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Landscape Preferences for Recreational Ecosystem Services in Urban Parks via Combining Multiple Social Media Data

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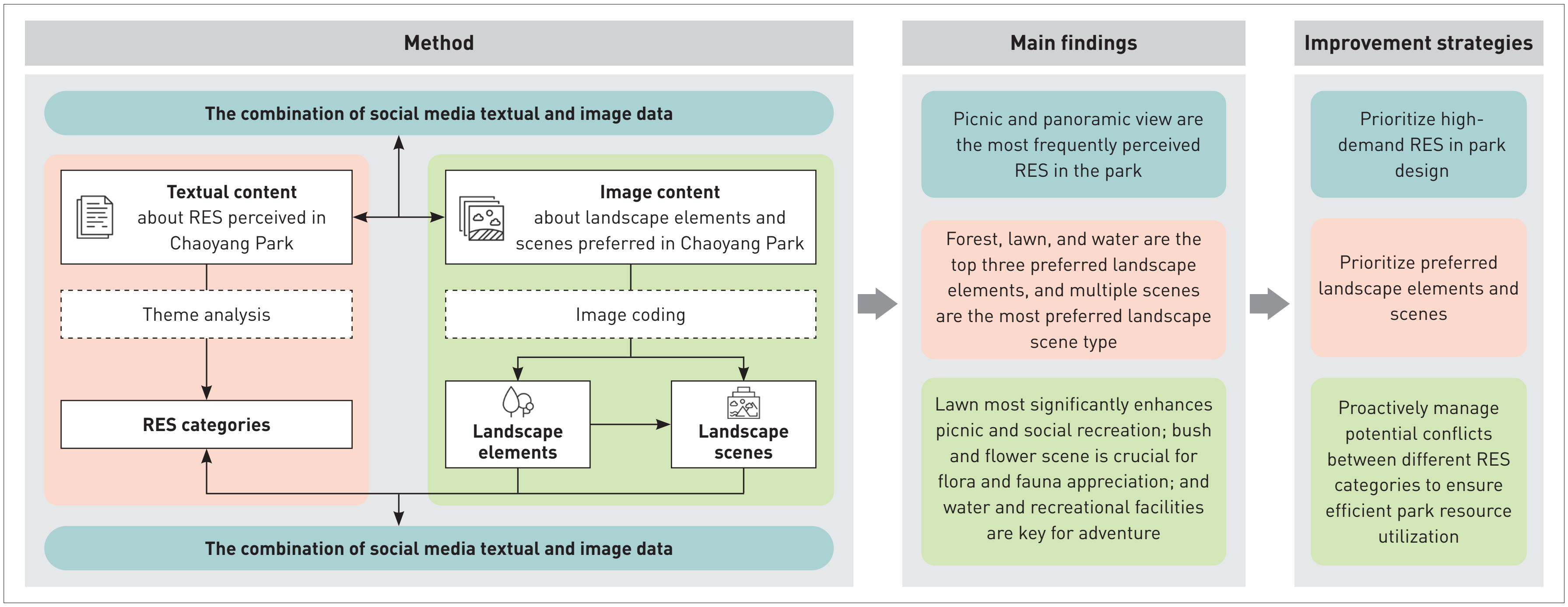
GRAPHICAL ABSTRACT



ABSTRACT

Recreational ecosystem services (RES) are diverse recreational opportunities offered by nature, playing a vital role in enhancing urban residents' physical and mental well-being. Urban parks serve as key venues for outdoor recreation, yet evolving resident preferences for different RES remain insufficiently understood. This knowledge gap hinders the adaptation of urban green spaces to shifting public demands. Social media data (SMD) offers rich insights into public perception, yet its potential remains underexplored and requires further development. To overcome these challenges, we developed a method that combines graphical and textual SMD to mitigate bias in single-data approaches and investigate landscape preferences for different RES. In this study, we took Chaoyang Park, one of the most popular urban parks in Beijing, as a case study. We performed topic analysis and image coding via NVivo to merge image and textural data. The Random Forest algorithm was utilized to identify the contribution of different landscape elements and scenes to RES. Our findings revealed that picnic and panoramic view were the most favored RES in parks, and people prefer scenes with various landscape elements, such as multiple scenes of lawns, water, and buildings. Notably, the contribution of specific elements varies across RES. For example, lawns significantly enhance social recreation, while bushes and flowers play a key role in supporting flora and fauna appreciation. These insights offer a practical foundation for timely adjustments in green space planning in high-density cities. By enhancing the understanding of landscape preferences for different RES via introducing a novel approach for integrating multiple SMD types, this study contributes to the refined management and sustainable development of urban parks.

KEYWORDS

Recreational Ecosystem Services; Social Media Data; Urban Park; Urban Green Space; Landscape Preference; Landscape Element; Landscape Scene

HIGHLIGHTS

- Develops a bimodal data fusion method combining social media text and image data to analyze landscape preferences
- Preferences for landscape elements and scenes vary across RES categories
- Water supports broader RES, highlighting its mental health role and attraction for physical activities
- Detailed facility classification is crucial for maximizing RES in park planning and meeting diverse needs

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1 Introduction

Urban parks provide diverse cultural ecosystem services (CES), with recreational ecosystem services (RES) constituting a key component[1]. RES are a range of recreational opportunities provided by nature, underscoring the natural environment's contribution to recreations[2]. Notably, RES in urban parks contribute significantly to public health and well-being[3–4]. Consequently, integrating RES into park design and management is essential to enhance park quality[5].

Current research on RES in urban parks predominantly focuses on macro-scale studies, assessing RES distribution and establishing evaluation frameworks[6–7]. However, micro-scale analysis of RES-supporting landscape elements and scenes remains limited[8]. This gap impedes targeted optimization of RES-specific park scenes. Although studies acknowledge that the capacity of a park to provide various RES relies on the availability of specific landscape elements and scenes[9–10], scholars often homogenize diverse RES categories and emphasize aggregate benefits, while neglecting differential landscape preferences across RES categories[8]. Therefore, further investigation is needed to identify the specific landscape elements and scenes that support different categories of RES.

Among few existing studies examining multiple RES categories, classifications vary by perspective, such as distinguishing between active and passive participation or classifying by the psychological drivers of recreation[11–12]. Recently, the Recreation Experience Mapping (REM) classified by Anton Stahl Olafsson is one of the frameworks that attract increasing attention in the assessment of RES[13]. Since its introduction in 2012, it has garnered increasing attention from scholars. For instance, Ole H. Caspersen et al. applied this framework to analyze both existing and potential recreations at golf courses, thereby promoting their transition toward multifunctionality[14]. Similarly, Andrej Christian Lindholst et al. compared various methods of mapping recreational and social values to better align them with urban planning objectives[15]. Many studies have approved Olafsson's classification framework as an effective approach to characterizing RES diversity, systematically integrating multiple recreation types and establishing direct landscape associations[16]. This enables precise capture of RES variations and landscape preferences, justifying its adoption as this study's RES classification framework.

Recently, social media data has been increasingly used to study RES and landscape preferences in urban parks[17]. Studies have shown that both images and text in social media can effectively capture the public's perceptions on RES and their preferences for landscape elements and scenes[18–20]. However, existing research often analyzes text or images in isolation[21–22], and fails to capture multidimensional perceptions (such as the interplay between visual experiences and emotional expressions). This could introduce observational bias, which may distort interpretations of social media content and limit the depth of analysis[23]. Althrough previous studies have suggested that combining multiple social media data types can support more comprehensive analysis[24–26], few studies have integrated both text and image data among the studies of RES in parks.

This study developed a bimodal data fusion method that integrates both text and image data from social media to examine the public preferences for landscape elements and scenes among different RES in urban parks, demonstrating a more comprehensive and efficient analysis method by using Chaoyang Park in Beijing as a case study. The findings can inform park planning and design practice and offer insights for high-density cities like Beijing. This study is conducted to answer the following four questions: 1) How to integrate social media text and image data for analyzing public preferences across RES categories? 2) Which RES are predominantly perceived by the public in the park? 3) What landscape elements and scenes do public prefer in the park? And 4) how do different preferences of landscape elements and scenes contribute to different RES?

2 Methods and Data

2.1 Study Area

This study focused on Chaoyang Park, which is the largest urban park in central Beijing, spanning 288.7 hm^2 including 68.2 hm^2 of water bodies, with the green coverage rate of 87%. Since its opening in September 2004, Chaoyang Park has become a comprehensive park that incorporates culture, sports, fitness, leisure, and ecology, significantly enhancing the environmental quality and providing more recreational opportunities for residents[27]. Due to its diverse range of RES, the park is a favored destination for the public and becomes one of the most frequented parks in Beijing, garnering significant attention on social media platforms[28–29]. An analysis of the landscape elements and scenes in Chaoyang Park can provide reliable references for developing and implementing practical interventions.

2.2 Research Framework

The research was divided into three sections (Fig. 1). Firstly, it used Python and keywords to gather text and image data on RES perceived in Chaoyang Park from LittleRedBook (LRB) to build

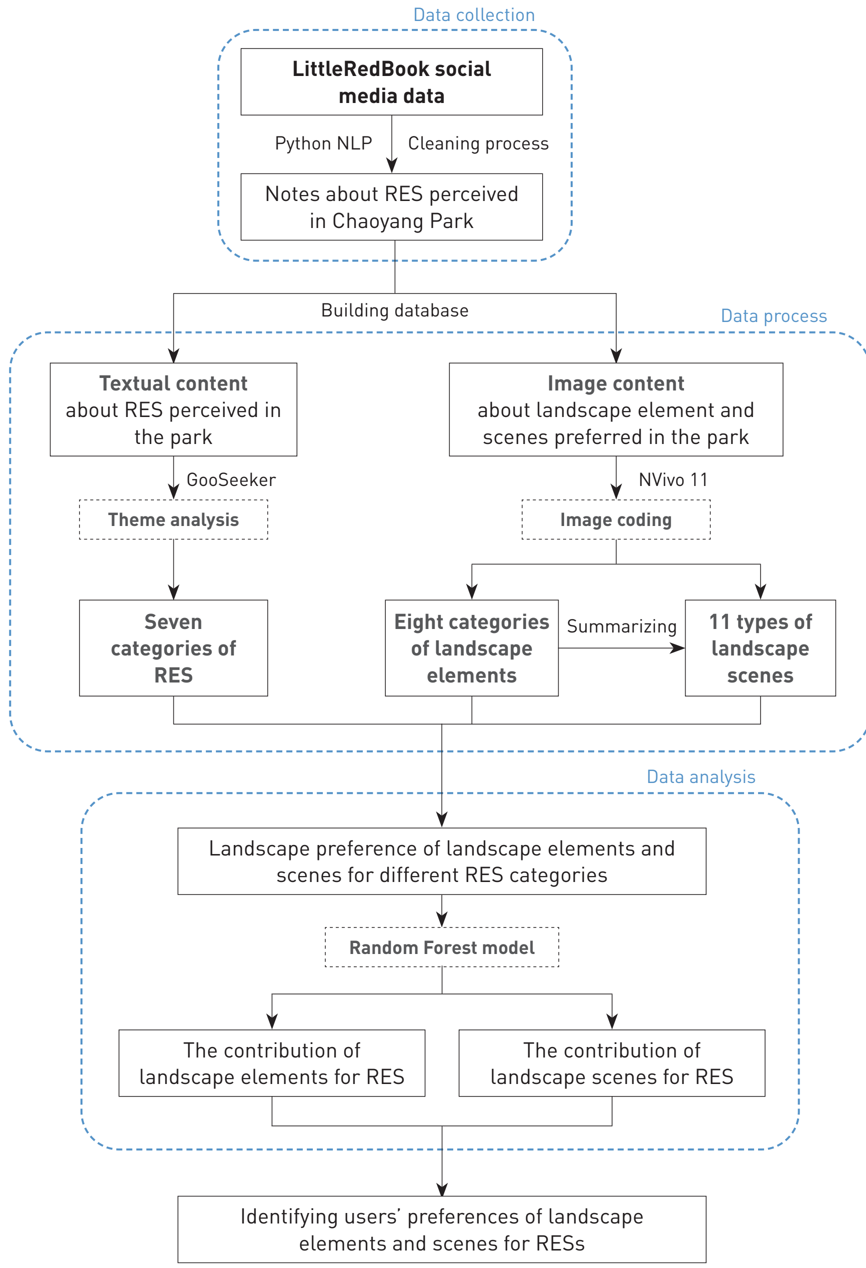

Fig. 1 Research framework.

text and image datasets. Established in 2013, the LRB is a social media network that encourages users to share and document their personal experiences, encompassing all facets of life. Typically, users contribute titles, thematic tags, geographical data, photographs, and explanatory text to describe the images and document their emotions. By April 2024, the LRB had 300 million active monthly users[30], offering a vast database of RES for this research.

Secondly, the collected text and image data were processed separately. On the one hand, a thematic analysis of the textual data categorized users' posts based on different categories of RES. On the other hand, the image data were encoded using NVivo to extract landscape elements and refine the landscape scenes depicted in the images. This step enables the integration of visual and literal data.

Thirdly, by combining the various RES categories identified from the texts with the landscape preferences identified from the images, the public preferences on landscape elements and scenes among different RES were determined. Then the Random Forest (RF) algorithm was used to further explore the contributions of these landscape elements and scenes to different perceived RES.

2.3 Data Collection

This study extracted the raw note data on RES perceived in Chaoyang Park between February and August 2023 by using the LRB's Application Programming Interface (API) in September 2023, focusing on the spring and summer seasons when outdoor recreations were most diverse and data-rich[31–32]. The keywords used for the search were "北京" (Beijing), "朝阳公园" (Chaoyang Park), "游玩" (touring), "玩乐" (amusement), "玩" (play), "放松" (relaxation), "休闲" (leisure/recreation), "娱乐" (entertainment), "户外" (outdoor), "绿地" (green space), "草地" (grassland), and "草坪" (lawn). Next, the notes geolocated in Chaoyang Park or mentioning Chaoyang Park in text were obtained as study samples of RES in the park. The notes include images and textual data describing users' behaviors and personal experiences. The released time and the username associated with each note were also collected.

After initial data collection, a data cleaning process was implemented. The notes were manually screened as follows:

1) The content of the note should be only related to Chaoyang Park. The note is invalid if it contains inaccurate location information or if the original text discusses various locations beside Chaoyang Park.

2) The notes related to promotion, marketing, and similar activities should be excluded, including the presence of specific keywords (e.g., "discount," "sale," "sponsored"), metadata suggesting commercial intent (e.g., links to commercial websites or branded hashtags), and the presence of direct advertising language. All ambiguous notes were manually reviewed to verify their promotional nature.

3) All notes should focus on genuine user experiences. The notes were required to outline recreation activities conducted in the park, with images depicting landscape elements relevant to the park's features.

4) Removing duplicate images within individual posts and excluding the irrelevant images like screenshots.

After data cleaning, a final valid dataset comprising 436 texts and their corresponding 1,551 images was obtained.

2.4 Textual Data Process

2.4.1 Classification of RES

In this study, Olafsson's classification of REM was adopted, which divides REMs into seven categories: wildness, feeling of forest, panoramic view, biodiversity, cultural history, activity and challenge, and service and gathering.

To better align this classification with the specific context of Chaoyang Park, the Word Frequency Analysis (WFA) on the collected data was performed by ROSTCM6①[33]. The results of WFA showed that camping (N = 108) and picnics (N = 182) were the two most prominent emerging types of recreation. At the same time, cultural history (N = 0) was rarely mentioned. In addition, the difference between "wildness" and "feeling of forest" in individual parks was slight. Based on these results, Olafsson's classification was adjusted in this study to better capture unique insights from social media data (Table 1): "picnic" and "camping" were added to reflect emerging recreational trends; "wildness" and "feeling of forest" were merged into "feeling of nature" to represent a sense of natural surroundings; and "cultural history" was removed due to its minimal impact on the public's overall experience in the park.

2.4.2 Theme Analysis

The study used Gooseeker② to ascertain the underlying subject of textual content[34–35] and subsequently categorized them into the seven RES categories (Table 2). Initially, keyword analysis③ was used to categorize the raw data, extracting over 10 keywords for each input. The main subject of each input was identified by filtering keywords and eliminating irrelevant phrases such as degree adjectives and locations. Finally, the thematic identification outcomes were manually fine-tuned.

2.5 Image Data Process

The image data processing comprised two sequential phases: 1) establishing a coding framework based on the grounded theory;

① ROSTCM6, developed by Wuhan University, is a comprehensive and freely available social computing platform designed to support humanities and social science research. The software integrates various text analysis functions, including word segmentation, word frequency statistics, traffic analysis, and clustering analysis (source: Ref. [33]).

② Gooseeker is a user-friendly software that enables semantic annotation and structural conversion of content, particularly social media data. Its reliability was demonstrated in previous research (source: Refs. [34–35]).

③ In Gooseeker, keyword analysis is a text analysis module. After text import, the system performs automatic word segmentation and offers filtering by part-of-speech, word frequency, etc., to help users quickly identify key feature words.

Table 1: Adjusted classification of RES used in this study

RES category	Description of relevant note	Example of relevant notes
Picnic	Activities involving eating or food preparation in outdoor natural settings, often including picnic mats or baskets	"Having a picnic."
Camping	Staying temporarily in outdoor areas using tents or similar shelters, often for recreation	"Go camping."
Feeling of nature	Emphasizing the overall feeling of relaxation in nature (rather than a specific element like flowers), where people experience the natural elements within a non-urban environment	"Walking, strolling, or meditating."
Panoramic view	Experiencing and appreciating expansive natural scenery that conveys a sense of vastness and freedom, such as open plains or mountain ranges	"Enjoying water features, forests, and meadows."
Flora and fauna appreciation	Activities that focus on the enjoyment and exploration of local plants and wildlife, aiming to appreciate nature's biodiversity; mentions specific names of flora and fauna in the text	"Appreciating tulips, feeding swans and ducks, etc."
Adventure	Dynamic, physically engaging activities conducted in natural settings, often supported by facilities or equipment, focusing on exploration, challenge, and health benefits	"Hiking, skating, climbing, etc."
Social recreation	Group-based outdoor recreation focusing on social interaction, collective enjoyment, and shared leisure experiences	"Frisbee team building, group activities, outdoor concerts, etc."

and 2) applying this framework to generate a classification of landscape elements and scenes. This hierarchical design ensured the methodological rigor while maintaining adaptability to site-specific characteristics.

2.5.1 Establishing Coding Framework

To systematically convert visual data into analyzable textual materials, a three-stage coding framework was established based on grounded theory[36]: open coding, axial coding, and selective coding. In open coding stage, researchers identified conceptual content, and strove to comprehensively document all the information present in the image. Axial coding aimed at developing linkages

Table 2: Examples of extracting textual data

Text example	Keyword	RES category
"There are quite few people in Chaoyang Park, and it is very fun to eat and drink on the lawn!"	Eat and drink; lawn	Picnic
"It's another wonderful must-visit place, no tickets, no reservations! Take a photo with the water!"	Must-visit; take a photo; water	Panoramic view
"This time, we enter from the West Gate and walk in the direction of Guanghe Bridge and see the people at the riverside campsite. We chose a shady place on the hillside to pitch our tent."	Camp; tent	Camping
"There is lawn and forest, you can fly a kite, play frisbee, and play balls."	Kite; frisbee; ball	Adventure

between various concepts and landscape element categories at a more detailed level. In the selective coding stage, a core category was determined for each item through systematic examination and comparison. By manually encoding by NVivo 11[④][37], this coding framework allowed researchers to effectively extract specific information from vast quantities of image data and classify landscape elements and scenes related to RES. To ensure accuracy, a cross-check verification through a coding team composed of three landscape architecture researchers was implemented.

2.5.2 Classification of Landscape Elements and Scenes

In this study, landscape elements refer to the discrete, identifiable physical components that constitute the visual environment, such as water, lawns, forest, garden facilities (e.g., landscape stone, sculptures), and landscape structures (e.g., pavilion, bridge). Landscape scenes, conversely, represent the holistic visual experience or character of a place, emerging from the specific combination, arrangement, and dominance of these underlying landscape elements within the image. Landscape elements serve as the basic components of scenes, while scenes

④ NVivo 11 is a powerful qualitative analysis software that enables effective management and analysis of various types of data, such as text, audio, and video, and is widely applied in fields including social sciences and market research; it has played a vital role in facilitating the structured qualitative analysis of landscape images (source: Ref. [37]).

represent functional units where these elements interact to deliver specific RES. Scene-level analysis facilitates targeted spatial interventions, as visitors experience composite environments rather than discrete elements.

To ensure the classification results' validity, objectivity, and analyzability, this study primarily referred to the classification of landscape elements in an existing study[38], with supplement and adjustment based on the axial coding results. These adjustments ensure that the classification aligns better with the scale of urban park, while enhancing relevance to the specific characteristics of Chaoyang Park and the social media context. Finally, all the landscape elements related to RES in Chaoyang Park were extracted and divided into eight main categories (Table 3). Due to the significant proportion of plant-related elements, the final classification refined the plants for calculation and finally divided them into three categories for further analysis.

Subsequently, landscape scenes for each RES were derived from the results of landscape elements. First, the textual descriptions of the RES scenes were combined with manual screening to select images that most accurately represent the landscape scene for each category of RES. For each image, the landscape scene was initially characterized by its predominant landscape elements. To ensure the objectivity of the recognition process, the Matrix Coding Queries tool in NVivo 11 was utilized to calculate the area proportion of each landscape element by the total area of the image, based on the pixel count. Specifically, the element covering the largest area was designated as the scene type for that specific image. However, if the scene elements were rich (meaning the difference between the top two elements was less than 10%), the RES scene would be classified as a combination of scenes with multiple elements. Finally, the landscape scenes were divided into 11 types (Tables 4, 5).

2.6 RF Analysis

The contribution of different landscape elements to various RES categories was analyzed by the RF algorithm. As a nonlinear machine-learning model, RF algorithm can effectively handle the complex relationships and potential interactions between features, and is less susceptible to data bias and perform well with imbalanced datasets. In this study, the algorithm can distinguish the contributions of individual landscape elements to different RES. The

Table 3: Classification of landscape elements

Landscape element category		Example
Plant	Forest	—
	Lawn	—
	Bush and flower	—
Road and pavement		Pavement, wooden walkway, paved square
Garden facility		Landscape stone, decorative wall and window, sculpture, landscape seat, garden lamp, planting bed, retaining wall
Recreational facility		Children's playground
Building		—
Landscape structure		Pavilion, booth, bridge
Water		Water body and features
Bare land		—

Table 4: Classification of landscape scenes

Landscape scene type	Example
Forest	Forest trail, dense forest area
Lawn	Open lawn, grass leisure area
Bush and flower	Flower bed area, ornamental bush
Road and pavement	Wooden plank road, hard event venue
Garden facility	Area with landscape stones, sculptures or seats as the main body
Recreational facility	Children's playground
Building	CITIC Tower, wedding church
Landscape structure	Pavilion, water pavilion, landscape bridge
Water	Lake view, waterfront landscape
Bare land	Bare land, unhardened surface
Multiple scenes	A grassland landscape nearby the water, a lawn with sculptures

Table 5: Examples of coding landscape elements and scenes from the image data

Open coding	Axial coding	Selective coding
"Yellow winter jasmine about 80 ~ 100 cm tall."	Winter jasmine	Bushes and flowers
"Sparkling streams at night."	Streams	Water
"A slightly barren waterside lawn in a semi-open space."	Lawn	Lawn
"Willow groves in the distance."	Willow	Forest

feature importance assessment can be conducted independently of inter-feature correlation, and the outcomes of multiple decision trees can be combined to generate more robust and reliable results.

During the data processing, different landscape elements and scenes were treated as independent variables and different RES categories as dependent variables. The calculation results illustrated the contributions of different landscape elements and scenes to various RES categories.

3 Results

3.1 Characteristics of RES Categories

By analyzing the text data, 736 RES items were identified (Table 6). Picnic was the most frequently mentioned RES (N = 182), accounting for 24.73% of all items, followed by panoramic view (N = 163) and feeling of nature (N = 139). Social recreation (N = 30) was the least prevalent, accounting for 4.08% of all RES items. Flora and fauna appreciation (N = 60) and adventure (N = 54) categories were also relatively less frequent, representing 8.15% and 7.34%, respectively. The temporal RES distribution of text notes revealed a clear seasonal trend, with numbers increasing steadily from early spring and reaching a sharp peak in May (Fig. 2). In May, picnic and panoramic view were the most frequently recorded categories.

Table 6: Descriptive statistic of RES categories in the text notes

RES category	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sum	Proportion	Mean	Variance
Flora and fauna appreciation	0	1	19	25	8	4	3	60	8.15%	8.57	93.62
Panoramic view	0	2	33	76	36	8	8	163	22.15%	23.29	749.57
Social recreation	0	1	12	11	4	1	1	30	4.08%	4.29	25.90
Camping	1	0	9	46	41	1	10	108	14.67%	15.43	385.62
Adventure	0	3	10	28	5	2	6	54	7.34%	7.71	90.24
Picnic	0	7	32	92	34	4	13	182	24.73%	26.00	1,024.33
Feeling of nature	0	7	46	57	22	5	2	139	18.89%	19.86	527.81
Total	1	21	161	335	150	25	43	736	—	—	—

ANOVA analysis of different RES categories

Source of variance	*SS*	*df*	*MS*	*F*	*p*-value	*F*-crit
Between groups	2,958.408	6	493.068	1.191	0.330	2.324
Within groups	17,382.571	42	413.871			
Total	20,340.979	48				

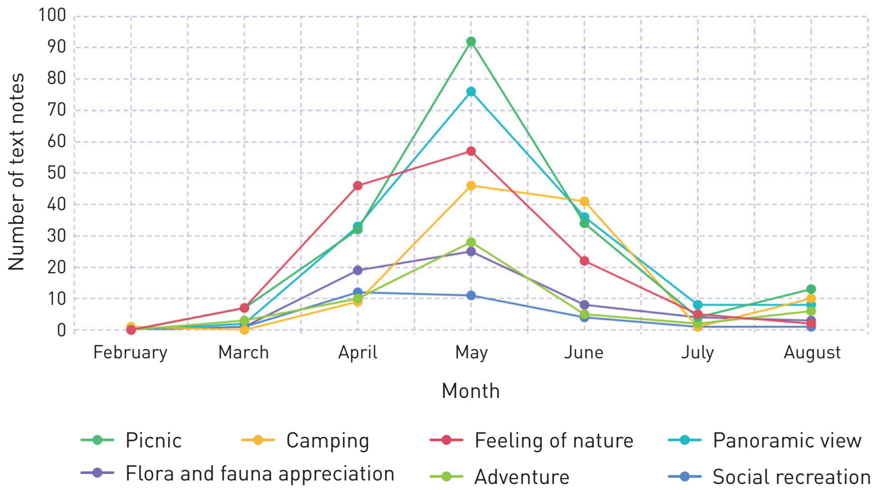

Fig. 2 Monthly distribution of RES categories in the text notes.

Activity levels declined in June but remained higher than in the preceding months.

In terms of the quantity of images associated with each RES category (Table 7), panoramic view ($N = 437$) ranked highest, followed by picnic ($N = 340$), feeling of nature ($N = 288$), and camping ($N = 248$). The category social recreation ($N = 39$) had the fewest images, accounting for only 2.51%. Similarly, the category flora and fauna appreciation ($N = 106$) and adventure ($N = 93$) had relatively fewer images, each accounting for 6.83% and 6.00%. The image data exhibited a similar seasonal rise, with the largest increase occurring in May, dominated by panoramic view images (Fig. 3). In June, the total number of images decreased, yet panoramic view continued to account for the largest share of postings.

Overall, both datasets showed a pronounced seasonal pattern, with RES occurrences concentrated in late spring and early summer and fewer records in colder months. The one-way ANOVA indicated no statistically significant differences among categories across

Table 7: Descriptive statistic of RES categories in images

RES categories	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sum	Proportion	Mean	Variance
Flora and fauna appreciation	0	1	23	51	10	10	11	106	6.83%	15.14	307.81
Panoramic view	0	4	55	171	133	44	30	437	28.18%	62.43	4,254.29
Social recreation	0	1	18	12	5	3	0	39	2.51%	5.57	47.62
Camping	1	0	16	109	84	5	33	248	15.99%	35.43	1,920.29
Adventure	0	3	16	40	12	5	17	93	6.00%	13.29	181.24
Picnic	0	9	38	173	70	15	35	340	21.92%	48.57	3,548.29
Feeling of nature	0	1	55	152	67	11	2	288	18.57%	41.14	3,149.14
Total	1	19	221	708	381	93	128	1,551	—	—	—

ANOVA analysis of different RES categories

Source of variance	*SS*	*df*	*MS*	*F*	*p*-value	*F*-crit
Between groups	18,395.102	6	3,065.850	1.601	0.171	2.324
Within groups	80,452.000	42	1,915.524			
Total	98,847.102	48				

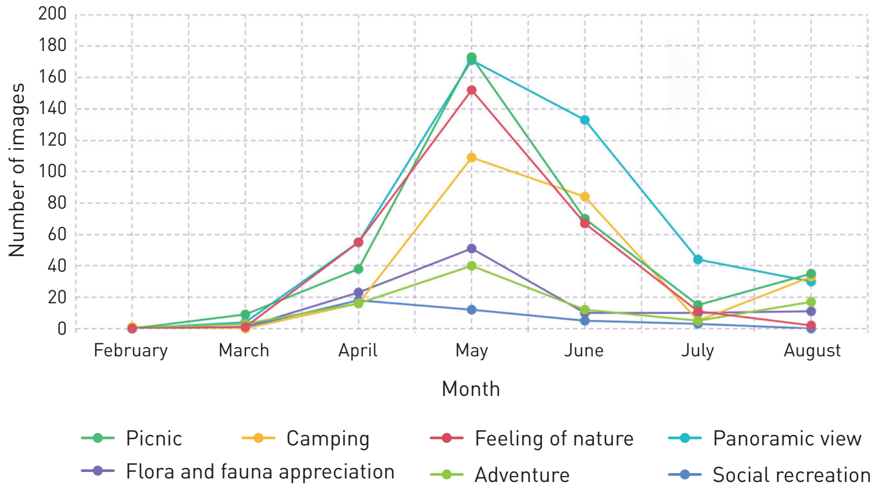

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Fig. 3 Monthly distribution of RES categories in the image notes.

months (text notes: F = 1.191, p = 0.330; images: F = 1.601, p = 0.171) (Tables 6, 7), suggesting that all RES categories followed a comparable temporal rhythm, characterized by a collective peak in May and sustained activity in June.

3.2 Characteristics of Landscape Preference

By identifying all landscape elements contained within the images (Table 8), forest (27.13%, 34.68%), lawn (21.51%, 25.08%), and water (17.28%, 16.77%) stood out as the dominant landscape elements, with both the image number and their area proportions significantly higher than others. Bare land shared the smallest fraction, accounting for only 0.30% in image number and 0.34% in area proportion. The most prominent scene was multiple scenes, representing 33.02% of the total number of images. This was followed by the scenes of forest (25.27%) and lawn (20.24%). On the other hand, scenes of road and pavement, garden facility, and landscape structure were the least significant categories, representing only 0.27%, 0.41%, and 0.68% of the overall distribution, respectively.

3.3 Contributions of Landscape Elements and Scenes to Different RES

The analysis results of the contributions of varied landscape elements to different RES (Fig. 4) revealed that landscape elements exerted varying influences on all RES, with forest being

Table 8: Descriptive statistics of landscape elements and scenes

Landscape element category	Number of images that contain the landscape element	Percentage of the image number that contain the landscape element	Area proportion of the element	Number of images of the landscape scene	Percentage of the image number of the landscape scene
Forest	1,251	27.13%	34.68%	186	25.27%
Lawn	992	21.51%	25.08%	149	20.24%
Bush and flower	354	7.68%	6.99%	24	3.26%
Road and pavement	249	5.40%	4.69%	2	0.27%
Garden facility	113	2.45%	1.50%	3	0.41%
Recreational facility	327	7.09%	2.40%	6	0.82%
Building	272	5.90%	4.23%	8	1.09%
Landscape structure	242	5.25%	3.32%	5	0.68%
Water	797	17.29%	16.77%	101	13.72%
Bare land	14	0.30%	0.34%	9	1.22%
Multiple scenes	—	—	—	243	33.02%

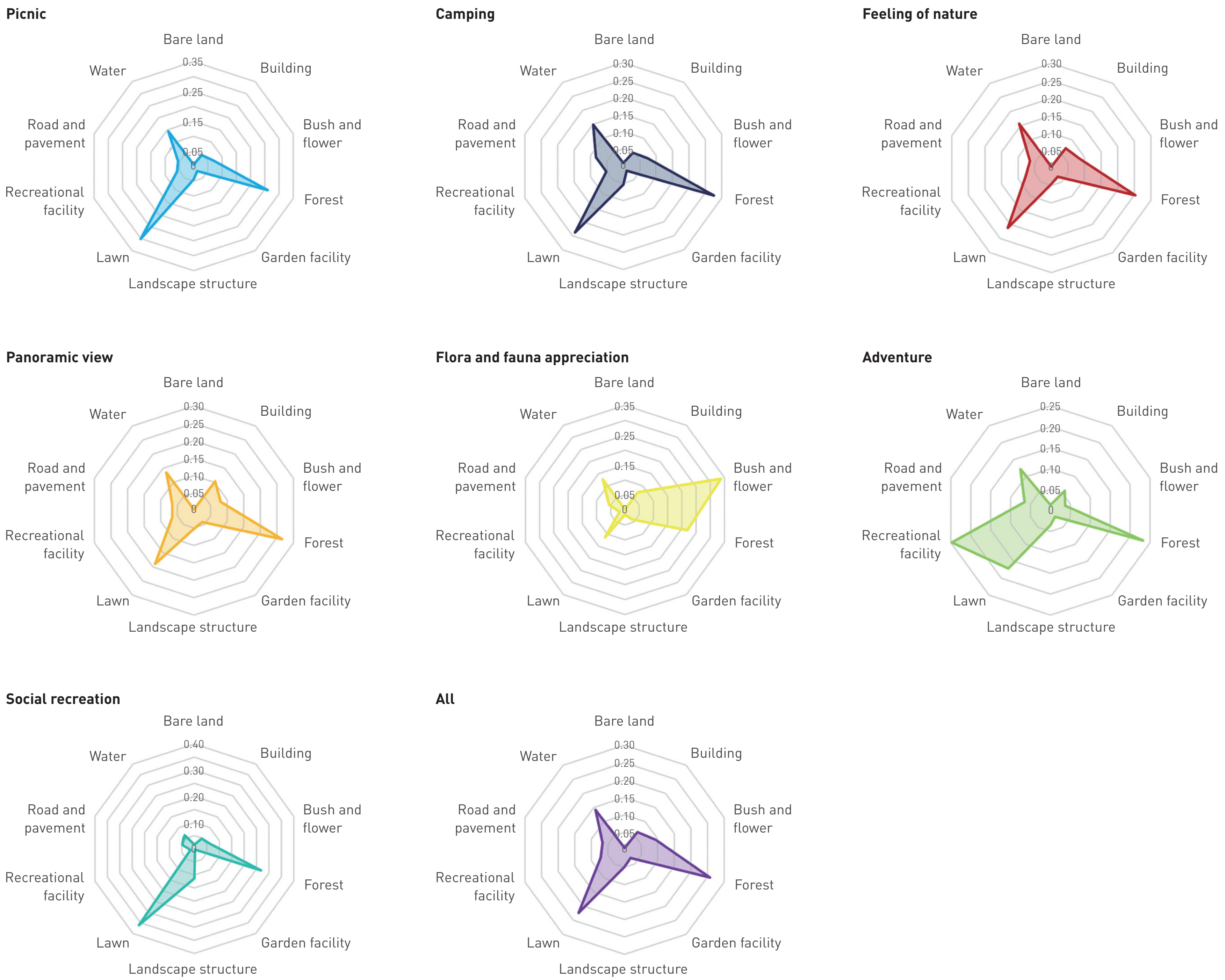

Fig. 4 The importance of landscape elements for all RES.

the most significant, followed by lawn and water. For RES categories of feeling of nature, camping, panoramic view, and picnic, they three (forest, lawn, and water) were also crucial. For social recreation, lawn contributed the most, followed by forest, landscape structure, and water. Regarding flora and fauna appreciation, bush and flower made the most significant contribution, followed by forest, water, and lawn.

There were also variations in the landscape scenes' contribution to different RES (Fig. 5). Overall, bush and flower, garden facility, lawn, water, and forest had the most substantial impact on public perception on RES. In terms of feeling of nature, bush and flower and multiple scenes had the highest contribution, followed by lawn, road and pavement, and forest. For panoramic view, building, lawn, and water were the most contributing scenes, followed by forest. In terms of flora and fauna appreciation, the contribution of bush and flower was highlighted. For

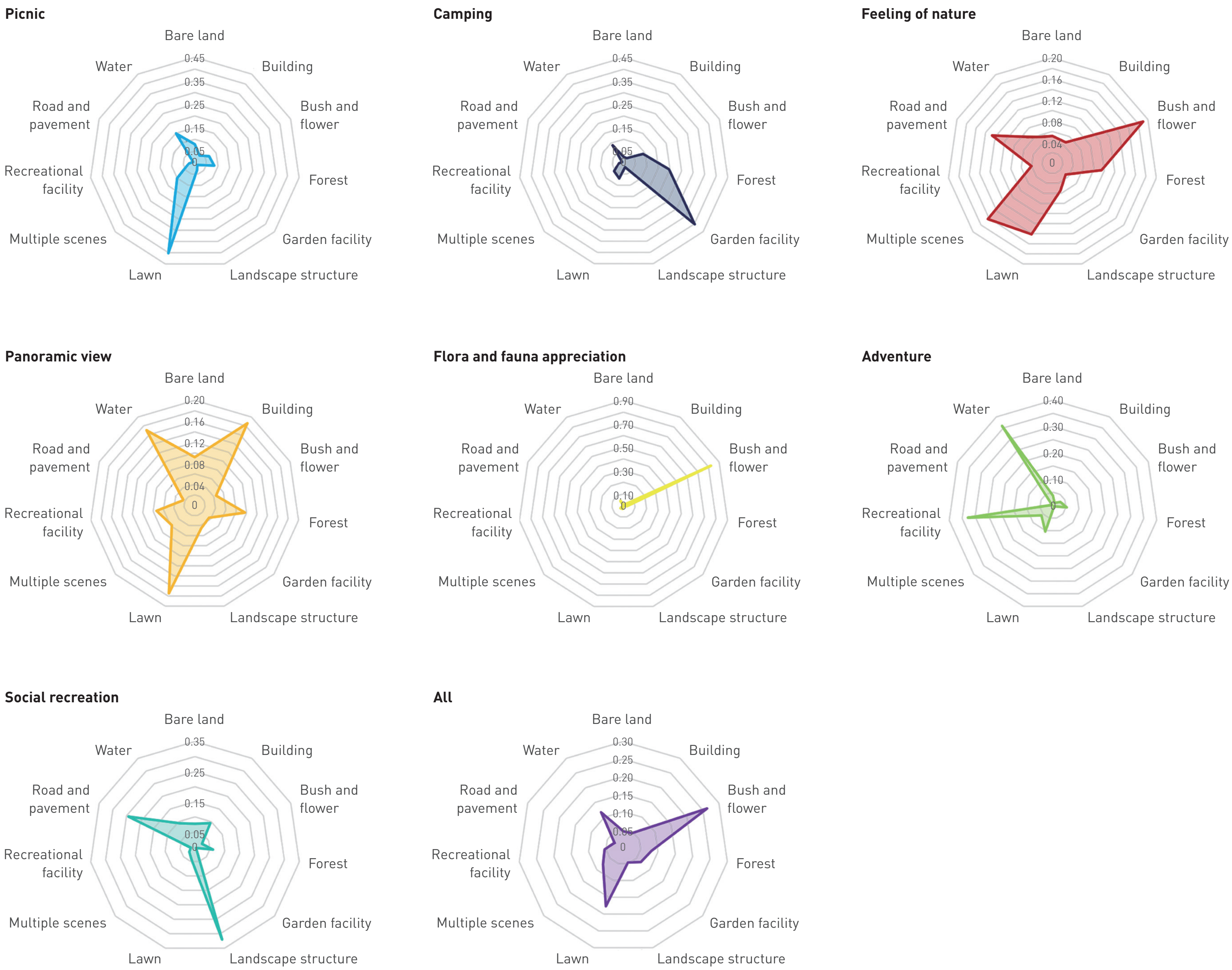

Fig. 5 The importance of landscape scenes for all RES.

adventure, the contributions of water and recreational facility were emphasized, followed by lawn, multiple scenes, and forest. Regarding the social recreation, the contributions of landscape structure and road and pavement were the highest, followed by building, water, and bare land. For picnic, the contribution of lawn was prominent, followed by the water, multiple scenes, and forest. Lastly, for camping, garden facility had a highest contribution, followed by forest.

4 Discussion

4.1 The Combination of Social Media Text and Image Data to Analyze Landscape Preferences for RES

In this study, text and image data from social media were combined to investigate public preferences for landscape elements and scenes across different RES. Differing from previous research that typically relied on either text or image data in isolation, this approach can reduce the observational bias introduced by single-source data.

Social media text and image data each provide unique insights into the perception of RES and have been increasingly applied in urban park studies due to their accessibility and granularity[39–41]. These two data types are complementary: text provides contextual information about intent and behavior, while images ground those descriptions in specific visual settings. Addressing that few studies have linked visual content directly with textual context to analyze RES, the bimodal data fusion method introduced in this study significantly improves the precision and validity of landscape preference analysis for RES. By bridging the gap between what people say they are doing and what they visually experience, this method supports a deeper understanding of the public's recreational perceptions and enables more nuanced urban park planning and design practice.

4.2 Overview of RES Categories

The analysis results revealed that panoramic view was the most prominently perceived RES categories, as indicated by the image counts across the RES. This finding is consistent with previous studies, highlighting a strong public preference for landscape appreciation[42]. This preference reflects the public's intrinsic motivation to interact with and appreciate nature, a function that urban parks increasingly fulfill as urbanization intensifies[43]. The results further showed that panoramic view, feeling of nature, and camping were the three most prominently perceived RES (Table 7). In contrast to previous studies reporting a growing popularity of camping activities in urban green spaces[44], camping appeared less prominent, occupying only intermediate positions rather than ranking among the top three categories. This relatively limited prominence likely reflects Beijing's restrictive policies on tent usage and the limited camping infrastructure within the park, which may influence Chaoyang Park's appeal as a primary camping destination[27–28]. This observation aligns with prior research, which emphasizes that infrastructure availability is a key determinant in the selection of campsites[45]. Furthermore, the study not only identified differences in the number of RES but also observed temporal changes in RES perceptions, as supported by ANOVA results. Notably, we found that public perception of all categories of RES peaked significantly in May. This surge coincided with favorable weather conditions and park-hosted recreational events, such as organized markets, concerts, and beer festivals. These findings further support previous research indicating that recreational service is one of the primary drivers of park visitation[35].

4.3 Preferences of Landscape Elements and Scenes for Different RESs

Overall, individuals prefer natural landscape elements for all RES, particularly forest, lawn, and water. This finding is consistent with previous research[46–47]. And this study goes further to investigate the landscape scenes for RES, capturing the interplay between natural and artificial elements. Notably, differing from previous studies that emphasize the negative impact of artificial facilities on the perception of RES[48–50], our results show that the introduction of a moderate amount of artificial elements, such as garden facilities and roads, can enhance the public perception of RES. On the contrary, this study suggests that a balanced landscape design in parks, which combines natural elements with functional facilities, may more effectively promote the perception of RES than creating a purely natural landscape.

Further analysis reveals that the impact of landscape elements and scenes varies across different RES. Similar to previous studies, lawn emerges as a crucial element for several RES, with RF analysis results confirming its significant contribution to picnic, camping, and social recreation. This finding also highlights that lawns serve as venues for various recreations. Notably, contrary to previous studies[51], this research uncovered the multifunctionality of water: our findings unexpectedly reveal that water also significantly contributes to adventure. This contrasts with previous studies suggesting that adventure zones were mainly concentrated along forest trails, cycling routes, and landmarked trails, with water features contributing primarily to visual aesthetics[13]. These unexpected findings could deepen our understanding of the nuanced preferences for different RES.

Besides, the study also noted that the impact of different park facilities on RES varies significantly, providing more detailed insights into RES perception in parks that was previously overlooked in existing literature. Contrary to existing studies, which often associate park facilities with leisure activity satisfaction[52–53], our findings highlight that different categories of park facilities affect the perception of various RES. For instance, our study found that garden facilities, such as benches, were shown to attract the public to engage in camping, while recreational facilities like climbing frames primarily influenced adventure. This variation underscores the importance of a detailed classification of facilities in maximizing RES in park planning and design, which could help meet the diverse needs of visitors and enhancing their overall park experience.

Moreover, it is noteworthy that buildings, especially surrounding landmarks have made unexpected contributions to panoramic view[54]. Contrasting with previous studies that primarily focus on the landscape elements within parks[55–57], this research suggests that the surrounding urban environment and specific architectural designs also play a significant role in shaping people's overall perceptions of RES in urban parks. It offers a fresh perspective on the impact of building elements on RES perception, broadening park designers' understanding of RES.

4.4 Application for Park Planning and Design Practice

Urban parks have become the main venue for RES for residents, with people's demands for park landscapes becoming more diverse. In this context, exploring the differences in public demands for landscape elements and scenes associated with various RES can provide valuable insights for implementation of green space management policies[58], while also enhancing public health fostered by the nature[59]. The findings emphasize the importance of incorporating RES into urban park planning and design, particularly in densely populated urban environments worldwide, where multifunctional urban green spaces are increasingly critical for inclusive urban living and for promoting public well-being. The study also contributes to global urban sustainability by operationalizing demand-responsive design principles through empirical user-generated content, thereby addressing the call for more user-centered, data-informed urban green space strategies. It thus offers a valuable framework and actionable insights for researchers and planners internationally seeking to enhance the RES provision and public health benefits of urban parks.

Based on these findings, the following actionable recommendations for park management and planning are proposed.

1) Prioritize high-demand RES in park design: emerging recreations, such as picnic and camping, exhibit high demand. Park design and renovation should provide open spaces suitable for setting up camping equipment and offering accessible, shaded grassy areas conducive to picnics. Concurrently, viewpoints should be incorporated, such as observation platforms offering expansive vistas, accompanied by appropriate behavioral guidance.

2) Prioritize preferred landscape elements and scenes: strategically introducing appropriate artificial elements can enhance park attractiveness by enriching the landscape. For instance, thoughtfully designed pathways can improve landscape appreciation, while increasing the variety and number of recreational facilities can prolong physical activity duration and enhance perception of diverse RES. New park designs should emphasize the integration of forests, lawns, and water bodies, while existing parks should prioritize their maintenance and enhancement.

3) Proactively manage potential conflicts between different RES to ensure efficient park resource utilization: park space utilization should be optimized, ensuring resources effectively aligned with the actual demands arising from diverse landscape elements and settings. For example, active recreations like social recreation are strongly associated with lawns and landscape structures, while passive recreations emphasizing feeling of nature are more linked to shrubs, flowers, and multiple natural scenes. Also, park management should mitigate usage conflicts arising from different RES experiences. Spatially, planning should consider separating potentially incompatible activities based on identified distinct landscape preferences. Concurrently, management strategy adjustments (such as public-use guide during peak periods) are necessary. In addition, targeted interventions are needed in underutilized areas. For instance, bare land, while contributing less overall, shows significant importance for opportunities of adventure and social recreation. Developing adventure-based recreations within bare land or designing small, resilient zones for gatherings can increase the park's attraction and enhance spatial utilization.

4.5 Limitations and Suggestions

While this study provides valuable insights, it also has certain limitations. Firstly, the identification of landscape scenes were characterized by the dominant element in the image. Although this approach improves the interpretability of landscape preferences for different RES, it may introduce slight discrepancies compared with actual park conditions. In the future, fieldwork and multi-seasonal data should be integrated to improve validation and achieve a more comprehensive understanding.

Secondly, constraints from LRB, such as the new anti-crawling mechanism implemented in September 2023, have limited our ability to obtain a larger dataset. Nonetheless, the study's sample size falls within an acceptable range comparing with similar research[60], a larger dataset in future research can enhance the generalizability of findings.

Thirdly, the reliance on data sourced exclusively from LRB might introduce a representation bias. The user demographics of LRB, which skew towards younger, predominantly female users who are active content creators, may not fully align with the broader spectrum of park visitors. Moreover, the study's reliance on social media data may underrepresent preferences of elderly or child visitors[21]. Future research could combine surveys to better capture the understanding of broader user groups.

Last, the study primarily focuses on spring and summer data, leaving a gap in the analysis of preferences during autumn and winter. Future research should capture preferences across all seasons to provide a more comprehensive understanding of seasonal shifts in landscape preferences for RES.

5 Conclusions

This study examined the landscape preferences for RES in urban parks by integrating social media text and image data by investigating the monthly distribution of varied RES in the Chaoyang Park. It explored the contributions of various landscape elements and scenes to different categories of RES, thereby uncovering the variations in landscaping preferences. Regarding the frequency of different RES in the text data, the most widely favored recreational pursuit was picnic, followed by panoramic view and feeling of nature. All categories of RES were found to have significant contributions from natural landscape elements, as demonstrated by the RF results. Among them, water made remarkable contributions. Furthermore, there were variations in landscape preferences for different categories of RES. For instance, the inclination of camping toward garden facilities was apparent (Fig. 5).

These findings demonstrated the significance of creating diverse landscapes for effective park administration, helping park managers understand the emerging shifts in public recreation. It serves as a dependable foundation for addressing the growing demand for natural exposure among individuals, and also helps reconcile conflicts between public accessibility and practical utilization of green spaces, ultimately maximizing public health and well-being.

Competing interests | The authors declare that they have no competing interests.

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结合多种社交媒体数据分析城市公园游憩生态系统服务的景观偏好

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摘要

游憩生态系统服务（recreational ecosystem services，RES）是指自然提供的多样化游憩机会，在提升城市居民身心健康方面发挥着重要作用。城市公园是重要的户外游憩场所，然而，居民对不同RES动态变化的偏好仍未得到充分探究。这一研究空白使得城市绿地无法满足不断变化的公众需求。社交媒体数据为了解公众感知提供了探知窗口，但其潜力仍有待进一步开发。基于此，本文提出了一种结合图像和文本社交媒体数据的方法，以减少单一数据方法的偏差，并调查公众对不同RES的景观偏好。本研究以北京最受欢迎的城市公园之一——朝阳公园为例，通过NVivo进行主题分析和图像编码，以合并图像和文本数据；利用随机森林算法识别不同景观元素和场景对RES的贡献。研究结果表明，野餐和全景是公园中最受欢迎的RES，并且人们偏爱具有各种景观元素的场景，例如由草坪、水体和建筑物构成的多元场景。值得注意的是，特定元素在不同RES中的贡献各异：例如草坪可显著增强社交游憩，而灌木和花卉在促进动植物欣赏方面发挥关键作用。这些研究结论为高密度城市绿地规划实践的及时调整提供了科学依据。通过引入一种整合多种社交媒体数据的新方法来加强对不同RES景观偏好的理解，本研究为城市公园的精细化管理和可持续发展提供了有益参考。

关键词

游憩生态系统服务；社交媒体数据；城市公园；城市绿地；景观偏好；景观元素；景观场景

文章亮点

- 开发了一种整合社交媒体文本和图像数据的景观偏好分析方法
- 景观元素和场景的偏好随RES类别而异
- 水体支持更广泛的RES，突显了其在心理健康方面的作用及对体力运动的吸引力
- 详细的设施分类对于在公园规划中最大化RES并满足多样化需求至关重要

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