buildings

Article

Research on Landscape Perception of Urban Parks Based on User-Generated Data

Wei Ren [1,†], Kaiyuan Zhan [1,2,†], Zhu Chen [2,3] and Xin-Chen Hong [2,*]

[1] College of Landscape Architecture and Art, Fujian Agriculture and Forestry University, Fuzhou 350100, China; ren-wei@fafu.edu.cn (W.R.); zky.yue@outlook.com (K.Z.)
[2] School of Architecture and Urban-Rural Planning, Fuzhou University, Fuzhou 350108, China; chen@umwelt.uni-hannover.de
[3] Institute of Environmental Planning, Leibniz University Hannover, 30419 Hannover, Germany
* Correspondence: xch.hung@outlook.com
† These authors contributed equally to this work.

Abstract: User-generated data can reflect various viewpoints and experiences derived from people's perception outcomes. The perceptual results can be obtained, often by combining subjective public perceptions of the landscape with physiological monitoring data. Accessing people's perceptions of the landscape through text is a common method. It is hard to fully render nuances, emotions, and complexities depending only on text by superficial emotional tendencies alone. Numerical representations may lead to misleading conclusions and undermine public participation. In addition, the use of physiological test data does not reflect the subjective reasons for the comments made. Therefore, it is essential to deeply parse the text and distinguish between segments with different semantic differences. In this study, we propose a perceptual psychology-based workflow to extract and visualize multifaceted views from user-generated data. The analysis methods of FCN, LDA, and LSTM were incorporated into the workflow. Six areas in Fuzhou City, China, with 12 city parks, were selected as the study object. Firstly, 9987 review data and 1747 pictures with corresponding visitor trajectories were crawled separately on the Dianping and Liangbulu websites. For in-depth analysis of comment texts and making relevant heat maps. Secondly, the process of clauses was added to get a more accurate representation of the sentiment of things based on the LSTM sentiment analysis model. Thirdly, various factors affecting the perception of landscapes were explored. Based on such, the overall people's perception of urban parks in Fuzhou was finally obtained. The study results show that (1) the texts in terms of 'wind', 'temperature', 'structures', 'edge space (spatial boundaries)', and 'passed space' are the five most representative factors of the urban parks in Fuzhou; (2) the textual analyses further confirmed the influence of spatial factors on perception in the temporal dimension; and (3) environmental factors influence people's sense of urban parks concerning specificity, clocking behavior, and comfort feelings. These research results provide indispensable references for optimizing and transforming urban environments using user-generated data.

Keywords: landscape perception; urban parks; user-generated data; LSTM sentiment analysis

check for updates

Citation: Ren, W.; Zhan, K.; Chen, Z.; Hong, X.-C. Research on Landscape Perception of Urban Parks Based on User-Generated Data. *Buildings* **2024**, *14*, 2776. https://doi.org/10.3390/buildings14092776

Academic Editor: Haifeng Liao

Received: 21 July 2024
Revised: 23 August 2024
Accepted: 31 August 2024
Published: 4 September 2024

1. Introduction

Landscape composition and the spatial characteristics of urban parks impact people differently [1,2]. Urban parks, as prevalent public spaces, are closely related to urban dwellers' daily production and life. Therefore, a deep understanding of various landscape perceptions is significant in enhancing the quality and values offered by urban parks. Landscape perception is regarded as the feeling and perception of the environment, which is the process of passive reception through the sense organs and then recognized, processed, and understood [3]. It also seeks the interaction between the objective landscape environment and subjective perception [4]. Academics have long noticed the critical influence of landscape perception factors on urban planning and development and sustainable landscape design [3,5,6].

The theoretical basis of landscape perception research has shown an integrative trend comprising objective and subjective schools [7,8]. In this context, using digital landscape technology (e.g., social media and digital maps) has become one of the chief ways to effectively solve the problems that landscape architecture faces [9,10]. A large amount of readily available web data has been used to reveal the content of landscape perception by Bubalo et al. (2019) in their study [11]. Rossetti et al. (2019) quantified landscape perception using discrete choice modeling and large-scale collected data [12]. Wang et al. (2022) proposed a new quantitative approach to identify and classify landscape perception by using a multichannel Electroencephalography (EEG) signaling model [13], but without an in-depth exploration of perceived motivation [14]. Researchers speculate that the reasons why users generate and share content are highly subjective, but this assumption about subjectivity has not been validated by empirical evidence. They have not found clear evidence to test these hypotheses, and all conclusions remain speculative. In addition, the landscape aesthetic perception is related to both individual objective elements and overall subjective impressions [15]. Lee et al. (2017) explored the influence of emotional factors on landscape perceptions by investigating residents' subjective opinions and values [16]. Jeon et al. (2020) examined the relationship between people's subjective perceptions of landscapes in different environments [17]. Xu et al. (2022) found that subjective results of people's perceptions of the streetscape were significantly better than objective data measurements. The subjective and objective perceptions are also found to be simultaneously consistent and divergent in this study [18]. Menatti and Heft's study (2020) suggests that the development of philosophy, geography, and psychology has led to specific socio-historical contexts and life-environmental experiences, and that these factors have a greater impact on human subjective perception [19]. This is all an inducement to probe more deeply into the intrinsic reasons why landscape perception occurs.

Furthermore, landscape perception is closely related to human mental activities. James Gibson argues that perception has constancy and selectivity. Constancy refers to the degree of stability of the objects we perceive, despite the changing stimuli that act on our senses. Perceptual selectivity refers to the fact that people perceive a few stimuli well, while perceiving the rest more vaguely. Of course, the term 'perception' is synonymous with 'awareness', but both can be called perception in English. This paper distinguishes between the two meanings. We define 'perception' as receiving and interpreting external stimuli through the senses. Based on this understanding of perception generation, we have conducted a series of studies on perception (Figure 1). 'Awareness', on the other hand, is the result of perception after subjective understanding and knowledge experience. Due to the confusion between perception and awareness, researchers often have problems distinguishing between the results and the causes of the formation of landscape perceptions. Over the past two decades, scholars have mainly focused on visual perception in the field of landscape perception [20]. In contrast, despite the rich cultural connotations of the text, it has often been trivialized as a secondary source and is usually used only for studies such as simple thematic analyses. Apart from that, user-generated data usually contains a large number of objective descriptions and subjective feelings at the same time. Humans can easily understand the meaning of such data. However, it is still challenging to comprehend the meaning of large amounts of data and distinguish between subjective and objective content in a short period.

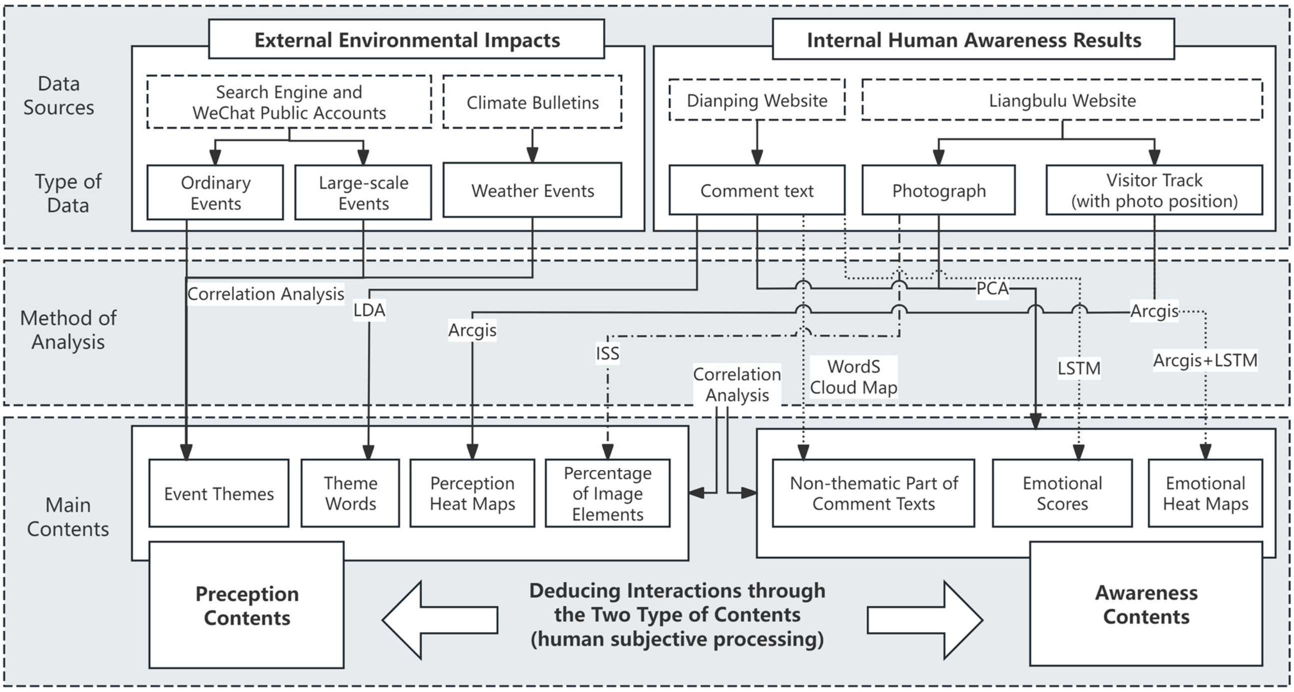


Figure 1. Research steps.

To solve the above problems, we introduce semantic segmentation of images and commented text to analyze the results of human subjective and objective perception based on user-generated data. A scalable method for extracting and visualizing multifaceted perspectives from text is finally constructed. Also, we explore the factors that influence the perception formation process on the perception of urban park landscapes. Based on LSTM sentiment analysis, the clause procedure is added to expand the accuracy of people's sentiments about things. It is of great significance to better guide the planning and management of urban parks and improve the leisure experience of residents.

2. Materials and Methods

2.1. Study Area

Fuzhou is the capital of Fujian Province, China, with a typical estuarine basin and predominantly hilly terrain. As one of the coastal cities in southeastern China, Fuzhou has a typical subtropical monsoon climate with warm, humid, and evergreen seasons. It also has a forest coverage rate of 57.26% and is rated as a national forest and greening city. The city has constructed an area-wide greenway network based on its unique geographic environment of mountains and seashores, which provides an excellent case study for urban park research. In this study, six study areas (Figure 2) in the main urban area under the jurisdiction of Fuzhou City were selected. A total of 12 urban parks, (Appendix A Table A1) were selected as study subjects. These parks cover many types, sizes, and ages and are located at varying distances from the city center.

The Fuway area combines Fuzhou's natural and cultural landscapes, running through and integrating numerous vital landmarks and scenic areas, making it a popular place for citizens. Fuzhou Huahai Park and Fuzhou National Forest Park areas represent specialized parks with unique and charming landscapes. A specialized park is a green space with specific content or form and appropriate recreational facilities. It is the classification of green space within China. The Jinji Mountain Park, Yantai Mountain Park, and West Lake Park areas are the focus of this study because of their advanced features in proximity to residential areas, convenient transportation, and rich historical and cultural connotations.

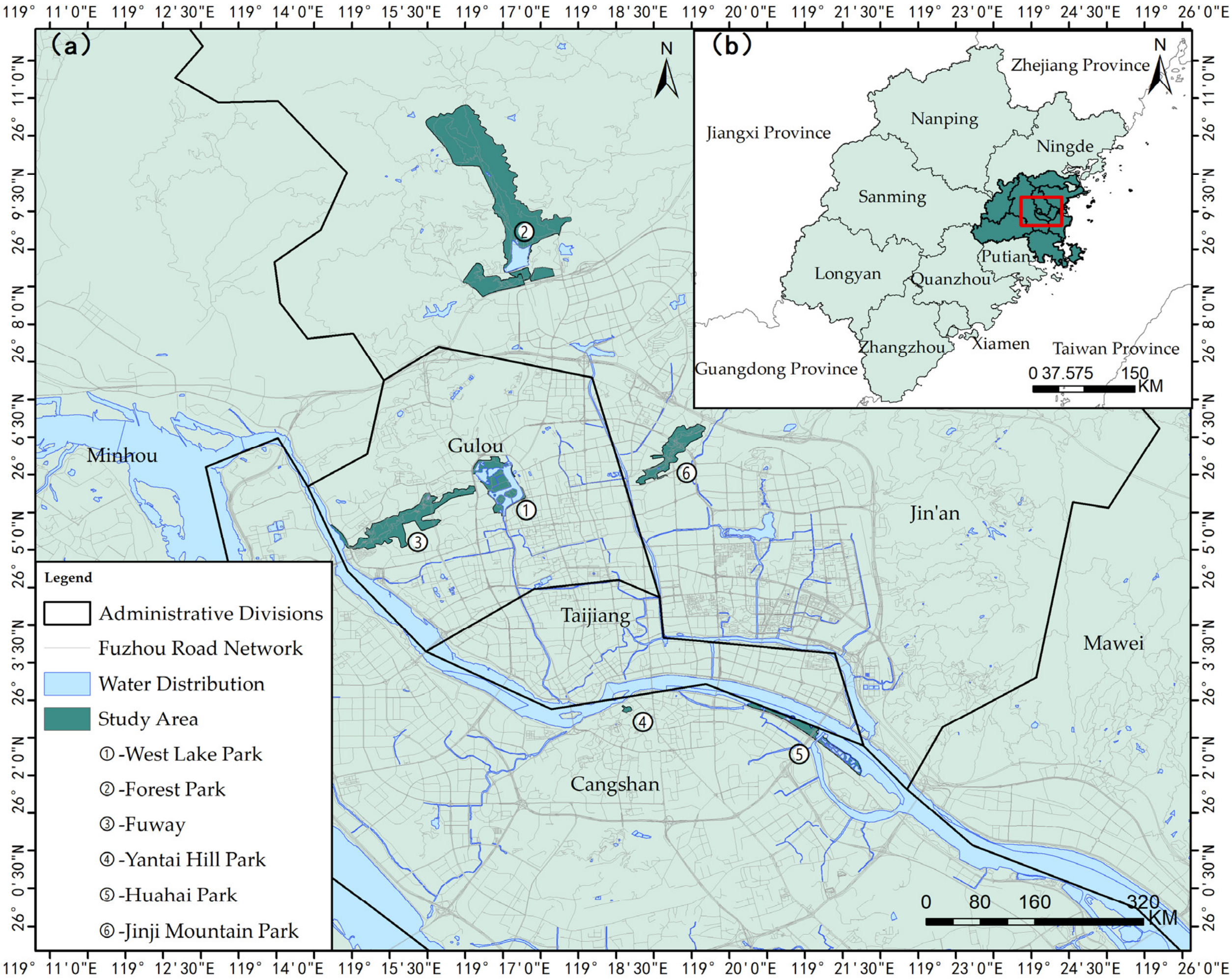


Figure 2. Study area map. (**a**) Distribution map of the six study areas; (**b**) Geographic location of the study areas on the map of China. The red square frame indicates the location of the study areas in Fujian Province in the picture.

2.2. Research Steps

2.2.1. Data Collecting

The comment text data of the Dianping website (https://m.dianping.com/) (accessed on 23 August 2024) is selected as the data source due to its vast database. Data cleaning is performed through manual auditing after crawling through city parks, searching for names and web searches. Duplicate, irrelevant, and invalid data, such as emojis, punctuation marks, and tags, were removed. A total of 9987 review data were obtained for the five years from 1 July 2018 to 1 July 2023 (Table A1). The data were crawled on the webpage using Python 3.7. As a leading professional outdoor platform in China, a large number of users favor Liangbulu (https://www.2bulu.com/) (accessed on 23 August 2024) because of its detailed route information, map annotation function, and social attributes. These advantages are the critical reason why we chose it as the data source. In Liangbulu, 1747 images and 1567 routes of interest were collected by combining manual and Python web data crawling. One of the interest routes contains the users' points of interest when taking pictures. Also, the name of the park was used as a search term in search engines and WeChat public accounts (https://mp.weixin.qq.com/) (accessed on 23 August 2024) to find specific events that can be perceived in the park. Finally, weather data during the same periods were downloaded from the 2345 Weather website (https://tianqi.2345.com/) (accessed on 23 August 2024), and the extreme weather conditions recorded in the Climate

Bulletin (https://www.weather.com.cn/fujian/zxfw/qhgb/07/3797835.shtml) (accessed on 23 August 2024) were also included.

2.2.2. Data Analysis

Comprehensively using tools and models such as jieba, LDA theme clustering model, LSTM sentiment analysis model, and deep learning complete convolutional network (FCN), we follow the research path of cleaning, deactivation of words, text segmentation, word frequency analysis, and LSTM sentiment analysis to complete the landscape perceptual contents analysis and sentiment analysis.

The Latent Dirichlet Assignment (LDA) theme clustering model is a probability-based model for generating document themes. It is a simple method of randomly combining a series of words to summarize the theme of an article. Potential semantic information can be mined to obtain a more condensed theme. In this study, we complete the theme extraction of the 9987 articles before the clause and the 52,830 texts data obtained after the clause, using the ‘sklearn’ toolkit in Python to realize the invocation of the LDA theme model. We only use the theme extraction function of the model and discard the clustering results, since the clustered themes randomly generated by the theme model do not have an apparent distinguishing effect.

The sentiment classification process is performed by mining and analyzing textual information to identify public sentiment and measure perceived satisfaction. Long Short-Term Memory (LSTM) is a variant of Recurrent Neural Network (RNN), which can capture contextual information in sequences and is often used for textual sentiment analysis. On the other hand, sentiment analysis is a branch of text categorization that analyzes subjective texts with emotional overtones (positive and negative), to determine the competent views, preferences, and emotional tendencies behind that text. In this study, the LSTM sentiment analysis model based on previous research is trained using the attraction review dataset from open-source platforms such as Scientific Data Bank. The training set was labeled with two types of sentiment, negative and positive, and the resultant accuracy (acc) was 0.9178. This study applies the model to output the negative and positive sentiment probability for all review texts.

To perform image semantic segmentation (ISS) on images taken by the user, we modified the open-source code and used a deep learning-based Fully Convolutional Network (FCN) approach. FCN is an end-to-end deep learning model for pixel-level ISS. It extracts image features through a Convolutional Neural Network (CNN) and uses an inverse convolutional layer to recover spatial information for pixel-level classification. This method can perform accurate semantic segmentation of various elements and analyze their percentage in the image.

2.2.3. Research Procedures

We distinguish between text, images, and visitor paths, and then distill perceptual and aware contents from the available data. Perceptual content includes stimuli from the external environment, themes recognized in the text, the percentage of elements in the semantic segmentation of images, and a perceptual heat map with photographed points. All things recorded in various forms are considered perceptual content. Therefore, the theme words extracted by LDA of the commentary text’s theme analysis are the main content of landscape perception. We obtain event themes by retrieving articles related to external stimuli, and the percentage of image elements by semantic segmentation. These are the results obtained by separating recorded things as perceptual subjects. The awareness contents separated from the same data include the non-subject parts of the review text, emotional scores, and emotional heat maps. These are presented respectively through word cloud maps, LSTM sentiment analysis, and graphical representation. While a single analysis of the results may be one-sided, combining perception and cognition may reveal the more profound mysteries affecting perception.

3. Results

3.1. Landscape Perception Contents Analysis

3.1.1. LDA Theme Clustering Analysis

The theme words were obtained after processing the theme model. They are used as one of the main contents of landscape perception contents. The top 20 theme words with actual significance in the frequency of occurrence are taken to form the trend of theme words over the years (Figure 3). Overall, the frequency of these theme words is proportional to the number of comment texts, showing the lowest in 2018–2019, reaching the highest in 2019–2020, then reaching a trough in 2021–2022, and finally rising. People's attention to the theme word 'Fuway' is the highest, and the attention to the theme word 'stacks' increases yearly, while the frequency of the theme words 'zoo' and 'animal' increases yearly. The frequency of 'zoo' and 'animal' theme words decreases year by year. In 2019–2020, people's cognitive content is more prominent, mainly focusing on 'Fuway', 'animal', 'scenery', 'children', and 'free'. People's landscape perceptions in 2021–2022 are more consistent with those in 2022–2023, shifting from those in 2019–2020 to focus on 'walks,' 'forest parks,' 'attractions', 'hours', and 'transportation'. Photo-taking has become the most convenient way to record and share life moments. This behavior, called 'Daka', occupies a higher frequency of the theme words. As a prevalent behavior in China in recent years, Daka originally refers to swiping a card to record attendance when commuting to and from work, and it is now derived to refer to arriving at a particular place or possessing a certain thing. The word is similar to the meaning of visiting this place, so the phonetic translation of Daka is used in this article. However, due to the emergence of the new coronavirus pneumonia, the frequency of overall outdoor environment and activity-related words such as 'Daka' has declined. Fuway was completed at the end of 2017, and the night lighting project was officially launched in May 2019. Investment has gradually increased in recent years, and supporting facilities have become increasingly complete. In contrast, the zoo with less popularity recently has been accompanied by a drop in visitor spending. This further shows that the construction date and freshness significantly impact public perception, and the trend change of LDA also proves that the behavior of 'Daka' can stimulate the public's interest and even lead to a trend.

We artificially categorized the theme words in the top 200 word frequencies into five preceptive dimensions: facility service, subjective evaluation, natural landscape, history and culture, and social activities (Figure 4). In the lower-left corner of each square in the figure, the full name of the word and the frequency of occurrence are displayed. The larger the square, the higher the frequency of perception. The cumulative frequency of the theme words in the facility service dimension reaches 17,326. The content of the theme words focuses on the relative geographic location of the park, the transportation ticket parking lot, and other aspects of the park's background and current situation. This indicates that accessibility, the current situation of the park, and the historical background are the subjective content of people's cognition and communication. The second is natural landscape and social activities, with a similar cumulative frequency of about 12,000. These two themes are more distinct and easily distinguishable. The natural landscape dimension includes the overall landscape, weather conditions, and various plants and vignettes. All the dimensions align with the order in which people verbally describe landscapes. In the social activity dimension, the content of the activity is the main subject of people's sharing. Socialization is one of the most vital goals of people's activities, comprising theme words such as 'Daka', 'friends', 'family', 'couple', 'dating', and so on. Meanwhile, we found that children, as a group, received the most attention of all activities. Additionally, the frequency of the theme words is relatively low in subjective evaluation and history and culture. In the subjective evaluation, the words 'time', 'childhood', 'memory', 'change', 'period of time', and so on all reflect that people are more sensitive to the perception of changing things. This also confirms that cognition is the result of perception and processing. It is worth noting that people often refer to the architectural style of Gulangyu Island using descriptions with historical or cultural terms, implying the similarities between these two dimensions, to some extent.

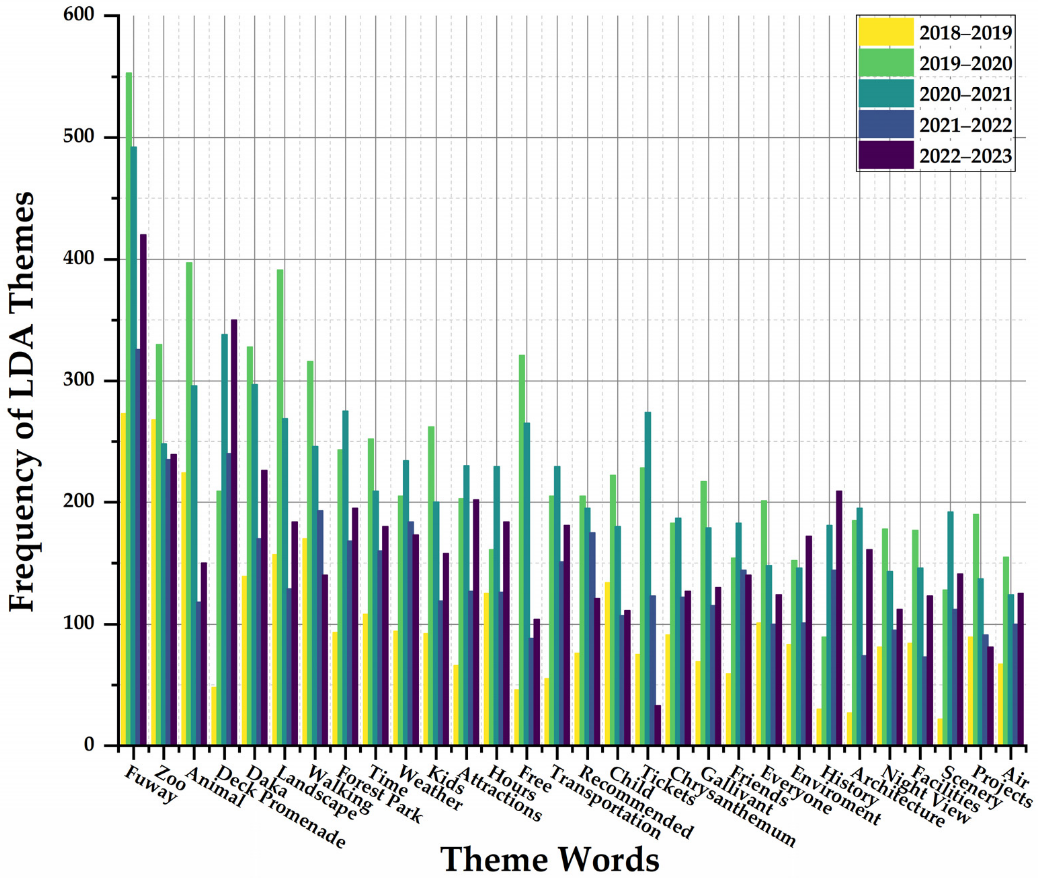


Figure 3. Trends of LDA theme over the years.

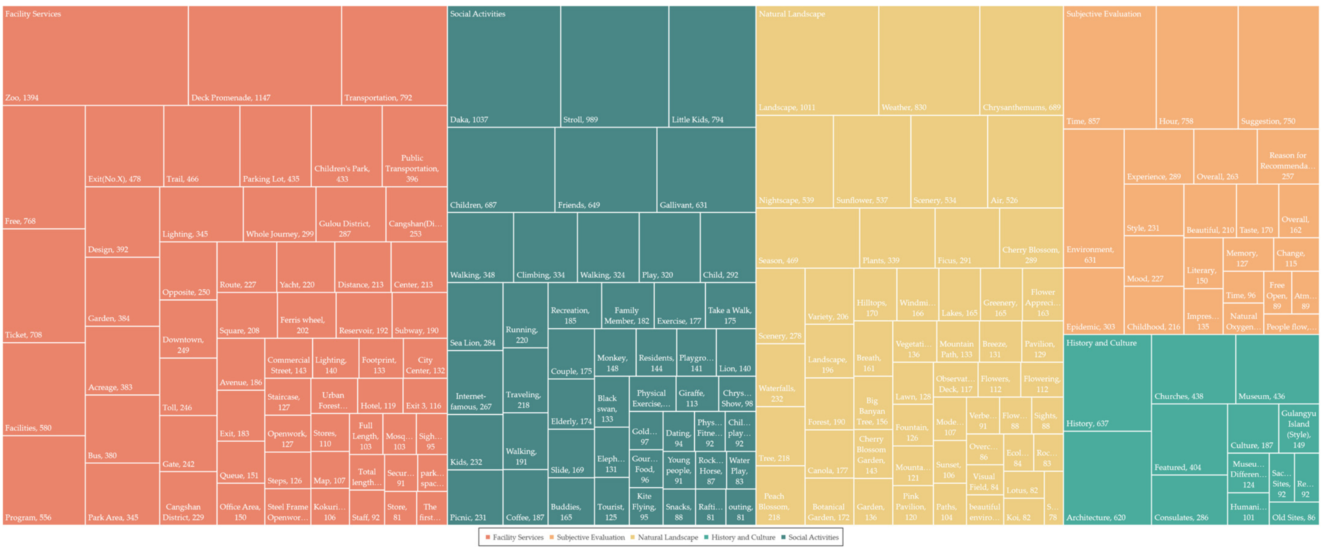


Figure 4. Tree map of subject term categories (top 200 frequency).

3.1.2. Image Semantic Segmentation (ISS) Analysis

Through the image in the semantic segmentation, we obtain 44 kinds of classification elements, such as benches, chairs, fences, and railings. They still exist with the same connotation and different types of elements. Therefore, the above elements with the same meaning were merged into the same kind of terms, presenting 11 types of elements (Figure 5). The results show the balance in proportion of each element in the six areas. When taking photos, people prefer to combine elements such as plants, sky, and buildings. In the overall environment, plants (e.g., trees and shrubs) add up to about 33% of the total green vision rate (the proportion of plant elements), reaching 1/3 of the total. In addition, the proportion of the element 'sky' reaches the largest, with an average value of 12.78%. The area with more tree elements has a corresponding decrease in the sky element. Fuway area has a smaller proportion of site elements than other areas, at only 1.70%. The wall element in the overall scene is more accessible to capture, with a proportion of 9.65%, 2–4% more than in other areas. The percentage of sky elements is significantly higher than in other areas, which is related to the positioning of Fuway as an urban forest trail with a crown-topped trail. This is also why the forest element of Fuway accounts for less than that of Forest Park and Flower Park, but the sky element is significantly higher. The percentage of tree elements in Yantai Hill Park area is lower than the average value, at only 21.01%. The percentage of building elements is higher, at 8.70%. Also, the percentage of wall elements is higher, at 7.7%. This indicates that people are more interested in architectural elements during photo shoots. This is because Yantai Hill is known as 'the Museum of International Architecture' in Fuzhou, and has many historical buildings in different styles.

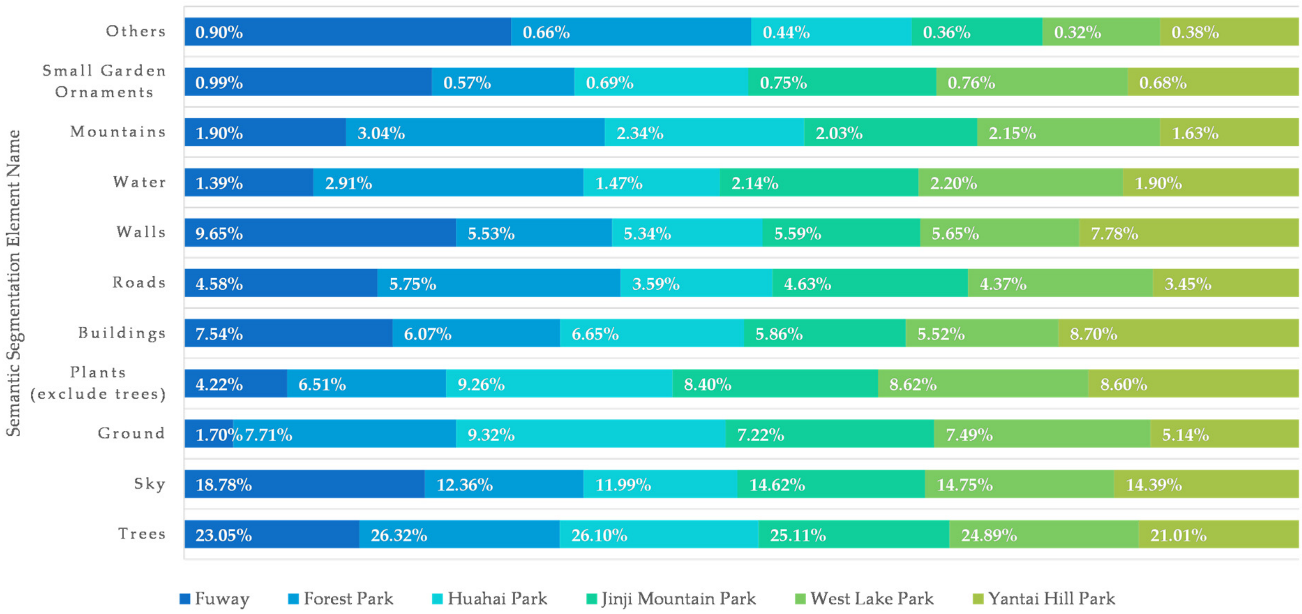


Figure 5. Percentage of image semantic segmentation elements.

3.1.3. Four Dimensions of Perceived Impact Assessment

According to the results of the correlation analysis (Table 1), 'shape', 'plants', 'species', 'lotus', 'big banyan tree', and 'windmill', with prominent landscape characteristics, have the most significant influence on perception. Visual perceptions of natural landscape features, similar to those described above, accounted for the largest share and dominated the impact assessment of the four dimensions. In the visual dimension, the only non-natural elements influencing perception are 'museum' and 'architecture'. This is probably because the study area includes distinctive architecture. In addition, no significant influence of soundscape on landscape perception was found in the auditory and olfactory dimensions. In contrast, olfactory features with keywords such as 'smell' and 'odor' were significantly related to emotional tendency. The sentiment means the value of the 'odor' feature is the lowest among all the influential thematic features, at only 0.198. We do not find that the overall somatosensory features significantly impact people's perception. Still, interestingly, the maximum wind force and the air quality index among the somatosensory indexes significantly correlate with the time of the text of the comments.

Table 1. Correlation results for the four dimensions of perceptual impact assessment.

Theme Name	Emotion and Comment Time Correlation	Sentiment and Dianping's Score Correlation	Correlation of Emotions to the Original Sentence	Correlation of Sentiment and Phrase Length	Verdict Result	Volume of Theme
modeling	−0.101	0.031	0.530 **	0.161	valid	115
species	−0.037	0.031	0.530 **	0.128	valid	232
big banyan tree	0.022	0.060	0.483 **	0.061	valid	164
trees	−0.057	−0.061	0.497 **	0.272 **	invalid	299
air	0.102 **	−0.040	0.494 **	0.199 **	invalid	996
Gulangyu island (style)	−0.056	−0.086	0.456 **	0.303 **	invalid	152
flower viewing	0.015	−0.002	0.476 **	0.302 **	invalid	192
windmills	−0.046	0.127	0.393 **	0.103	valid	172
characteristic	0.029	0.127 **	0.458 **	0.155 **	invalid	453
museums	0.155	−0.013	0.550 **	0.046	valid	129
beautiful scenery	−0.103	0.097	0.480 **	0.006	valid	336

** Significant correlation at 0.01 level (two-tailed); Table is an excerpt, see Appendix A Table A2 for detailed table.

3.1.4. Impact Assessment of Event Keywords

The events regarding perceptual impact were screened by keyword search. We screened the events that may affect perception on public. Then, the keywords were derived from the generalized summary events. Events and holidays affecting the city were selected as large-scale events. In contrast, those having an influence only within or near the study area were regarded as ordinary events. The events that affected the meteorology of the Fuzhou city region in a short period were selected as meteorological events. Those impacting the climatic conditions of Fuzhou over a long period were seen as climatic events. The results show that both event types, large-scale and ordinary events, correlate significantly with people's affective tendencies (Tables 2 and 3). However, since the length of the sentence following the clause also correlates with the affective scores, it does not confirm that the population necessarily perceives the occurrence of the event. In contrast, weather events significantly correlated with text sentiment scores and were unaffected by sentence length. Only a few comments related to extreme weather on post-disaster repairs.

Table 2. Results of Spearman's correlation analysis of three types of event influences.

	Event Types	Item Name	Comment Time	Dianping's Score	Raw Emotional Tendency Score	Phrase Length
commenting on the affective tendency score	large events	correlation coefficient	−0.058	0.062	0.381 **	0.145 **
		p-value	0.140	0.111	0.000	0.000
	ordinary events	correlation coefficient	0.005	0.039 *	0.438 **	0.162 **
		p-value	0.787	0.043	0.000	0.000
	meteorological events	correlation coefficient	0.118	−0.028	0.414 **	0.084
		p-value	0.326	0.815	0.000	0.483

* At the 0.05 level (two-tailed), the correlation is significant, ** At the 0.01 level (two-tailed), the correlation is significant.

Regarding the sentiment tendency of event keywords, the people most likely perceive the three large-scale events: Lunar New Year, National Day, and Epidemic. Additionally, carding, remodeling, activities, free opening, and repair are the most easily recorded events in the general category. Concerning meteorological conditions, people often record events such as cold, warmth, and rain that can easily cause changes in body perception.

Table 3. Results of Spearman correlation analysis of climate event influences.

		Comment Time	Comment Emotional Tendency Score	Minimum Wind Speed	Maximum Wind Speed	Air Quality Index
comment time	correlation coefficient *p*-value	1.000	−0.047 ** 0.000	−0.003 0.759	−0.069 ** 0.000	−0.025 * 0.011
comment emotional tendency score	correlation coefficient *p*-value	−0.047 ** 0.000	1.000	−0.008 0.411	−0.004 0.698	0.003 0.775
minimum wind speed	correlation coefficient *p*-value	−0.003 0.759	−0.008 0.411	1.000	0.963 ** 0.000	−0.129 ** 0.000
minimum wind speed	correlation coefficient *p*-value	−0.069 ** 0.000	−0.004 0.698	0.963 ** 0.000	1.000	−0.136 ** 0.000
air quality index	correlation coefficient *p*-value	−0.025 * 0.011	0.003 0.775	−0.129 ** 0.000	−0.136 ** 0.000	1.000

* At the 0.05 level (two-tailed), the correlation is significant, ** At the 0.01 level (two-tailed), the correlation is significant.

3.2. Landscape Awareness Contents Analysis

3.2.1. LSTM Sentiment Analysis

The sentiment propensity of the comment text derived from LSTM sentiment analysis is quantified as a percentage probability through value summing. The comments with an emotional tendency value greater than 0.5 are considered positive sentiments, while those less than −0.5 are negative. The values of texts in the interval from −0.5 to 0.5 are neutral. Among the 9987 comments, 6259 are positive, accounting for 62.67%; 3098 (31.67%) are neutral emotional tendencies; and the rest of 630 texts are negative emotions, accounting only for 6.31%. The overall sentiment tendency of the six regions tends to be more positive. People rated Westlake Park the highest, with a positive sentiment value close to 1 (the maximum value) but the highest number of outliers. The Fuway and Forest Park areas had emotional scores below 0.5. The entire area was rated neutral overall, with a slight standard deviation (Figure 6).

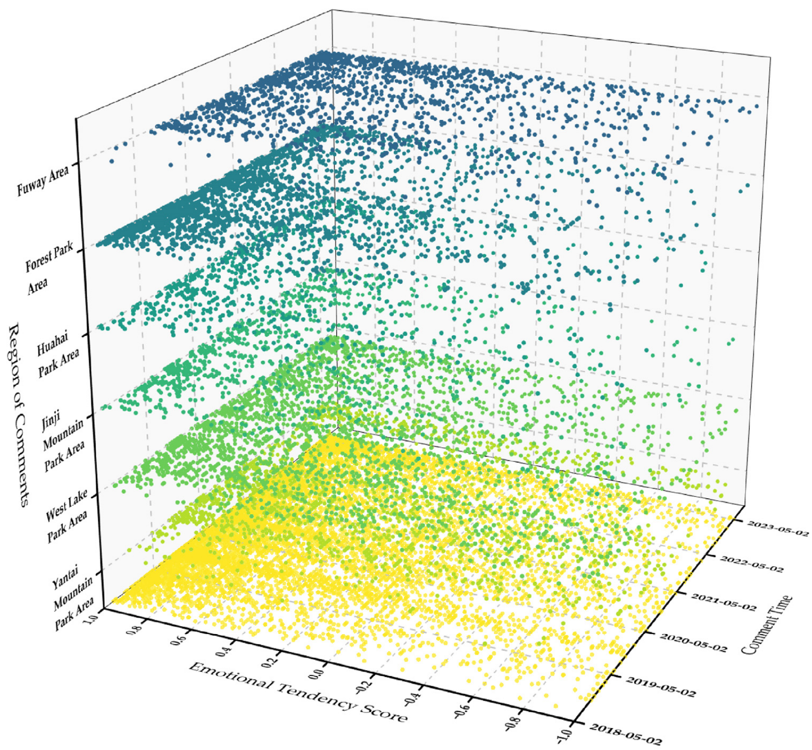


Figure 6. LSTM emotional tendency scatter plot.

Comment texts are often considered to directly reflect user perceptions in studies. However, we argue that this approach is too general and may lead to results lacking precision. Therefore, we attempted to use sentiment analysis results to measure awareness in this study. Specifically, we determined that the feature impacted the text if it significantly correlated with the text sentiment. To improve the precision of our analysis, we subjected long comment texts to a clause-by-clause process to determine the sentiment tendency of a feature. Simply put, if the overall sentiment of the text is correlated with the text-divided phrase length instead of its content, the sentiment of the text is seen as invalidated. In the determination process, we conducted the correlation analysis between text length and sentiment to ensure the accuracy of the results, as well as for the Four Dimensions of Perceived Impact Assessment.

3.2.2. Principal Component Analysis

Many factors influence perception, but we are still uncertain about which ones play a significant role. Therefore, we conducted a principal component analysis on 12 relevant indicators. The results show that the variance explained by these five principal components is 18.2%, 17.7%, 13.6%, 12.5%, and 10.8%, respectively, with a cumulative explained variance of 72.8% (Tables 4 and 5). The first principal component was related to maximum and minimum wind speed and 'ground'. The second component was mainly associated with minimum temperature, maximum temperature, and 'door. The third primarily presented the 'wall' and 'door'. The fourth component was more relevant to 'ground', 'tree' and 'road', and the fifth component reflected the texts of 'road', 'tree', and 'sidewalk'. These five components are named in the order of 'wind', 'temperature', 'structures', 'edge space (space boundary)', and 'passed space', due to the use scenarios of urban parks.

Table 4. Component matrix [a].

	Component 1	Component 2	Component 3	Component 4	Component 5
comments off on emotional tendency score	0.226	−0.148	−0.171	−0.060	0.192
maximum temperature	−0.300	**0.826**	−0.151	0.219	−0.257
minimum temperature	−0.274	0.812	−0.133	0.247	−0.328
minimum wind speed	0.680	0.410	0.558	−0.019	0.121
maximum wind speed	**0.704**	0.473	0.479	−0.038	0.078
wall	0.618	−0.265	−0.199	0.490	−0.202
sky	0.266	0.297	−0.362	−0.622	0.287
tree	−0.489	0.012	0.540	0.055	0.159
road	−0.160	0.119	0.163	0.528	**0.595**
sidewalk	−0.090	0.114	−0.309	0.425	0.667
ground	−0.309	−0.359	**0.632**	0.115	−0.191
door	0.438	−0.226	−0.188	**0.534**	−0.286

[a.] Five components were extracted. Bold indicates the principal component with the largest share.

Table 5. The rotated component matrix [a].

	Component 1	Component 2	Component 3	Component 4	Component 5
comments off on emotional tendency score					
maximum temperature		0.943			
minimum temperature		0.957			
minimum wind speed	0.977				
maximum wind speed	0.968				
wall			0.853		
sky					

Table 5. *Cont.*

	Component 1	Component 2	Component 3	Component 4	Component 5
tree				0.574	
road					0.802
sidewalk					0.821
ground				0.784	
door			0.802		

Extraction method: principal component analysis. Rotation method: Kaiser normalized maximum variance method. [a]. The rotation has converged after 5 iterations.

4. Discussion

4.1. Similarities and Differences in Perceptual Contents

The analysis in this study is based on people's perceptions of urban parks. The studied urban parks in China are similar in their perceived dimensions, including environmental introduction, facilities and services, landscapes, and activities. Still, they are different in the subject of perceived content. Among the urban parks in Fuzhou that we studied, the main body of comment texts of people's sharing is more about introducing the background and environment. The first record of perceived content accounts for comparably less. On the contrary, in the survey of urban parks in Beijing, tourists perceive recreational activities and aesthetics and appreciation more frequently, and tourists prioritize the social interaction needs and visual aesthetics brought by the natural landscape, as well as the conditions of transportation facilities and consumption in the park [21]. In contrast, in the study of Wuhan urban parks, the use of parks has a strong relationship with the characteristics of the surrounding environment [22]. The public has the highest perceived frequency of recreational experience, followed by the park environment, facilities and services. The area, facilities, and accessibility are the focus of the public's needs [23]. We suspect that people in different regions have their own interpretations of what is prioritized in expressions. This is influenced by cultural backgrounds, language habits, social norms, education systems, and communication styles. For example, in China, people in the South tend to be more focused on padding and subtlety, while people in the North tend to be more forthright and straightforward. Meanwhile, the city parks represented by Beijing and Tianjin are mostly scenic tourist areas [24], which give more prominence to the perception of the architectural landscape dimension, with high-frequency words describing the diverse architectural forms and contents as well as elaborating on the feelings of the intermingling of culture and history [25]. On the other hand, the representative urban parks in Wuhan and Fuzhou are perceived less regarding historical and cultural aspects. One of the reasons for this situation is the difference in urban environment. Horizontally comparing the review texts of Fuzhou city parks, we also found that the parks with a long history have more review introductions. Moreover, the texts of the comment can better reflect the perception of cultural accumulation and historical heritage. Combining cognitive content and principal component analysis, we also found that people are more likely to notice the changes in space and the things within it over time.

Compared with China, the construction of foreign city parks does not clearly emphasize the historical and cultural aspects, but rather focuses more on the service functions of the parks, including a variety of social activities as well as the services provided by the facilities and venues. This approach judges the functionality of parks from a more objective perspective based on the user's point of view. However, users of domestic parks have relatively little intuitive experience with the facilities unless the service function seriously affects them. This is mainly because China's urban parks are partly constructed and planned on the basis of historical and cultural sites such as gardens, and these parks have been transformed from private to public spaces, forming Chinese urban parks with distinctive characteristics [26]. This difference reflects the philosophy and focus of different countries and regions in urban park planning.

Combining the classification ratio of visitors' routes and landscape perception content, we found that in urban parks that are closer to residential areas, such as Fuway, Huahai Park, and West Lake Park, the percentage of comment texts describing personal behavior will relatively increase, accounting for 15% or more. On the contrary, in Forest Park, a park farther away from the city, the proportion of personal behavior is only 0.75%. Personal behavior, as the most substantial part of the subjective will of the individual, best reflects the purpose of the people. Walking has also become one of the main activities carried out by people in the city parks, often for physical exercise and to relieve psychological pressure. The behaviors characterized by words such as 'Daka', 'exercising', 'taking pictures', and 'strolling', are also popular among people. Similar activities such as exercise, relaxation, and plant viewing are also practiced in foreign countries [27]. We have also noticed that with the development of new media technology and the popularity of short videos, the Daka trend has often become one of the primary reasons people travel to China. Private management companies usually operate overseas city parks, so there are frequently keywords for commercial activities such as 'bazaar' and 'food' [28]. In China, activities of a commercial nature are usually separated into specific areas (e.g., commercial streets or pedestrian streets), such as the practical example of Yantai Hill Commercial Walking Street in Fuzhou. On the other hand, urban parks are more focused on public non-profit welfare rather than profit. Therefore, activities such as chrysanthemum and goldfish exhibitions are reflected frequently in the review text. In subsequent research, we plan to investigate different types of parks in various regions, even worldwide, and thereby synthesize and compare the empirical findings in differentiated social and cultural contexts.

In the text, we also found that when users express negative emotions, they tend to be closely related to the negative events experienced by the individual. Thus, comments against a uniform thing appear to present polarized emotion, which is in line with the findings of Sim et al. [29]. Our study also validates the conclusion that Lai and Deal's natural factors produce positive emotions for people's feelings [30]. However, the results in the semantic segmentation of images show that the green visibility rate of the six city parks is close to 33%. Among them, there is still a gap between the 42.24% green space rate and the 45.40% green coverage rate of Fuzhou City in 2020 [31]. This implies that people take photographs to differentiate themselves from the large area of greenery especially. Besides, they also prefer to take the elements, such as buildings and landscape vignettes, as the main subjects of the photographs.

4.2. Suggestions for Urban Park Space

Based on the sentiment analysis of park reviews, we search for attraction name keywords to extract and categorize the data of significant attraction reviews, obtaining the number of reviews to calculate the sentiment mean of the review information. The obtained results are assigned to the park attractions to generate the emotional heat map (Figure 7). The ArcGIS 10.5 platform is employed to conduct the kernel density analysis and then visualize the sentiment mean value to supplement the spatial data. The perceptual heat map consists of the heat maps of photo location points and tourist routes obtained by density analysis.

In the emotional heat map, fewer attraction names could be retrieved. In conjunction with the perceptual heat map, the higher density of stopping to take photos of location points and visitor routes only partially overlapped with the distribution of higher sentiment in the sentiment map. We believe that it may be that when people comment on urban parks, they give more prominence to the overall description of the park, and they will only highlight the events that caused negative impacts, rather than describing each attraction in detail. This is a reminder to upgrade the landscape in orientations with high perceived heat values to make it more attractive. Less research has focused on the emotion or mood of landscapes regarding their geospatial location. The study by Brian Park and Kim et.al. (2020) indicated visitor emotions through the two axes of happy and not happy and whether or not the landscape can arouse emotions in a total of four quadrants of data to represent visitor emotions. The emotion values were shown in geospatial locations to derive a tour path that evokes pleasurable emotions [32]. In contrast, they removed comment texts that contained two or more emotion dimensions, ignoring the complexity and diversity of emotions that people expressed in the texts. This approach fails to adequately capture the richness and multilayered nature of emotional expression, which may lead to a one-sided understanding of emotional data. This gap has been partially filled in our study by using segmenting sentences, including all sentences containing with different emotions in the one sentence. Based on the research results, we can identify some problems in the urban parks studied. For example, Figure 7c shows that the zoo located in the southwest direction in the Forest Park area, despite its high median emotional value, is not well distributed by the surrounding roads due to its distance from the entrances and exits, and it is recommended to improve the accessibility within the area by truncating the curves. Similarly, (Figure 7f) suggests upgrading the entrances to Fuway, except for Exit 3 and Exit 5, and optimizing and upgrading the road from the southeastern entrance to the central observation deck of Yantai Hill Park. In the future, we can increase the points of attractions in the sentiment distribution map by separating the attractions with explicit references to get a complete map, which can bring more relevant and practical suggestions for urban parks. It is also possible to upgrade and simplify converting comments to attraction emotions and upload them to the cloud to realize real-time updated emotion distribution maps. The purpose regarding interaction design, real-time crowd monitoring, and even user experience-guided design can be achieved better.

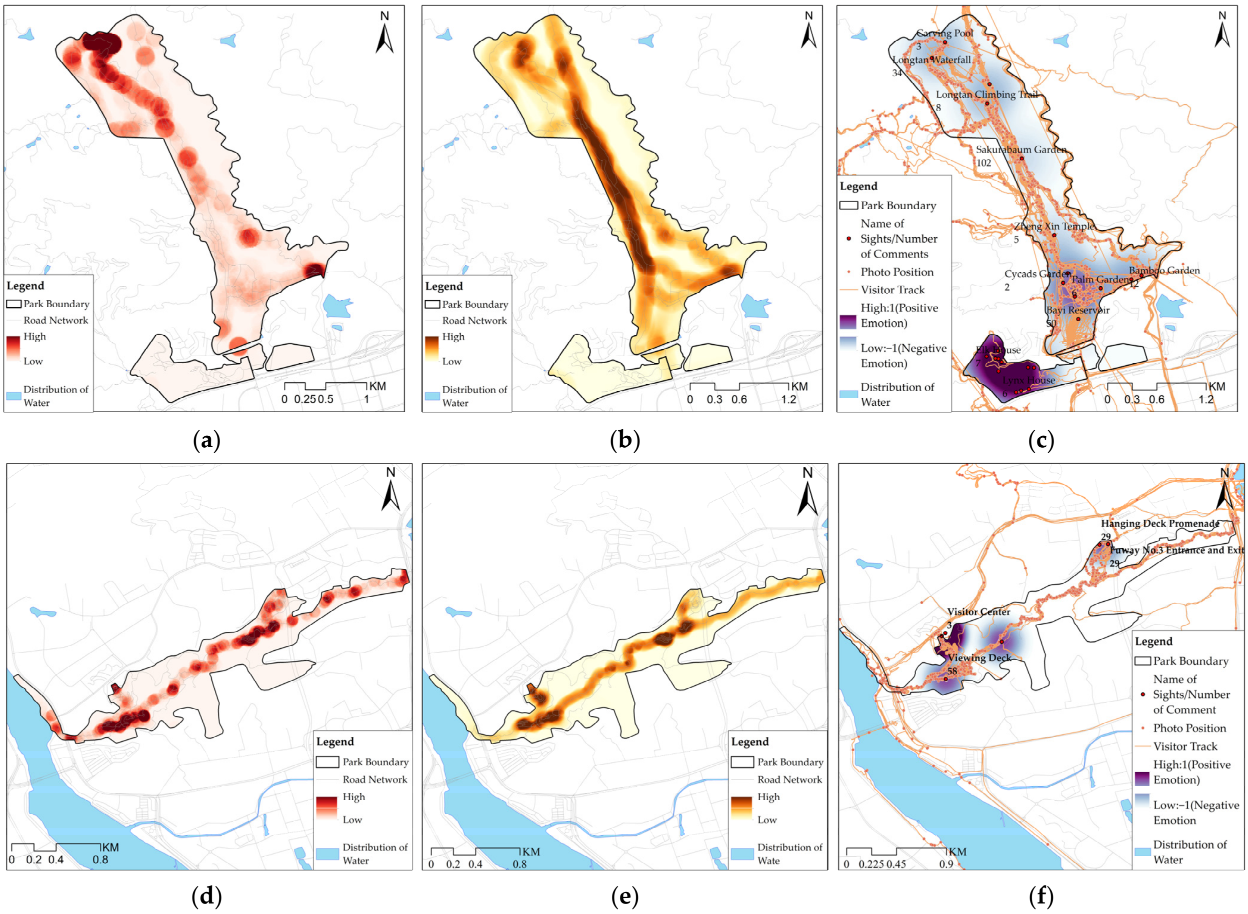


Figure 7. (**a**) Density map of photo location points in the Forest Park area; (**b**) density map of visitor track in the Forest Park area; (**c**) emotional distribution map in the Forest Park area; (**d**) density map of photo location points in the Fuway area; (**e**) density map of visitor track in the Fuway area; (**f**) emotional distribution map in the Fuway area. The picture is an excerpt, and other pictures are detailed in Figure A1 of the Appendix A.

Based on the results of the PCA analysis, we explored how different environmental factors affect people's perception of urban parks, and relevant keywords were retrieved in the comment text. We also generated word cloud maps after word splitting. The results show that 'Breeze' is most easily perceived in urban parks and is often accompanied by the emotions of comfort and idleness (Figure 8a). The perception of 'Wind' is closely related to 'Road', which may be related to Chinese people's habit of walking. In addition, the scenery around the road and the undulation of the terrain are also primary perceptions (Figure 8b). Attention to 'wall' was focused on the historical buildings in Yantai Mountain Park (Figure 8c) Among the buildings, the red brick wall and the unique classical architectural style became prevalent for photo-taking. The 'Door' as a keyword becomes the main component due to the Daka. However, the review text mainly describes several entrances and their locations (Figure 8d). It does not develop a detailed description of the 'Door'. The 'Ground' does not appear as a distinct environmental feature in the word cloud map. The 'Sky' is notable for its color, whether the blue of a clear sky or the brilliance of a sunset (Figure 8f). 'Sidewalks' were ignored due to the small sample size. Overall, environmental factors influence people's perception of urban parks through specialness, clocking behavior, and comfort. This also indicates three main directions for the enhancement of urban park spaces.

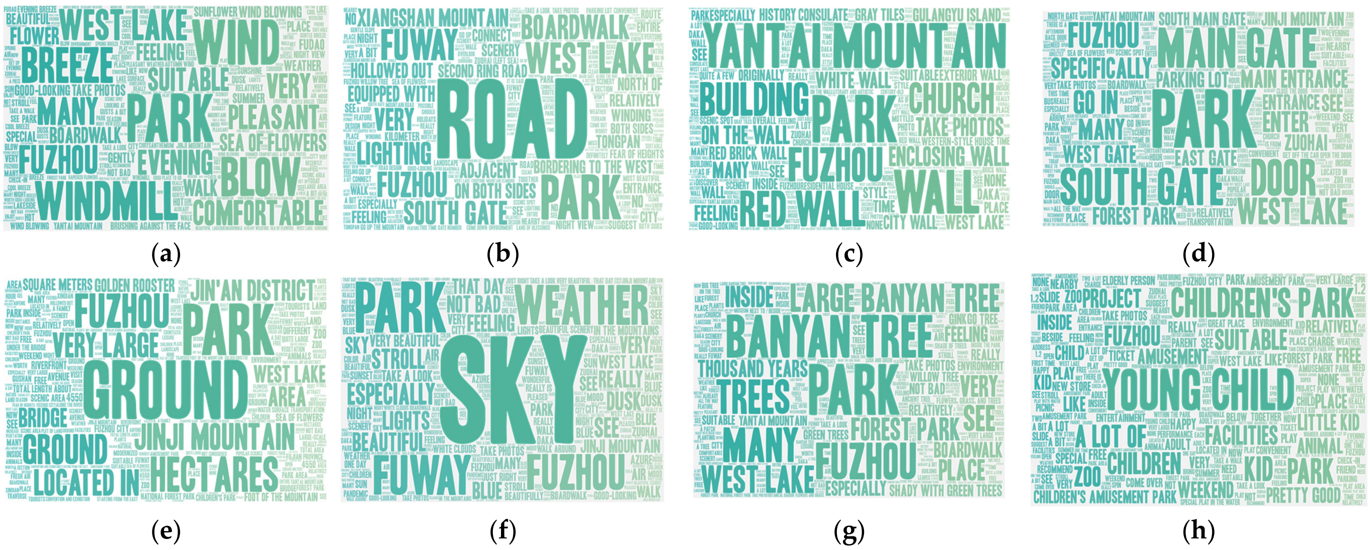


Figure 8. Words cloud maps. (**a**) Theme of wind; (**b**) theme of road; (**c**) theme of wall; (**d**) theme of gate; (**e**) theme of ground; (**f**) theme of sky; (**g**) theme of tree; (**h**) theme of child.

Looking back at the review texts, we found those are relevant to children possessing the feature of concentrated perceptual theme. They chiefly focus on fun, children's parks, and children as a group. The content usually emphasized child-friendly entertainment features and came from moms' and dads' exchanges and opinions. By comparing Figures 6 and 9, we also noticed that the comment texts about children were posted at a more even time. Unlike other themes, the level of perception changes yearly, showing a continuous demand for unique spaces for children.

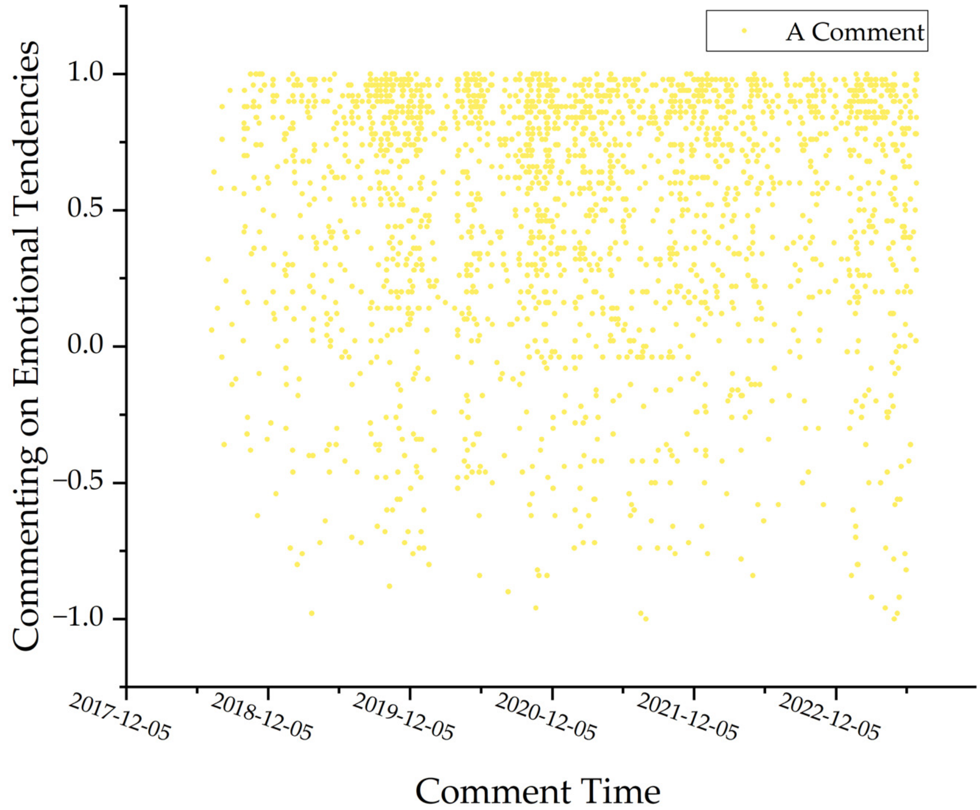


Figure 9. Scatterplot of emotional tendencies of comments on the theme of 'child'.

4.3. Comparison of Analytical Methods

In this study, since the themes obtained from the clustering of the LDA theme analysis model were unsatisfactory, we used it only to extract the core 'themes' of the review texts, and did not adopt the clustered themes. Compared with the word frequency of textual clustering, which is also the main content of landscape perception (Figure 4), the LDA theme model highlights the core content of landscape perception, consistent with Shang et al.'s study [21]. Although the theme model weakens the influence of lengthy descriptions of scene background and introduction, it also inevitably reduces the evaluation of subjective emotions and more detailed descriptions of the current scene, such as 'like' and 'suggest', 'saw', and 'weekend'.

While analyzing a comment text, in addition to conducting an in-depth analysis of the content of the text, researchers usually examine it in depth from several perspectives. The time factors and the influence of environmental conditions are two commonly used entry points. Temporal factors may include the specific period in which the comment was posted, such as the timeliness and the trend over time. External conditions, on the other hand, may cover the potential impacts of ecosystem services, park types, and landscape attributes on comment content [33,34]. Taking this aspect into account, in our study, we therefore also examined the influence of the external physical environment and the occurrence of specific events on perception. This is shown by the fact that things linked to memory and elements that affect humans directly have a greater impact on perception. In addition, researchers conduct detailed categorization and cluster analysis of users of reviews based on their primary characteristics, such as age, gender, and region. By categorizing these users into groups or clusters, researchers can more specifically explore the influencing factors behind each group and how these factors affect the formation of review content and attitudes under different conditions [30,35]. Koblet and Purves translate specific descriptions of reviews into easily observable forms of data [36]. We discard a detailed and line-by-line textual content analysis due to the sheer amount of comment data, even though their approaches inspired our analysis. In our study, we innovatively switch to using sentiment to replace the results of the public's perception of something. However, we still need to study further how to determine what information the comments convey. Currently, the common recognition break model usually uses punctuation as the basis for simple sentence division and classification. The large language models, such as Chatgpt4.0 or Claude, present a relatively high accuracy in analyzing the text and breaking sentences. However, they still suffer from the problem of error-prone batch processing of comment text.

5. Conclusions

This study explores the factors influencing the perception formation process on the perception of urban park landscapes by using perceptual psychology as the theoretical framework. We proposed a scalable method based on user-generated data to extract and visualize practical information. People's overall perception of urban parks in Fuzhou City, China, was investigated based on analyses of various website data. The results show that 'wind', 'temperature', 'structures', 'edge space (spatial boundaries)', and 'passed space' are the five components that best represent the urban parks in Fuzhou. The four categories of events were not found to affect perception significantly. In addition, textual analysis revealed evident effects of temporal and spatial factors on perception. Environmental factors influence people's sense of urban parks through specificity, clocking behavior, and comfort feelings. Study findings can provide valuable theoretical support and practical guidance for urban park design and management through the proposed multidimensional analysis approach. Future research will focus on improving the accuracy of textual descriptions and reducing errors in the analysis process. Furthermore, we will also explore the cross-influence of various factors to understand the complexity of urban park landscape perception more comprehensively.

Author Contributions: Conceptualization, W.R., K.Z., and X.-C.H.; methodology, W.R. and K.Z.; software, K.Z.; validation, W.R. and X.-C.H.; formal analysis, W.R. and K.Z.; resources, W.R. and X.-C.H.; data curation, K.Z.; writing—original draft preparation, W.R., K.Z., and X.-C.H.; writing—review and editing, W.R., K.Z., Z.C., and X.-C.H.; visualization, K.Z.; funding acquisition, W.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Humanities and Social Sciences Research Youth Foundation, Ministry of Education, China (Grant No. 20YJC760079), the Research Program on Educational Teaching Reform in Undergraduate Colleges and Universities in Fujian Province (Grant No. FBJG20210091), Fujian Agriculture and Forestry University Graduate Course Case Bank Project (Grant No. 712018AL2306) and the National Natural Science Foundation of China (NO.52208052).

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy restrictions.

Acknowledgments: The authors are grateful for the assistance of other members of the subject group in gathering the data.

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

Appendix A

Table A1. Statistical table of data.

Name of Park Area		Type of Park	Comment Data Volume		Picture	Route of Interest
Fuzhou West Lake Park Area	Fuzhou West Lake Park	citywide comprehensive park	2000	2561	263	173
	Zuohai Park	citywide comprehensive park	561			
Fuzhou National Forest Park Area	Fuzhou National Forest Park	specialized park	963	2446	831	938
	Fuzhou Children's Park	specialized park	477			
	Fuzhou Zoo	specialized park	833			
	Fuzhou Chiqiao Park	specialized park	173			

Table A1. *Cont.*

Name of Park Area		Type of Park	Comment Data Volume		Picture	Route of Interest
Fuway Area	Fuway	citywide comprehensive park	926	1628	159	69
	Meifeng Mountain Park	citywide comprehensive park	227			
	Jinniu Mountain Sports Park	citywide comprehensive park	124			
	Fuway (Fuway Entrance No. 3)	citywide comprehensive park	351			
Fuzhou Yantai Hill Park Area		specialized park	1724		66	20
Fuzhou Huahai Park Area		specialized park	952		123	92
Fuzhou Jinji Mountain Park Area		citywide comprehensive park	676		305	275
summarize			9987		1747	1567

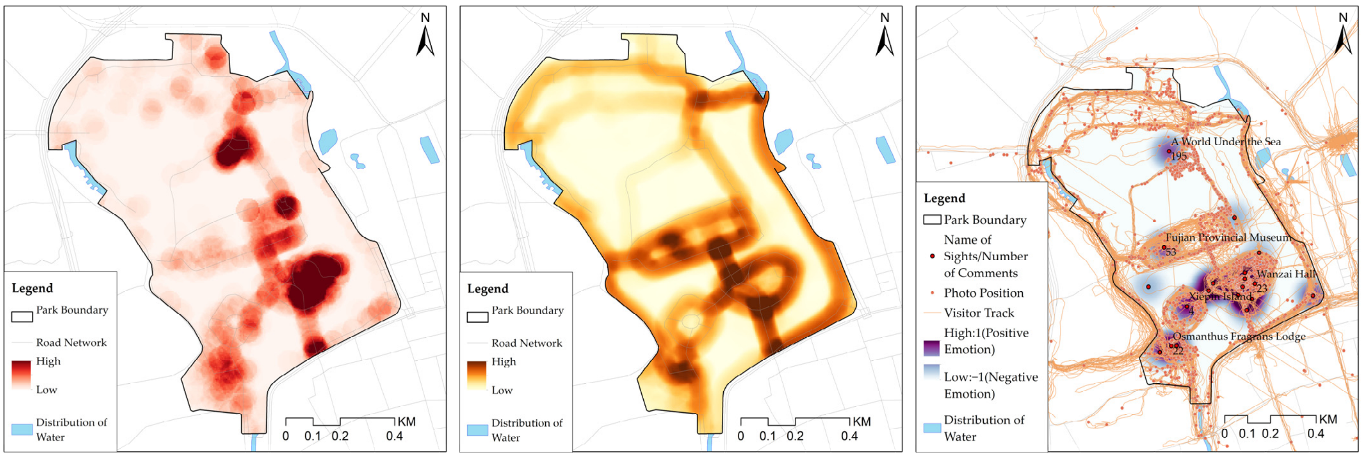
Table A2. The four dimensions of visual, auditory, olfactory, and somatosensory perceptions influencing assessment results.

Theme Name	Emotion and Comment Time Correlation	Sentiment and Dianping's Score Correlation	Correlation of Emotional to the Original Sentence	Correlation of Sentiment and Phrase Length	Verdict Result	Volume of Theme
modeling	−0.101	0.031	0.530 **	0.161	valid	115
species	−0.037	0.031	0.530 **	0.128	valid	232
big banyan tree	0.022	0.060	0.483 **	0.061	valid	164
trees	−0.057	−0.061	0.497 **	0.272 **	invalid	299
air	0.102 **	−0.040	0.494 **	0.199 **	invalid	996
Gulangyu island (style)	−0.056	−0.086	0.456 **	0.303 **	invalid	152
flower viewing	0.015	−0.002	0.476 **	0.302 **	invalid	192
windmills	−0.046	0.127	0.393 **	0.103	valid	172
characteristic	0.029	0.127 **	0.458 **	0.155 **	invalid	453
museums	0.155	−0.013	0.550 **	0.046	valid	129
beautiful scenery	−0.103	0.097	0.480 **	0.006	valid	336
waterfalls	0.000	0.111	0.494 **	−0.047	valid	249
chrysanthemums	−0.002	0.060	0.410 **	0.102 *	invalid	586
smell	−0.141	−0.070	0.506 **	0.250	valid	42
banyan tree	0.042	0.061	0.484 **	0.097	valid	317
rapeseed flower	0.029	−0.042	0.343 **	−0.058	valid	167
song	0.019	0.009	0.508 **	0.281 **	invalid	124
cloudy day	0.154	0.014	0.415 **	0.033	valid	88
old site	0.030	0.210	0.522 **	0.324 **	invalid	84
beautiful environment	0.026	0.204	0.384 **	0.384 **	invalid	93
church	0.017	−0.044	0.465 **	0.156 **	invalid	426
scenery	−0.013	0.041	0.472 **	0.064	valid	643
ecology	−0.138	0.038	0.551 **	0.068	valid	112
night view	−0.156 **	0.061	0.491 **	−0.028	valid	609
music	−0.070	0.110	0.455 **	0.227 *	invalid	81
seasons	0.020	0.086	0.439 **	0.103 *	invalid	483
museums	0.016	0.048	0.469 **	0.020	valid	460
verbena	−0.029	0.078	0.387 **	0.107	valid	89
weather	−0.005	0.056	0.417 **	0.084 **	invalid	998
consulate	−0.063	−0.183 **	0.446 **	0.166 **	invalid	272
landscapes	−0.056 *	−0.010	0.519 **	−0.058 *	invalid	1395
architecture	−0.052	0.060	0.455 **	0.022	valid	766
sky	−0.098	0.080	0.514 **	0.183	valid	81
flower	−0.049	−0.217 *	0.311 **	0.193 *	invalid	118
sunflower	−0.020	0.071	0.375 **	0.064	valid	497
landscape	−0.082	−0.102	0.444 **	0.263 **	invalid	293
rockery	0.023	−0.056	0.405 **	0.275 *	invalid	86

Table A2. *Cont.*

Theme Name	Emotion and Comment Time Correlation	Sentiment and Dianping's Score Correlation	Correlation of Emotional to the Original Sentence	Correlation of Sentiment and Phrase Length	Verdict Result	Volume of Theme
garden	−0.120	0.080	0.377 **	0.153 *	invalid	242
peach blossom	0.053	−0.018	0.459 **	0.406 **	invalid	293
view	0.046	0.040	0.487 **	0.306 **	invalid	94
scenery	−0.177 *	−0.124	0.417 **	0.128	valid	136
sacred ground	−0.080	−0.097	0.423 **	0.016	valid	105
fragrance	−0.037	−0.141 *	0.401 **	0.248 **	invalid	305
cherry blossom garden	−0.073	0.194 *	0.384 **	0.162	valid	136
vegetation	0.058	−0.018	0.405 **	0.139	valid	138
fountains	0.062	0.080	0.509 **	0.314 **	invalid	121
sunset	−0.033	−0.092	0.384 **	−0.035	valid	118
sound	0.006	0.053	0.307 **	0.284 **	invalid	233
stench	0.074	0.141	0.379 **	−0.121	valid	112
greening	−0.050	−0.030	0.338 **	0.135	valid	184
breeze	−0.135	0.008	0.439 **	0.266 **	invalid	171
forest	0.086 **	0.027	0.342 **	0.029	valid	1332
lawn	0.037	−0.096	0.403 **	0.162	valid	128
mountain paths	−0.193 *	−0.051	0.323 **	0.088	valid	149
plants	−0.078	0.026	0.331 **	0.188 **	invalid	345
flowers	−0.005	−0.024	0.353 **	0.137	valid	93
lakes	−0.133	0.149	0.416 **	0.236 **	invalid	169
history	−0.058	0.042	0.322 **	0.135 **	invalid	716
hilltops	0.132	0.042	0.376 **	0.008	valid	178
koi	0.122	0.057	0.301 **	0.364 **	invalid	80
cherry blossom	0.010	0.065	0.426 **	0.078	valid	271
pink dye	0.002	0.012	0.290 **	0.025	valid	113
path	0.035	0.137	0.300 **	0.161	valid	123
observation deck	0.008	−0.035	0.334 **	0.414 **	invalid	117
humanities	−0.077	−0.129	0.442 **	0.286 **	invalid	149
former residence	−0.036	0.125	0.369 **	0.485 **	invalid	91
pavilion	−0.048	0.013	0.297 **	0.218 *	invalid	132

* At the 0.05 level (two-tailed), the correlation is significant, ** At the 0.01 level (two-tailed), the correlation is significant.



(**a**) (**b**) (**c**)

Figure A1. *Cont.*

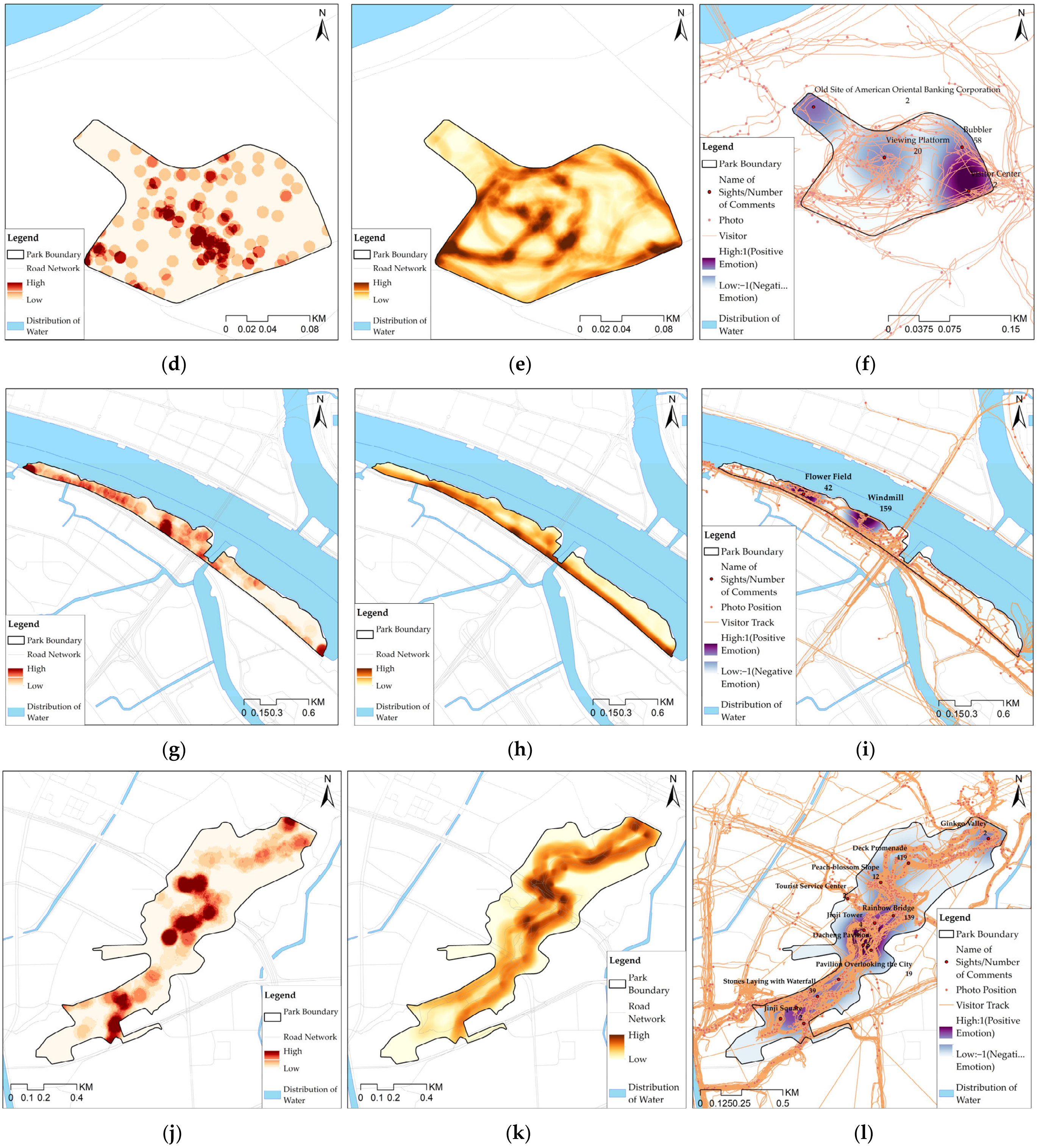


Figure A1. (**a**) Density map of photo location points in the West Lake Park area; (**b**) density map of visitor track in the West Lake Park area; (**c**) dmotional distribution map in the West Lake Park area; (**d**) density map of photo location points in the Yantai Hill Park area; (**e**) density map of visitor track in the Yantai Hill Park area; (**f**) emotional distribution map in the Yantai Hill Park; (**g**) density map of photo location points in the Huahai Park area; (**h**) density map of visitor track in the Huahai Park area; (**i**) emotional distribution map in the Huahai Park area; (**j**) density map of photo location points in the Jinji Mountain Park area; (**k**) density map of visitor track in the Jinji Mountain Park area; (**l**) emotional distribution map in the Jinji Mountain Park.

References

1. Deng, L.; Li, X.; Luo, H.; Fu, E.-K.; Ma, J.; Sun, L.-X.; Huang, Z.; Cai, S.-Z.; Jia, Y. Empirical study of landscape types, landscape elements and landscape components of the urban park promoting physiological and psychological restoration. *Urban For. Urban Green.* **2020**, *48*, 126488. [CrossRef]
2. Li, S.Y.; Chen, Z.; Guo, L.H.; Hu, F.; Huang, Y.J.; Wu, D.C.; Wu, Z.; Hong, X.C. How Do Spatial Forms Influence Psychophysical Drivers in a Campus City Community Life Circle? *Sustainability* **2023**, *15*, 10014. [CrossRef]
3. Zube, E.H.; Sell, J.L.; Taylor, J.G. Landscape perception: Research, application and theory. *Landsc. Plan.* **1982**, *9*, 1–33. [CrossRef]
4. Liu, B.Y. Towards Landscape Interaction: Inheritance and Development of Landscape Perception and Visual Evaluation. *Landsc. Archit.* **2022**, *29*, 12–17.
5. Kaymaz, I.C. Landscape planning. In *Landscape Perception*; Academic Press: Cambridge, MA, USA, 2012; pp. 251–276.
6. Jiang, H.B.; Song, M.K.; Xiao, Y. Research on Visual Landscape Comfort Evaluation of Waterfront Space: A Case Study of Huangpu River and Suzhou Creek in Shanghai. *Landsc. Archit.* **2022**, *29*, 122–129.
7. Zhou, X.; Liu, Z.Y.; Shi, J.Y. Evaluation on Visual Landscape Perception under the Support of Digital Footprint: A Case Study of Historic Urban Landscape of the Qinhuai River Area. *Landsc. Archit.* **2022**, *29*, 18–25.
8. Guo, L.H.; Cheng, S.; Liu, J.; Wang, Y.; Cai, Y.; Hong, X.C. Does social perception data express the spatio-temporal pattern of perceived urban noise? A case study based on 3,137 noise complaints in Fuzhou, China. *Appl. Acoust.* **2022**, *11*, 1242. [CrossRef]
9. Cheng, S.; Zhang, X.H.; Cheng, Y.N. Prospect of the Application of Digital Landscape Technology in the Field of Landscape Architecture in China. *Landsc. Archit.* **2021**, *28*, 46–52.
10. Hong, X.C.; Cheng, S.; Liu, J.; Guo, L.H.; Dang, E.; Wang, J.B.; Cheng, Y. How Should Soundscape Optimization from Perceived Soundscape Elements in Urban Forests by the Riverside Be Performed? *Land* **2023**, *12*, 1929. [CrossRef]
11. Bubalo, M.; Zanten, B.T.V.; Verburg, P.H. Crowdsourcing geo-information on landscape perceptions and preferences: A review. *Landsc. Urban Plan.* **2019**, *184*, 101–111. [CrossRef]
12. Rossetti, T.; Lobel, H.; Rocco, V.; Hurtubia, R. Explaining subjective perceptions of public spaces as a function of the built environment: A massive data approach. *Landsc. Urban Plan.* **2019**, *181*, 169–178. [CrossRef]
13. Wang, Y.; Wang, S.; Xu, M. Landscape Perception Identification and Classification Based on Electroencephalogram (EEG) Features. *Int. J. Environ. Res. Public Health* **2022**, *19*, 629. [CrossRef]
14. Bubalo, M.; van Zanten, B.T.; Verburg, P.H. Aesthetic appreciation of the cultural landscape through social media: An analysis of revealed preference in the Dutch river landscape. *Landsc. Urban Plan.* **2018**, *177*, 128–137.
15. Shuttleworth, S. Landscape appraisal: The "objective/subjective" debate. *Landsc. Res.* **1981**, *6*, 33.
16. Lee, C.H.; Son, Y.H.; Tak, Y.R.; Sung, J.S. Local Residents' Subjective Perceptions: Finding Meaning in the Landscape of Everyday Life. *J. Archit. Plan. Res.* **2017**, *34*, 147–160.
17. Jeon, J.Y.; Jo, H.I. Effects of audio-visual interactions on soundscape and landscape perception and their influence on satisfaction with the urban environment. *Build. Environ.* **2020**, *169*, 106544. [CrossRef]
18. Xu, X.; Qiu, W.; Li, W.; Liu, X.; Zhang, Z.; Li, X.; Luo, D. Associations between Street-View Perceptions and Housing Prices: Subjective vs. Objective Measures Using Computer Vision and Machine Learning Techniques. *Remote Sens.* **2022**, *14*, 891. [CrossRef]
19. Menatti, L.; Heft, H. Editorial: Changing Perspectives on Landscape Perception: Seeking Common Ground Between the Psychological Sciences and the Humanities. *Front. Psychol.* **2020**, *11*, 159. [CrossRef] [PubMed]
20. Khaledi, H.J.; Khakzand, M.; Faizi, M. Landscape and Perception: A systematic review. *Landsc. Online* **2022**, *97*, 1098. [CrossRef]
21. Shang, Z.Y.; Cheng, K.X.; Jian, Y.Q.; Wang, Z.F. Comparison and Applicability Study of Analysis Methods for Social Media Text Data: Taking Perception of Urban Parks in Beijing as an Example. *Landsc. Archit. Front.* **2023**, *11*, 8–21. [CrossRef]
22. Lyu, F.; Zhang, L. Using multi-source big data to understand the factors affecting urban park use in Wuhan. *Urban For. Urban Green.* **2019**, *43*, 126367. [CrossRef]
23. Ye, Y.; Qiu, H. Exploring Affecting Factors of Park Use Based on Multisource Big Data: Case Study in Wuhan, China. *J. Urban Plan. Dev.* **2021**, *147*, 05020037. [CrossRef]
24. Zhang, S.; Zhou, W. Recreational visits to urban parks and factors affecting park visits: Evidence from geotagged social media data. *Landsc. Urban Plan.* **2018**, *180*, 27–35. [CrossRef]
25. Lei, Z.X.; Luo, J.J.; Feng, Y.R.; Gao, J. Analysis of Cultural Perception of Beining Park in Tianjin Based on Online Review Data. *Landsc. Archit.* **2023**, *30*, 99–105.
26. Shi, M. From Imperial Gardens to Public Parks: The Transformation of Urban Space in Early Twentieth-Century Beijing. *Mod. China* **1998**, *24*, 219–254. [CrossRef]
27. Chen, S.; Haase, D.; Qureshi, S.; Firozjaei, M.K. Integrated Land Use and Urban Function Impacts on Land Surface Temperature: Implications on Urban Heat Mitigation in Berlin with Eight-Type Spaces. *Sustain. Cities Soc.* **2022**, *83*, 103944. [CrossRef]
28. Song, Y.; Fernandez, J.; Wang, T. Understanding Perceived Site Qualities and Experiences of Urban Public Spaces: A Case Study of Social Media Reviews in Bryant Park, New York City. *Sustainability* **2020**, *12*, 8036. [CrossRef]
29. Sim, J.; Miller, P. Understanding an Urban Park through Big Data. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3816. [CrossRef]
30. Lai, S.; Deal, B. Parks, Green Space, and Happiness: A Spatially Specific Sentiment Analysis Using Microblogs in Shanghai, China. *Sustainability* **2023**, *15*, 146. [CrossRef]

31. The 14th Five-Year Plan for Urban Landscaping in Fuzhou. Available online: https://www.fuzhou.gov.cn/zgfzzt/sswgh/fzssswghzswj/202310/t20231013_4697985.htm (accessed on 27 June 2024).
32. Park, S.B.; Kim, J.; Lee, Y.K.; Ok, C.M. Visualizing theme park visitors' emotions using social media analytics and geospatial analytics. *Tour. Manag.* **2020**, *80*, 104127. [CrossRef]
33. Wang, Z.; Miao, Y.; Xu, M.; Zhu, Z.; Qureshi, S.; Chang, Q. Revealing the differences of urban parks' services to human wellbeing based upon social media data. *Urban For. Urban Green.* **2021**, *63*, 127233. [CrossRef]
34. Kong, L.; Liu, Z.; Pan, X.; Wang, Y.; Guo, X.; Wu, J. How do different types and landscape attributes of urban parks affect visitors' positive emotions? *Landsc. Urban Plan.* **2022**, *226*, 104482. [CrossRef]
35. Kovacs-Györi, A.; Ristea, A.; Kolcsar, R.; Resch, B.; Crivellari, A.; Blaschke, T. Beyond Spatial Proximity—Classifying Parks and Their Visitors in London Based on Spatiotemporal and Sentiment Analysis of Twitter Data. *ISPRS Int. J. Geo Inf.* **2018**, *7*, 378. [CrossRef]
36. Koblet, O.; Purves, R.S. From online texts to Landscape Character Assessment: Collecting and analysing first-person landscape perception computationally. *Landsc. Urban Plan.* **2020**, *197*, 103757. [CrossRef]