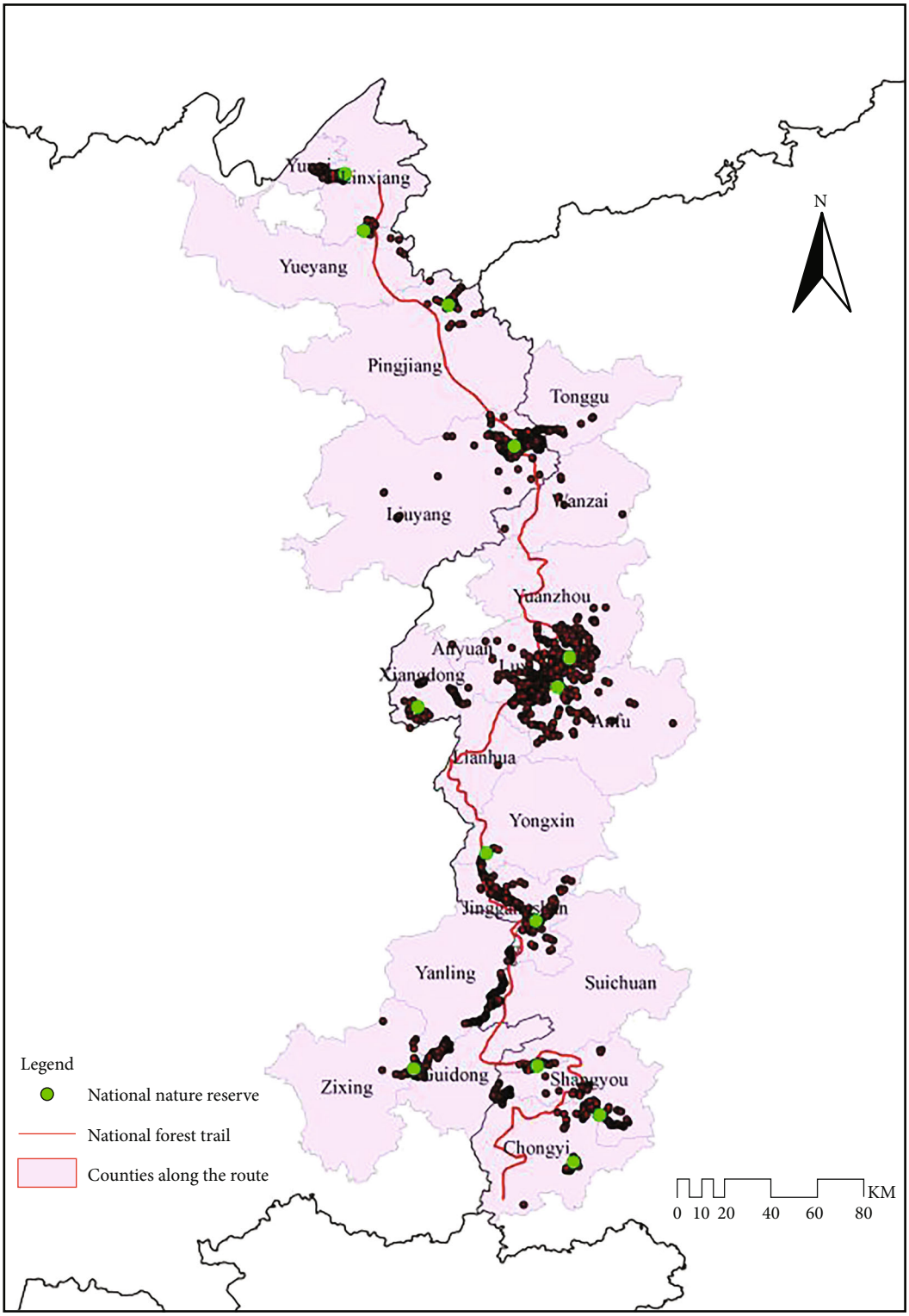


Figure 3: Distribution of picture points along the trail.

Table 3: Picture landscape category description.

Category	Basic content
Biological landscape (BL)	Plants and animals
Physiographic landscape (PL)	Rolling mountains, gullies and caves, pictographic rocks, peak forests, gravel landscapes
Water landscape (WL)	Rivers and lakes, waterfalls, ponds, wetlands, springs, streams, snowy area
Celestial phenomena and climate landscape (CPCL)	Sunrise and sunset, solar and lunar eclipses, stars; ice, snow, frost, and dew; cloudy and foggy landscapes, rime and rain
Architecture and cultural relics (ACR)	Humanistic landscape complex, such as teaching and research experimental sites, construction projects and production sites, cultural activity sites, religious and sacrificial activity sites, and memorial sites and commemorative event sites Practical buildings and core facilities, such as bridges, channels, dams, tombs, characteristic blocks, and characteristic shops Landscape and sketch architecture, such as tourist image landmarks, tower-shaped buildings, sculptures, stele forests, stone carvings, and water wells Architectural relics, such as military sites and former residences of celebrities Movable cultural relics, such as documents, manuscripts, books, and materials of various times in history
Tourism facilities (TF)	Facility buildings, that is, physical buildings that provide accommodation, catering, shopping, and other services, such as hotels, inns, post stations, scenic gates, visitor centers, toilets, and garbage stations Identification facilities, such as guidance signs, location signs, commentary signs, and environmental protection signs Sanitary facilities, such as trash cans Transportation facilities, such as buses, cars, cruise ships, parking lots, and cable cars Recreational service facilities, such as viewing pavilions, platforms, roadways, walking paths, plank roads, ropeways, piers, tables, and chairs and stools for rest Safety facilities, such as railings Water supply and power supply systems, such as electricity boxes and telephone poles
Outdoor equipment (OE)	Alpenstock and mountaineering bags and tents
People (P)	People-centered locals, travelers, and others
Other (O)	Other

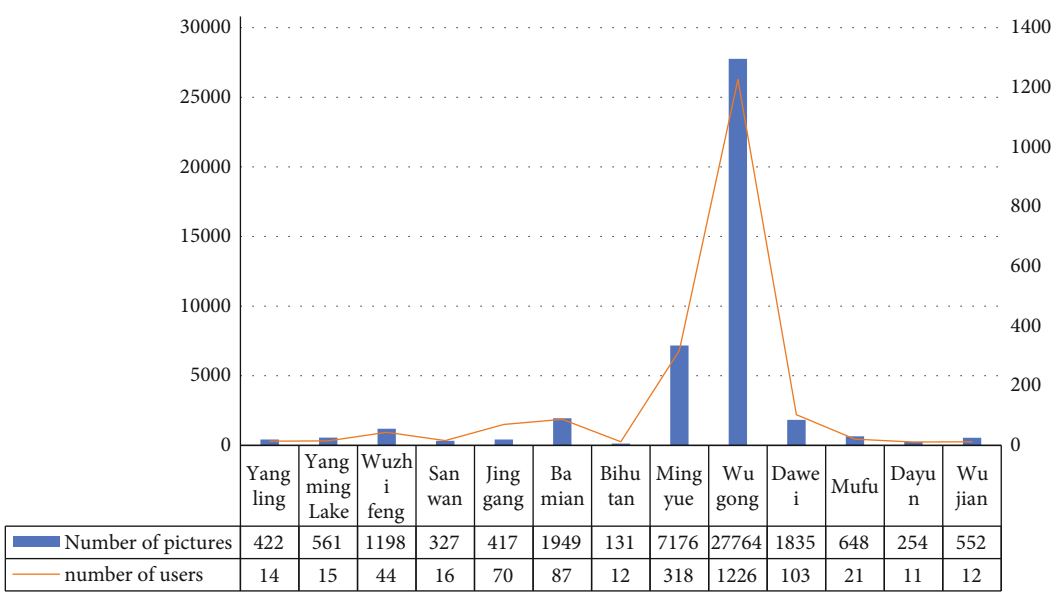


Figure 4: Pictures and users in each nature reserve.

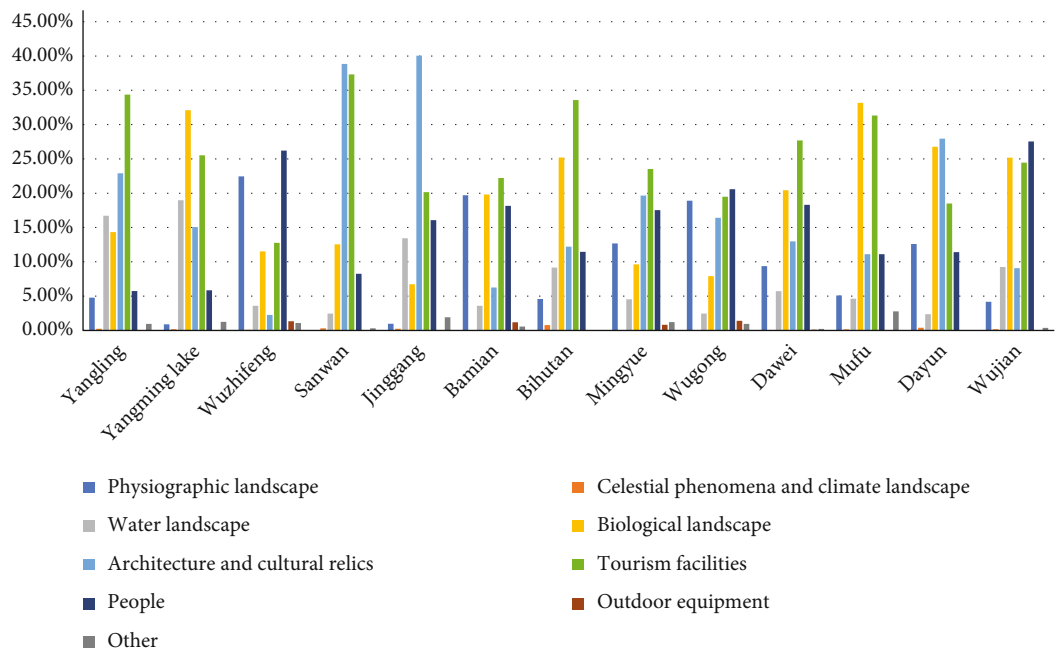


Figure 5: The proportion of landscape types in each nature reserve.

Table 4: Quantity of each landscape type.

Category	Basic content	Number of pictures
Physiographic landscape	/	7107
Celestial phenomena and climate landscape	/	4566
Water landscape	/	1566
Architecture and cultural relics	/	7037
People	/	8393
Outdoor equipment	/	488
Biological landscape	Plants	4419
	Animals	129
Tourism facilities	Various types of roads in recreational service facilities	4563
	Identification facilities	3803
	Transportation facilities	337
	Other	411
Other		415
Total		43234

the entire trail, but it gradually emerged in the 1400–1600 m interval, and then, it maintained a significant proportion of interest until reaching the highest altitude.

5. Discussion

Social media data can be used as an alternative to traditional surveys and to investigate tourists' preferences for nature-based experiences in protected areas [41]. According to the results obtained using data from the 2bulu outdoor assistant, the tourists' preference for animals was much lower than that for plants, but we cannot simply rely on the number of photos to determine the lack of animal resources in nature reserves along the route or tourists' dislike of animals. The reason for this may be that some animals are difficult for tourists to observe during their journeys, such as nocturnal animals and rare species, which results in the biodiversity being insufficient for group representation, thus limiting the ability of social media to fully capture tourists' preferences [27]. In tourism facilities, roads and sign systems are strongly favored by tourists. This is because roads play an important connecting role in scenic areas, providing space for tourists to enjoy natural scenery and tourism activities [42] and constituting a beautiful and rich landscape along with other landscape elements in the conservation areas, such as mountains, water, plants, and buildings. The preference for identification facilities is affected by the limited perception of tourists and the remoteness of tourism activities,

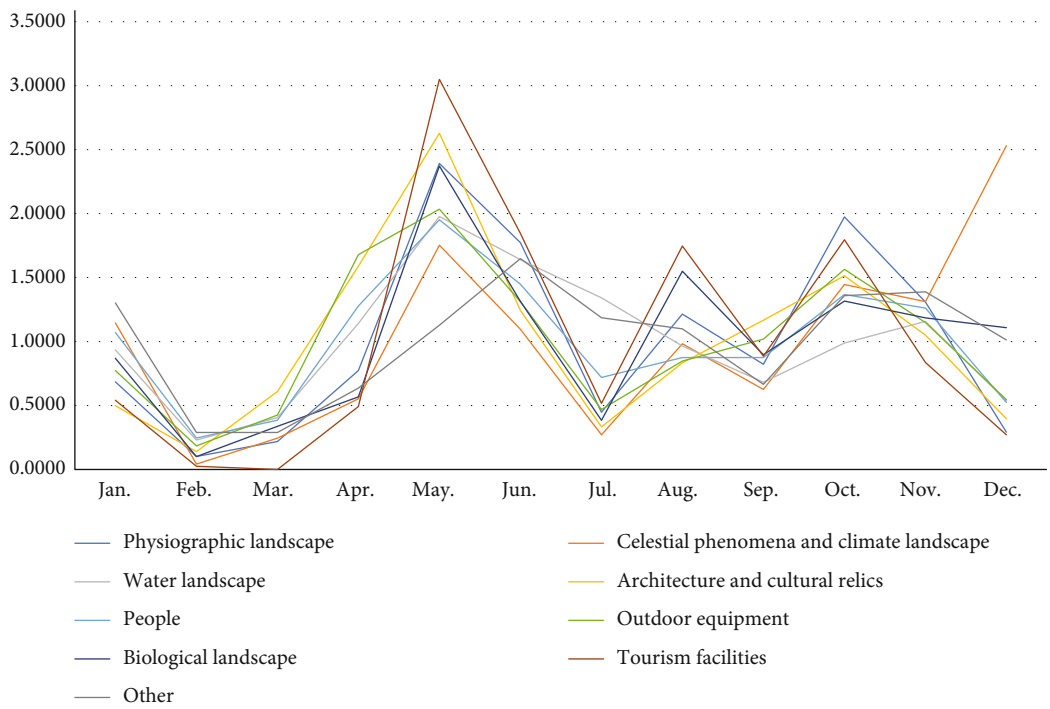


Figure 6: Monthly seasonal index of each landscape type.

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
PL	0.6855	0.1013	0.2178	0.7733	2.3909	1.7729	0.4474	1.2140	0.8223	1.9738	1.3086	0.2921
CPCL	1.1459	0.0420	0.2444	0.5519	1.7530	1.0959	0.2707	0.9829	0.6255	1.4455	1.3114	2.5309
WL	0.9349	0.2299	0.4061	1.1418	1.9770	1.6398	1.3410	0.9655	0.6820	0.9885	1.1571	0.5364
BL	0.4987	0.1398	0.6095	1.5884	2.6280	1.2427	0.3325	0.8338	1.1662	1.5145	1.0501	0.3958
ACR	1.0709	0.2456	0.3854	1.2772	1.9508	1.4478	0.7196	0.8748	0.8748	1.3676	1.2619	0.5235
TF	0.7729	0.1843	0.4253	1.6787	2.0342	1.3114	0.4687	0.8479	1.0191	1.5642	1.1481	0.5451
P	0.8693	0.1001	0.3374	0.5676	2.3720	1.3125	0.3846	1.5499	0.8965	1.3168	1.1853	1.1081
OE	0.5410	0.0246	0.0000	0.4918	3.0492	1.8443	0.5164	1.7459	0.8852	1.7951	0.8361	0.2705
O	1.3012	0.2892	0.2892	0.6361	1.1277	1.6482	1.1855	1.0988	0.6651	1.3590	1.3880	1.0120

Figure 7: Monthly seasonal index heat map.

which makes it difficult for tourists to obtain objective information about the important attributes of tourist destinations [43], so they have to rely on various types of identification facilities. This also reflects from the side that each nature reserve should pay more attention to tourists' demands for infrastructure and the connection between wilderness and modernity in the subsequent sustainable management.

Tourism is an industry that is more sensitive to external factors, major events, holidays, and various emergencies, which can easily cause short-term fluctuations in the tourism industry [44], especially short-term high-intensity holiday tourist flows, which are more obviously restricted by various conditions, such as time, space, and information, and exhibit different temporal and spatial characteristics from the peak period [45]. The "festival effect" of tourists' preference for landscape in nature reserves along the route is obvious. The May Day holiday, summer vacation for students, and National Day Golden Week created the three small peaks of preference for various landscape types along the route. The uniqueness of the landscape has had an impact on the aesthetic evaluation of the landscape [46]. The unique celestial phenomena and climate landscape, such as snow and rime in winter, are strongly preferred by tourists. In spring, the temperature rises, everything recovers, and the biological landscape attracts tourists' attention. Because the weather is hot in summer, people have a high preference for water landscape [23]. This is because people have natural hydrophilicity, and close contact with water

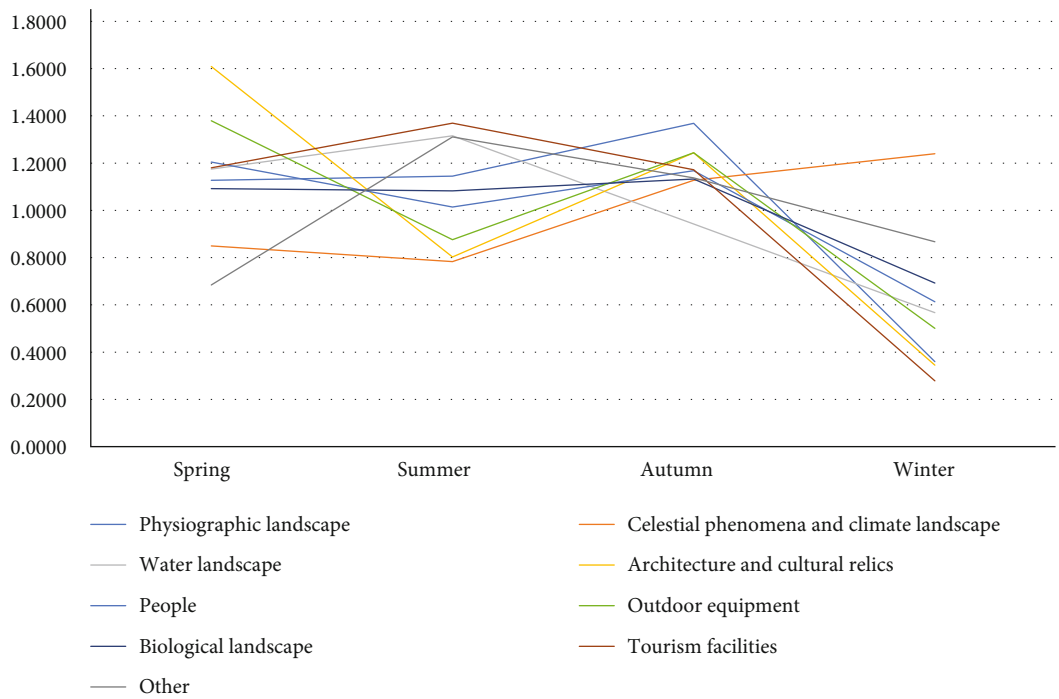


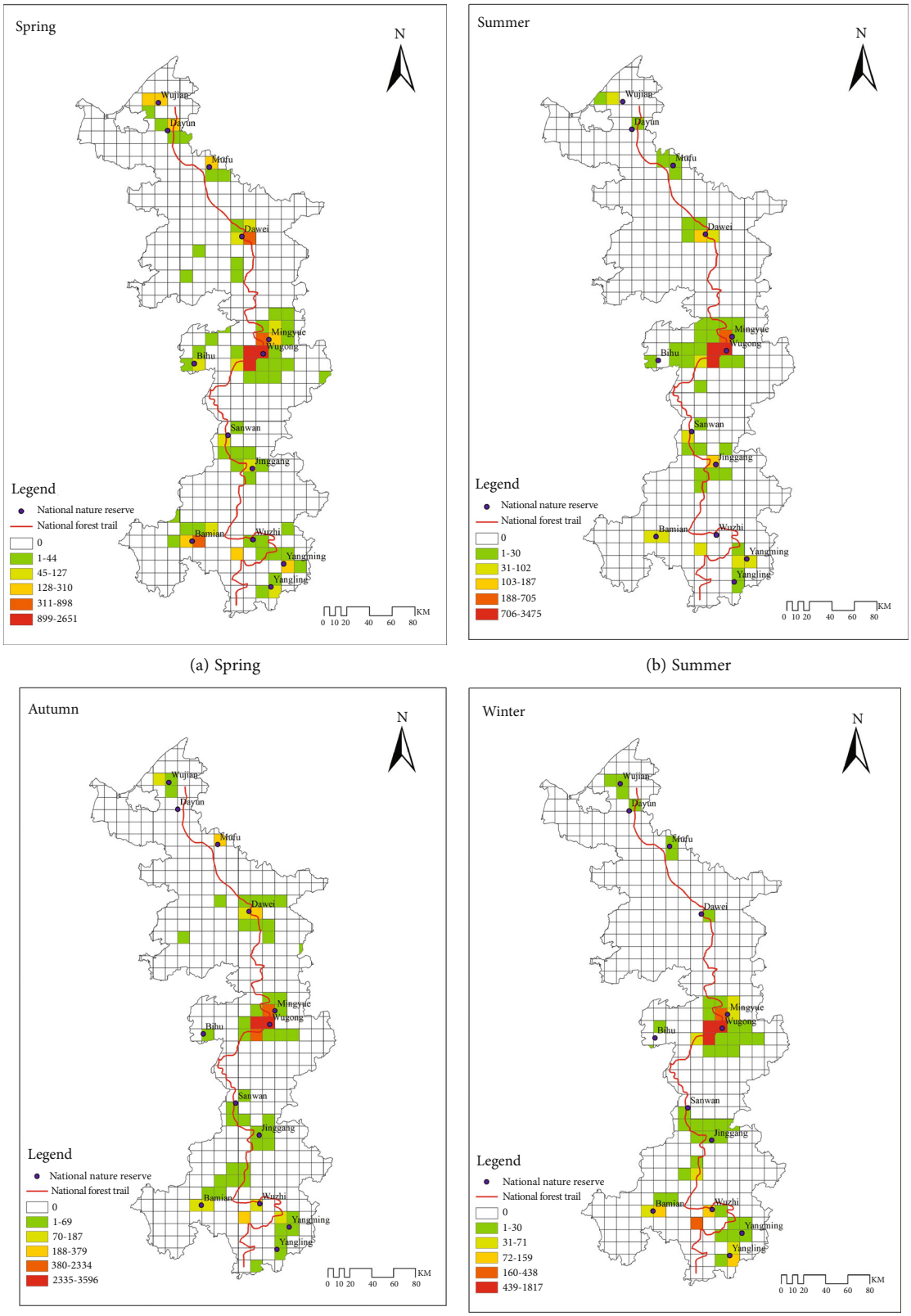
Figure 8: Seasonal index of each landscape type.

	Spring	Summer	Autumn	Winter
PL	1.1273	1.1448	1.3682	0.3596
CPCL	0.8498	0.7832	1.1275	1.2396
WL	1.1750	1.3155	0.9425	0.5670
BL	1.6086	0.8030	1.2436	0.3448
ACR	1.2045	1.0141	1.1681	0.6133
TF	1.3794	0.8760	1.2438	0.5008
P	1.0923	1.0823	1.1328	0.6925
OE	1.1803	1.3689	1.1721	0.2787
O	0.6843	1.3108	1.1373	0.8675

Figure 9: Seasonal index heat map of various landscape types.

can make people feel excited [47]. This is also similar to Wilkins' conclusion that in some ecological areas, tourists choose to stay closer to roads or water bodies in particularly hot weather [48]. Food and outdoor equipment are also the landscape types most preferred by tourists in summer because the temperature in summer is high. In high-altitude areas such as Wugong Mountain, the preferences for these landscape types are suitable. Tourists usually set up tents for camping and enjoying the sunrise and sunset on Wugong Mountain. In autumn, tourists' attention to the physiographic landscape was the highest among the four seasons because the climate in autumn is comfortable and suitable for tourists to partake in outdoor activities.

The content of the photos is very important, but the fact that people take photos in certain places is also important [23]. Through spatial visualization of the various landscape photos, we found that the public's perception and accessibility to natural places affected the people who visit and indirectly affected the types of photos taken [49]. Because of its complex terrain and magnificent scenery, Wugong Mountain enjoys a high reputation in the hiking industry. It is known as Southern Wugong and North Taibai. At present, the development of its scenic spots is concentrated in the Jinding area and the Mingyue Mountain area [50]. Therefore, through kernel density analysis, we found that various landscapes have always been in a high concentration state on Wugong Mountain and Mingyue Mountain. The hiking culture encourages challenge, dedication, and teamwork [50]. By analyzing landscape preferences at different altitudes, we also found that tourism facilities and people were of greatest concern at all altitudes, and the most preferred tourism facilities were identification facilities and roads. Based on the classified pictures, we found that most of the identification facilities in the low-altitude areas played a guiding and explanatory role, whereas the high-altitude signs were more focused on the tourists' courage to challenge themselves and realize their sense of fulfillment, such as the altitude signs in the Jinding and Fayunjie scenic spots.



(a) Spring

(b) Summer

(c) Autumn

(d) Winter

Figure 10: Distribution map of the fishnet uploaded by tourists across the four seasons.

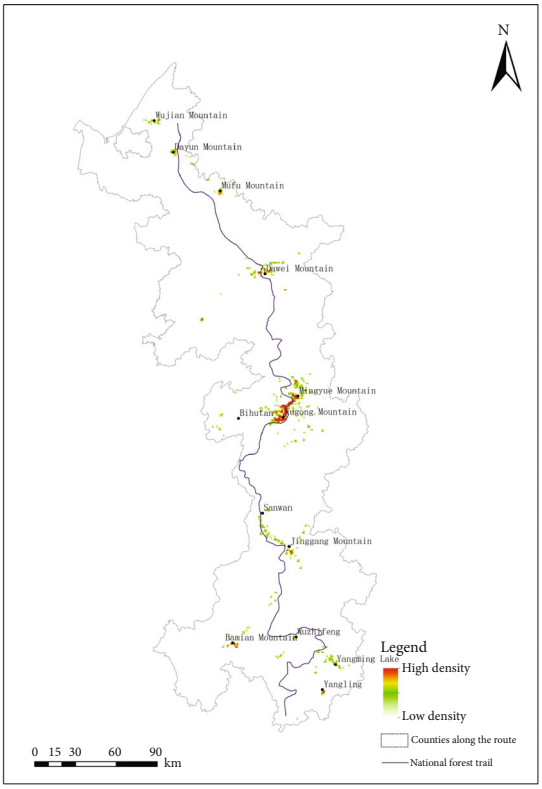
(a) Physiographic landscape

(b) Celestial phenomena and climate landscape

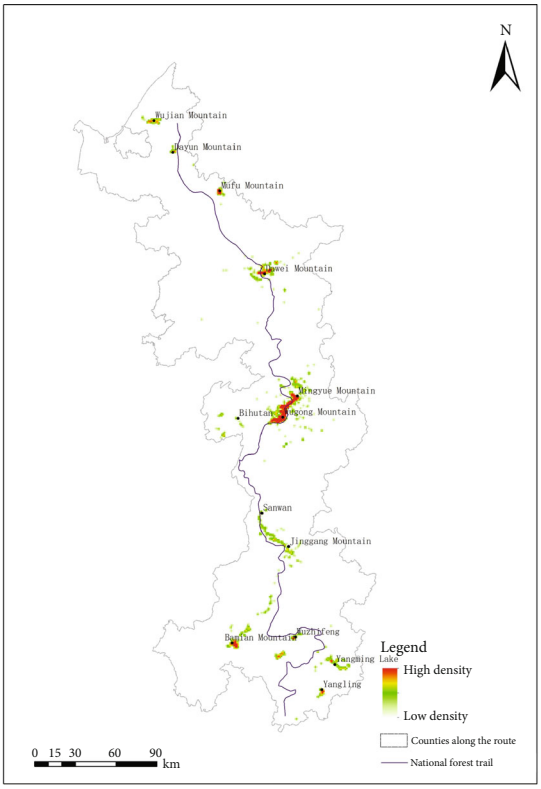
(c) Water landscape

(d) Biological landscape

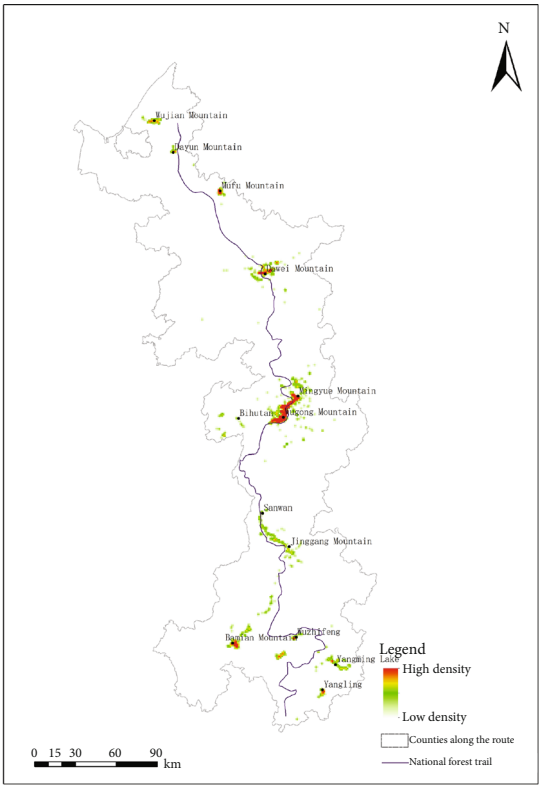
Figure 11: Continued.



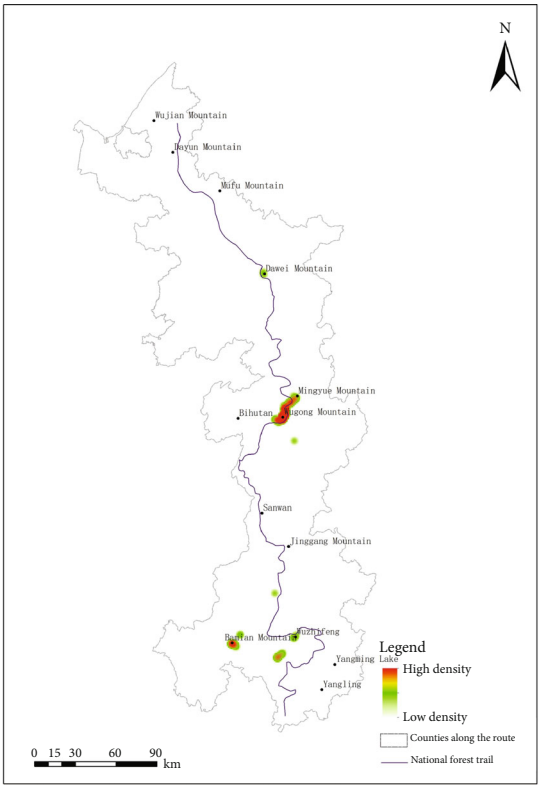
(e) Architecture and cultural relics



(f) Tourism facilities



(g) People



(h) Outdoor equipment

Figure 11: Kernel density distribution of the different landscape types.

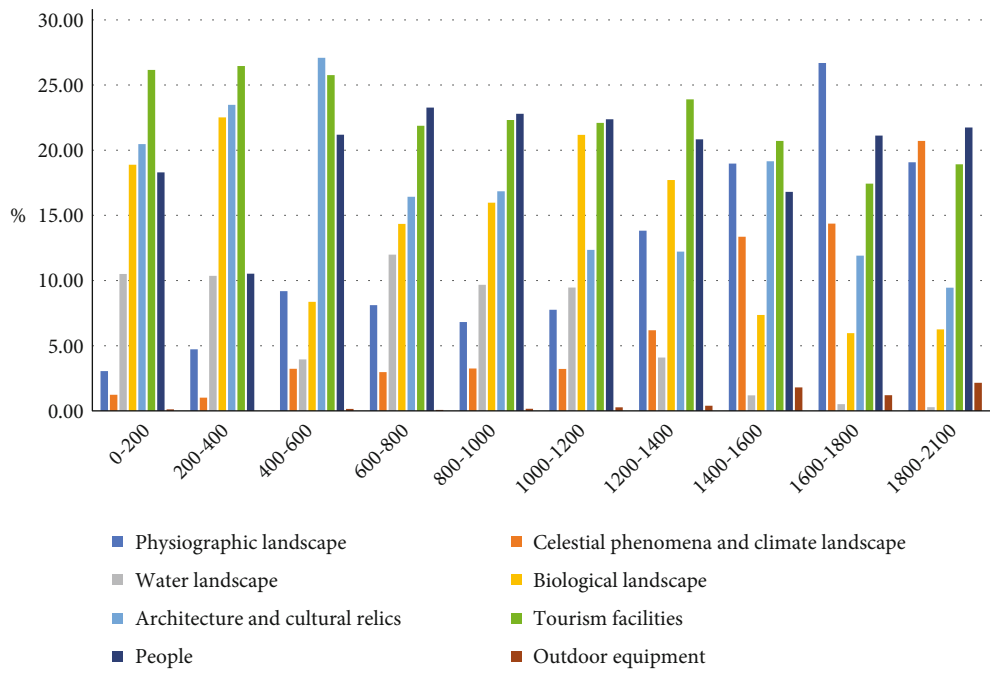


Figure 12: Proportion of each landscape type at different altitudes.

Most of the roads are trails through the forest, which meet the needs of tourists who wish to explore nature and hike the trails. By analyzing these characteristics, we found that most of the photos were of tourists walking, photos of other landscapes, and photos showing interactions among teams, which reflects the fact that tourists are driven by aesthetics and proof of accomplishments when using photos as a recording tool to express their landscape preferences [46], and it also reflects certain social relationships [34].

6. Conclusions

China's National Forest Trail mainly provides outdoor hikers with a strip of leisure space in which to deeply experience nature. Through the analysis of 10 landscape categories along the line at different time and space scales, this research draws the following conclusions: (1) the capture ability of the landscape reduced the representativeness of social media in terms of the preferences of tourists. Roads and identification facilities are particularly preferred by tourists in nature reserves along the trails. (2) According to the monthly seasonal index, the preferences for various landscape types are related to the tourism intensity, and the tourism intensity is significantly related to holidays. Therefore, based on the seasonal index of the four seasons, it can be concluded that tourists' preferences for and attention to the various landscape types are mainly affected by the climate and temperature, as well as the impact of landscape specificity. This landscape preference model is characterized by viewing flowers and leaves in spring, being hydrophilic in summer, climbing in autumn, and enjoying the snow in winter. (3) Spatially, it exhibited an agglomeration pattern characterized by the concentration in the central area and scattering in the northern and southern regions. Wugong and Mingyue are the most popular protected areas along the trail, and tourists pay more attention to the landscape types along the trail in the southern section than in the northern section. (4) There are significant differences among tourists at different altitudes, and tourism facilities and characters are the most preferred types. In the process of uploading photos to express their landscape preferences, tourists are driven by aesthetics and proof of motives, and it also reflects certain social relationships.

The data samples of this study come from social media, and the method utilized is universally applicable to other types of protected areas or large-span linear tourism units. Moreover, the research results of this paper can provide important reference for trail builders and managers of protected areas along the route. Trail builders can understand where tourist hotspots are along the trail, where potential areas for future development are concentrated, what landscape attraction types of the natural protection areas are along the trail, and how to connect the protection areas along the trail in future. As for the managers of each nature reserves, they should set up appropriate tourism activities according to the landscape preferences of tourists in four seasons and strengthen the follow-up sustainable management to improve the infrastructure service of scenic spots. Finally, there are some limitations in this paper. Because of the capturability of social media itself, when exploring future preferences for biodiversity, it may be wise to use data from different social media platforms or to combine the data with traditional surveys to overcome the limitations of using only social media data.

The data samples of this study come from social media, and the method used is also applicable to other types of protected areas or large-span linear tourism units, which is universal.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

Acknowledgments

This work was supported by the Science and Education Joint Project of Hunan Natural Science Foundation: Research on public landscape preference of nature reserve in Hunan Province based on multisource data analysis (2021JJ60014).

References

[1] Y. Xie, B. Wu, Y. Zhang, and M. Wang, "Types, typology and features of China's protected area tourism products," *Areal Research and Development*, vol. 40, pp. 69–74, 2021.

[2] Q. Li and L. Wang, "Conflicts and coordination of tourism resource use in protected areas in China," *Progress in Geography*, vol. 39, no. 12, pp. 2105–2117, 2020.

[3] D. Wang, "Tourism resources and tourism landscape," *Tourism Forum*, vol. 1, pp. 11–14, 1998.

[4] K. Maciejewski, A. D. Vos, G. S. Cumming, C. Moore, and B. Duan, "Cross-scale feedbacks and scale mismatches as influences on cultural services and the resilience of protected areas," *Ecological Applications*, vol. 25, no. 1, pp. 11–23, 2015.

[5] M. Hernandez-Morcillo, T. Plieninger, and C. Bieling, "An empirical review of cultural ecosystem service indicators," *Ecological Indicators*, vol. 29, pp. 434–444, 2013.

[6] T. Panagopoulos, "Linking forestry, sustainability and aesthetics," *Ecological Economics*, vol. 68, no. 10, pp. 2485–2489, 2009.

[7] D. Alexander, "Visualizing the perceived environment using crowdsourced photo geodata," *Landscape and Urban Planning*, vol. 142, pp. 173–186, 2015.

[8] E. L. Shafer and J. Meitz, *It seems possible to quantify scenic beauty in photographs*, Forest Service Research Paper, 1970.

[9] T. C. Daniel, "Whither scenic beauty? Visual landscape quality assessment in the 21st century," *Landscape and Urban Planning*, vol. 54, no. 1-4, pp. 267–281, 2001.

[10] R. Kaplan, "The analysis of perception via preference: a strategy for studying how the environment is experienced," *Landscape Planning*, vol. 12, no. 2, pp. 161–176, 1985.

[11] M. J. Scott and D. V. Canter, "Picture or place? A multiple sorting study of landscape," *Journal of Environmental Psychology*, vol. 17, no. 4, pp. 263–281, 1997.

[12] J. A. Donaire, R. Camprubí, and N. Galí, "Tourist clusters from Flickr travel photography," *Tourism Management Perspectives*, vol. 11, pp. 26–33, 2014.

[13] N. Balomenou, B. Garrod, and A. Georgiadou, "Making sense of tourists' photographs using canonical variate analysis," *Tourism Management*, vol. 61, pp. 173–179, 2017.

[14] K. Svobodova, P. Sklenicka, K. Molnarova, and M. Salek, "Visual preferences for physical attributes of mining and post-mining landscapes with respect to the sociodemographic characteristics of respondents," *Ecological Engineering*, vol. 43, pp. 34–44, 2012.

[15] X. Li, S. Fan, N. Kühn, L. Dong, and P.-Y. Hao, "Residents' ecological and aesthetical perceptions toward spontaneous vegetation in urban parks in China," *Urban Forestry & Urban Greening*, vol. 44, article 126397, 2019.

[16] Å. Ode, G. Fry, M. S. Tveit, P. Messager, and D. Miller, "Indicators of perceived naturalness as drivers of landscape preference," *Journal of Environmental Management*, vol. 90, no. 1, pp. 375–383, 2009.

[17] O. Kalivoda, J. Vojar, Z. SkIvanová, and D. Zahradník, "Consensus in landscape preference judgments: the effects of landscape visual aesthetic quality and respondents' characteristics," *Journal of Environmental Management*, vol. 137, pp. 36–44, 2014.

[18] T. Gerstenberg and M. Hofmann, "Perception and preference of trees: a psychological contribution to tree species selection in urban areas," *Urban Forestry & Urban Greening*, vol. 15, pp. 103–111, 2016.

[19] R. Kaplan and S. Kaplan, *The Experience of Nature: A Psychological Perspective*, Cambridge University Press, 1989.

[20] X. Tang and X. Wang, "Landscape visual environment assessment (LVEA): concept, origin and development," *Journal of Shanghai Jiaotong University (Agricultural Science)*, vol. 25, pp. 173–179, 2007.

[21] X. Song, D. R. Richards, and P. Y. Tan, "Using social media user attributes to understand human-environment interactions at urban parks," *Scientific Reports*, vol. 10, no. 1, 2020.

[22] L. J. Sonter, K. B. Watson, S. A. Wood, and T. H. Ricketts, "Spatial and temporal dynamics and value of nature-based recreation, estimated via social media," *PLoS One*, vol. 11, no. 9, article e0162372, 2016.

[23] U. Schirpke, C. Meisch, T. Marsoner, and U. Tappeiner, "Revealing spatial and temporal patterns of outdoor recreation in the European Alps and their surroundings," *Ecosystem Services*, vol. 31, pp. 336–350, 2018.

[24] A. À. Callau, M. Y. P. Albert, J. J. Rota, and G. David Serrano, "Landscape characterization using photographs from crowdsourced platforms: content analysis of social media photographs," *Open Geosciences*, vol. 11, pp. 558–571, 2019.

[25] Y. Do and J. Y. Kim, "An assessment of the aesthetic value of protected wetlands based on a photo content and its metadata," *Ecological Engineering*, vol. 150, article 105816, 2020.

[26] P. Bell, "Content analysis of visual images," in *Handbook of Visual Analysis*, Handbook of Visual Analysis, 2001.

[27] A. Hausmann, T. Toivonen, R. Slotow et al., "Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas," *Conservation Letters*, vol. 11, no. 1, pp. 1–11, 2018.

[28] S. Stepchenkova and F. Zhan, "Visual destination images of Peru: comparative content analysis of DMO and user-generated photography," *Tourism Management*, vol. 36, pp. 590–601, 2013.

[29] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "Deep face: closing the gap to human-level performance in face verification," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, 2014.

[30] Y. Kang, N. Cho, J. Yoon, S. Park, and J. Kim, "Transfer learning of a deep learning model for exploring tourists' urban image using geotagged photos," *International Journal of Geoinformation*, vol. 10, no. 3, p. 137, 2021.

[31] D. Kim, Y. Kang, Y. Park, N. Kim, and J. Lee, "Understanding tourists' urban images with geotagged photos using convolutional neural networks," *Spatial Information Research*, vol. 28, no. 2, pp. 241–255, 2020.

[32] X. Xiao, C. Fang, and H. Lin, "Characterizing tourism destination image using photos' visual content," *International Journal of Geo-Information*, vol. 9, no. 12, p. 730, 2020.

[33] K. Zhang, Y. Chen, and C. Li, "Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: the case of Beijing," *Tourism Management*, vol. 75, pp. 595–608, 2019.

[34] S. Y. Kim, C. H. Park, and H. Lee, "How do travelers express happiness? : focusing on the classification of happiness travel photo," *Journal of Tourism Studies*, vol. 33, no. 1, pp. 91–121, 2021.

[35] P. Wang, Y. Yan, Y. Chen, and Q. Wu, "The differences in visual representation of tourism destination based on cross-cultural perspective-a case of Tibet through the camera lenses of Chinese and American tourists," *Journal of Zhejiang University (Science Edition)*, vol. 45, pp. 242–250, 2018.

[36] K. Krippendorff, "Content analysis: an introduction to its methodology," *Journal of the American Statistical Association*, vol. 79, no. 385, p. 240, 1984.

[37] K. A. Neuendorf, *The Content Analysis Guidebook*, Philadelphia University Library, 2002.

[38] X. Su, B. Spierings, M. Dijst, and Z. Tong, "Analysing trends in the spatio-temporal behaviour patterns of mainland Chinese tourists and residents in Hong Kong based on Weibo data," *Current Issues in Tourism*, vol. 23, no. 12, pp. 1542–1558, 2020.

[39] B. Ma, X. Chen, and F. Chen, "Multi-scale temporal and spatial differentiation characteristics of Dunhuang tourism flow based on social big data," *Economic Geography*, vol. 41, pp. 202–212, 2021.

[40] B. Yan, J. Zhang, L. Li, H. Peng, C. Zheng, and L. Qian, "Differences in tourists' experience of post-disaster landscapes," *Resources Science*, vol. 38, pp. 1465–1475, 2016.

[41] E. Di Minin, H. Tenkanen, and T. Toivonen, "Prospects and challenges for social media data in conservation science," *Frontiers in Environmental Science*, vol. 3, p. 63, 2015.

[42] L. Zhong, J. Chai, T. Xie, and Q. Shi, "Assessment on trail impacts by tourism activities in Huangshizhai scenic spot of Zhangjiajie National Forest Park," *Geographical Research*, vol. 27, pp. 1071–1077, 2008.

[43] Z. Pan and B. Liang, "Interpretative validity research of tourism panels based on fuzzy comprehensive evaluation of Shanghai historic districts," *Resources Science*, vol. 37, pp. 1860–1870, 2015.

[44] X. Xie, G. Sun, and C. Han, "Impact of event tourism on tourism industry of Xinjiang," *Arid Land Geography*, vol. 33, pp. 487–492, 2010.

[45] C. Zhang and J. Bao, "Impact of holiday policy upon tourist flow in world heritage site: taking Wulingyuan of Hunan as a case," *Geographical Research*, vol. 26, pp. 1295–1303, 2007.

[46] X. Li, Z. Zhao, Y. Zhang, and M. Zhong, "Backpackers' landscape preference and spatial structure based on photo analysis: take the Qinling Taibai Mountain's backpackers as an example," *Areal Research and Development*, vol. 39, pp. 114–120, 2020.

[47] Z. Li and J. Zhu, "Waterscape planning and design of modern campus," *Journal of Anhui Agricultural Sciences*, vol. 3, pp. 23–27, 2011.

[48] E. J. Wilkins, P. D. Howe, and J. W. Smith, "Social media reveal ecoregional variation in how weather influences visitor behavior in US National Park Service units," *Scientific Reports*, vol. 11, article 2403, 2011.

[49] D. R. Richards and D. A. Friess, "A rapid indicator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media photographs," *Ecological Indicators*, vol. 53, pp. 187–195, 2015.

[50] Z. Wang, B. Wen, Z. Fang, and M. Liang, "Change of behavior patterns and differentiation of group characteristics of hiking tourists: explanation based on means-end chain theory," *Tourism Tribune*, vol. 33, pp. 105–115, 2018.