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Coupling Coordination Evaluation of Lakefront Landscape Spatial Quality and Public Sentiment

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Abstract: The comprehensive quality evaluation of the lakefront landscape relies on a combination of subjective and objective methods. This study aims to evaluate the coupling coordination between spatial quality and public sentiment in Wuhan's lakefront area, and explore the distribution of various coupling coordination types through machine learning of street view images and sentiment analysis of microblog texts. Results show that: (1) The hot and cold spots of spatial quality are distributed in a contiguous pattern, whereas the public sentiments are distributed in multiple clusters. (2) A strong coupling coordination and correlation exists between spatial quality and public sentiment. High green visibility, high sky visibility, and natural revetment have remarkable positive effects on public sentiment. In comparison, high water visibility has a negative effect on public sentiment, which may be related to the negative impact of traffic-oriented streets on the lakefront landscape. (3) Lakefront areas close to urban centers generally show a low spatial quality–high public sentiment distribution, which may be related to factors such as rapid urbanization. This study can help planners identify critical areas to be optimized through coupling coordination relationship evaluation, and provides a practical basis for the future development of urban lakefront areas.

Keywords: lakefront landscape; machine learning; sentiment analysis; coupling coordination relationship

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1. Introduction

As a specific spatial location in cities, urban waterfronts have played an important role in the history of urban development [1]. Historically, waterfronts were mainly used for industry, manufacturing, and transportation [2]. In the postindustrial era, the introduction of leisure, recreation, and tourism functions into waterfronts has gradually made waterfront redevelopment a global phenomenon [3,4]. Today, waterfronts have become an important tool for shaping the image of cities and promoting economic investment [5–8]. They are also important public open spaces in the eyes of citizens [9]. As an essential part of the waterfront, the urban lakefront space is also an important open space and urban landscape [10], and has a multifaceted positive impact on human health and well-being [11]. Current research on urban lakefront areas is mostly focused on landscape design and ecosystem quality [12–16]. Moreover, the research on comprehensive landscape quality is still in its infancy.

The urban lakefront landscape is the area where land and water meet adjacent to the lake; it is also the aesthetic experience of the area [17]. Studies have shown that the comprehensive quality of the lakefront landscape is the result of the joint action of physical elements of space and public sentimental perception [18,19]. Therefore, its evaluation relies on two aspects, namely objective spatial quality and subjective sentimental perceptions [20,21]. Space and sentiment are essentially circular [22]. Sentiments assume a bridging role between human perceptions and the surrounding environment and reflect changes in one's attitudes and experiences of the environment and people around them [23,24]. Within a given space, spatial quality affects public sentiment [25]. The results of sentiment analysis can reflect the public sentiment state in the space and be used for comprehensive landscape quality assessment [26,27].

In the existing studies, the evaluation of objective spatial quality is mostly based on qualitative discussion and analysis through on-site social surveys, and the assessment of subjective sentiment perceptions is mainly conducted based on tracking surveys, field observations, or psychological experiments [28–30]. These methods are usually costly and labor intensive. They also suffer from limited sample sizes and time-consuming problems. The emergence of big data and open data has brought new ways of data collection, providing methods for large-scale quantitative measurements [31]. Urban street view images and social media data have many advantages, such as wide coverage, low acquisition cost, timeliness, and abundance, which can enable large-scale automated assessment of urban environments and public perceptions [32].

Urban street view images cover a wide range of areas and show the real form of the streetscape from a human-centered perspective, providing an accurate and objective data source for assessing the quality of urban space [33,34]. Some scholars have started to judge the physical quality of the environment in urban large-scale study areas based on street view images; the assessment results based on street view images are generally consistent with those based on field observations and have a high accuracy rate [35–38]. This approach also increases the possibility of large-scale automatic assessment of urban spatial quality based on street view images. In China, the Baidu Map Street View (BMSV) image dataset records street view images of more than four hundred cities and thousands of counties [39]. It also provides street view information with high resolution and a large amount of detailed information [40]. The use of street view images in combination with machine learning algorithms can extract useful visible information from complex street environments [41].

Social media data are an important data source that reflects the public's thoughts and attitudes toward a place. The emergence of social media has changed the way people interact as social actors and the interactions of urban networks, making it useful for understanding public reactions and interactions to a landscape or place [42,43]. In particular, social media data contain geolocation information, which makes evaluating urban environments based on public perceptions possible. Sina Microblog, the most popular social networking platform in China [44], had 462 million monthly active users and 200 million daily active users at the end of the fourth quarter of 2018 [45]. Its large amount of data provides a representative measure of the entire community.

Wuhan, the largest city in Central China, was used as the subject of this study. Wuhan is the city with the largest number of urban lakes in China, and its lake types and land use patterns in lakefront areas are relatively rich [46], which is representative and of reference value. Similar to other cities in the world, Wuhan's lakes have gradually been surrounded by the city and have become inner-city lakes during the process of urbanization [47]. Moreover, due to the excessive and unreasonable urban expansion [48,49], the natural landscape has been replaced by the built environment [46,50], hindering the public's access to the natural landscape. In recent years, the public's pursuit of a high quality of life has been increasing, and the public's concern and demand for lakefront landscapes has been growing. Previous researchers have mostly focused on ecological restoration strategies for Wuhan city's lakefront landscape [51], land use development changes in the lakefront area [52], or the quality of the lakefront landscape of a single or a few urban lakes [53,54]. Little attention has been paid to the distribution of spatial qualities of the lakefront landscape and its level of coupling and coordination with public sentiment at the municipal level, which is important for the future construction of a lakefront area. Therefore, we decided to carry out a study to evaluate the coupling and coordination of lakefront landscape spatial quality and public sentiment in Wuhan, a representative lake city, in order to help city managers find key areas for future planning and development of the lakefront area.

Following the basis of previous research, multi-source big data and geospatial analysis methods can be used in a comprehensive evaluation study of Wuhan's lakefront landscape.

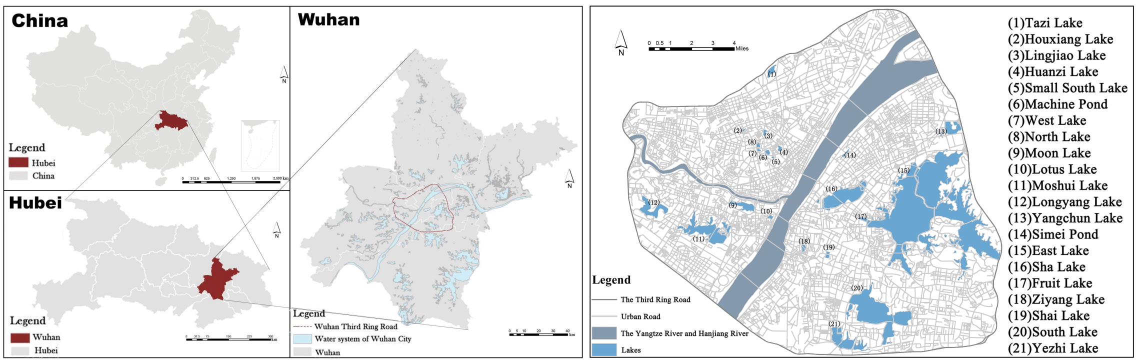
We extracted Baidu street view images and microblog text data in Wuhan's lakefront area to evaluate on a large scale the coupling and coordination of objective spatial quality and subjective public sentiment of comprehensive landscape quality by using machine learning and sentiment analysis methods, respectively. The purpose of the study is threefold: first, to study the distribution of spatial quality and public sentiment of a Wuhan lakefront landscape based on street view images and microblog texts, respectively; second, to explore the correlation and relevance between the two and to establish a planning link from spatial quality to public sentiment; third, to characterize the distribution of spatial coupling and coordination degree between spatial quality and public sentiment in each lakefront landscape, to judge the coordination type of each analysis unit, and to determine the key areas to be optimized. Finally, the spatial coupling and coordination degree of spatial quality and public sentiment of each lakefront landscape are characterized, the coordination type of each analysis unit is judged, and the key areas that need to be optimized are determined to provide a theoretical basis and empirical research foundation for future planning, design, and renewal of urban lakefronts.

2. Materials

2.1. Study Area

Wuhan is located at longitude 113°41′–115°05′ E and latitude 29°58′–31°22′ N. It is the capital city of Hubei Province, with a total land area of 8569.15 km and a resident population of 12,326,518. The Yangtze River, the third-largest river in the world, and its largest tributary, the Han River, run through the center of the city, dividing the central city of Wuhan into Wuchang, Hankou, and Hanyang, forming a pattern of three towns across the river [55]. The rivers, lakes, and harbors in the city are intertwined, and the water area accounts for a quarter of the total area of the city, which is known as the "City of 100 Lakes" [56]. According to the "Wuhan Urban Lakes Protection Regulations" issued by the Wuhan Municipal Water Bureau, Wuhan has 166 lakes, 40 of which are located in the central city [57]. Tang Xun Lake (47.6 km^2) is currently the largest urban lake in China, and Wuhan East Lake was listed as the first national key scenic tourism area in 1982 [58]. In modern times, Wuhan has changed the layout and development of the city's lakefront. It is committed to exploring a way to make the lakefront a feature of the city by building a metropolitan ecological city.

Wuhan has three ring roads. The third ring road, with a total length of 91 km surrounding the entire central city, is the junction between the city and the suburbs. It has been developed as the central activity area and the main center of the city planned for Wuhan. The area is relatively fast growing economically, culturally, industrially, and commercially, with less than 15% of the city's land; however, it gathers more than 60% of the population and 50% of the economic output [53]. Moreover, Sina Microblog users are very active mainly within this area. Therefore, the area for this study was delineated as the lakefront area of 21 major lakes within the third ring road (Figure 1).



(a) Location of the study area (b) All lakes studied

Figure 1. Location of Wuhan and all lakes studied.

2.2. Data Sources and Preprocessing

2.2.1. Wuhan Lake Data

Landsat8 satellite remote sensing images with ranks 123/38 and 123/39 were downloaded from Geospatial Data Cloud (available online: http://www.gscloud.cn/ (accessed on 8 April 2018) to extract the lake data of Wuhan City (Table 1).

Table 1. Remote sensing picture dataset.

Satellite	Sensor	Resolution (m)	Data Identification	Date	Cloudage (%)
Landsat8	OLI	30/15	LC81230392018098LGN00	8 April 2018	8.9

In ENVI 5.3, the Automatic Water Extraction Index (AWEI) is used to extract lake data through unsupervised classification, eliminating shaded features that are easily confused with water body information. The formula is as follows:

$$AWEI_{sh} = BLUE + 2.5GREEN - 1.5(NIR + SWIR1) - 0.25SWIR2 \quad (1)$$

where $BLUE$ is the blue light band, $GREEN$ is the green light band, NIR is the near-infrared band, and $SWIR1$ and $SWIR2$ are the short-wave infrared bands [59]. Finally, the lake data of Wuhan can be extracted by visual interpretation.

2.2.2. Street View Data

Baidu Maps (Beijing, China), a desktop and mobile web mapping service application and technology provided by Baidu, has the advantage of high collection frequency and wide collection range [60]. On 23 April 2010, Baidu Maps officially announced the opening of the Map Application Programming Interface (API) to a wide range of developers for the development of mapping applications under multiple operating systems. Given the absence of Google Maps in China, Baidu Maps is considered a good alternative with its high usage and credibility as an important urban research value. In this study, the image data of BMSV within the study area were downloaded through the BMSV API (available online: http://lbsyun.baidu.com/ (accessed on 12 May 2021).

In accordance with previous studies [61,62], a 1000 m buffer zone of the lake was set as a lakefront zone, which is equivalent to a 15 min walking distance for a person [63]. First, we downloaded the urban geospatial street vector data from the Open Street Map platform (available online: https://www.openstreetmap.org/ (accessed on 1 May 2021) and exported the data of the 1000 m lakefront buffer zone within the third ring road of Wuhan City in Arc GIS 10.7 (Environmental Systems Research Institute, Redlands, CA, USA). Then, we wrote a program in Python language to sample the street vector data at 200 m intervals on the road network within the buffer area at equal intervals. Finally, we downloaded the static street view images of the sampled points through BMSV API to characterize the physical spatial quality of the waterfront lake area at the sampled points.

A total of 14,767 location points were collected in the study area, including 29,534 street view vector images with a resolution of 1024 × 512 pixels. Some of the images were too dark or overexposed to produce error interference. Thus, manual cleaning had to be performed, and 27,588 street view images with 13,794 location points were left (Figure 2).

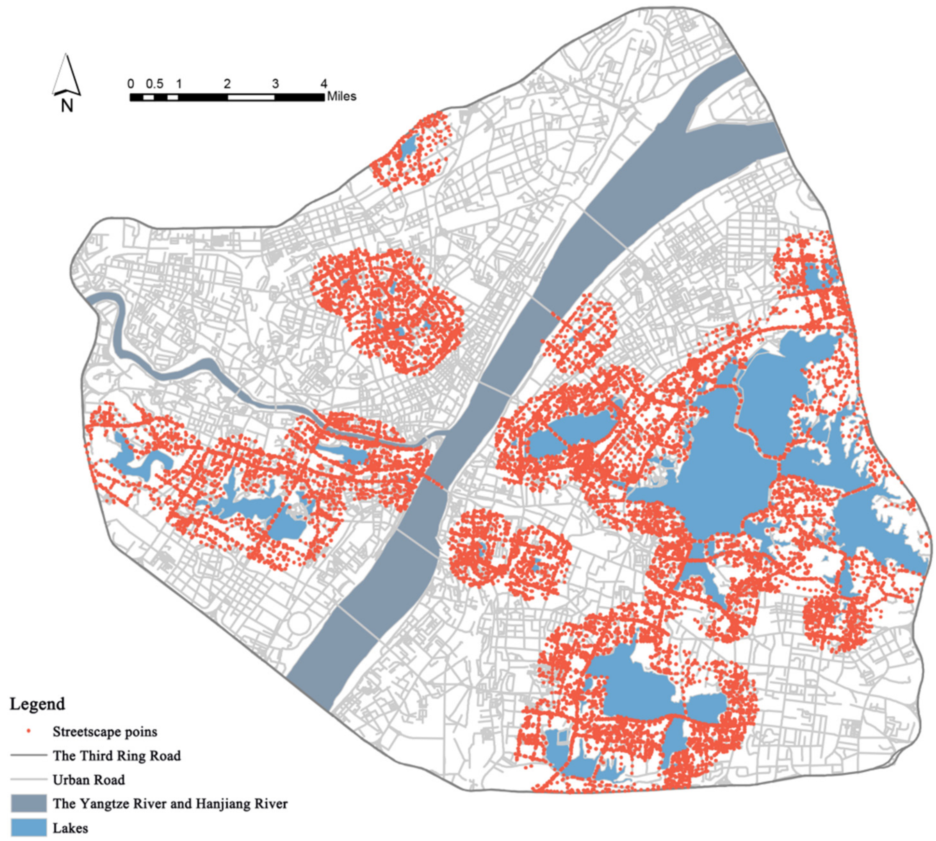


Figure 2. Distribution of streetscape points in the lakefront area.

2.2.3. Microblog Data

Sina Microblog (Beijing, China) is a microblogging service operated by Sina Corporation. Users can post messages via web pages, wireless application protocols, external programs, and cell phone short message service or multimedia messaging service [64]. Sina Microblog is a platform for sharing, distributing, and accessing information based on user relationships and had 130 million average daily text posts and 480,000 average daily long posts in the fourth quarter of 2018, making it one of the most visited websites in mainland China [45,65].

Microblog users can share their current geographical location on the network platform. A total of 318,899 microblog data points for the whole of 2018 in the study area were obtained through Sina Microblog's official open API (WBM.sinav2API; Sina, Beijing, China). The data include the content, location (latitude and longitude), and time of publication.

The original microblog text contains various interfering information, such as "http" hyperlinks, spaces, punctuation marks, subject tags, and @other-users tags. Data cleaning of the microblog text was required to eliminate errors and improve the efficiency of word separation for sentiment analysis by using regular expressions in Python ("re" module) to remove links, "@", "#", "[]" and other irrelevant information (Table 2). The cleaned data were visualized in Arc GIS 10.7, and the location within the third ring of Wuhan was selected to obtain 997,832 microblog data. The data distribution is shown in Figure 3, including 313,904 microblogs on the lakefront.

Table 2. Microblog data samples.

	Original Comments	Comments after Cleaning	Point x	Point y	Data Time
1	Ugh annoying. Did not go out to research, there is no information, there is no information stalled, cannot proceed and do not dare to rush http://t.cn/z8A9ITe? (accessed on 13 May 2018). Leave regrets	Ugh annoying. Did not go out to research, there is no information, there is no information stalled, cannot proceed and dare not rush Leave regrets	30.53759	114.2956	Sun 13 May 18:06:08 +0800 2018
2	After seeing the teeth, take the subway to Wuchang train station, and the train leaves at 3:12 P.M. http://t.cn/z8AU8Yt? (accessed on 13 December 2018)	After seeing the teeth, take the subway to Wuchang train station, and the train leaves at 3:12 P.M.	30.53515	114.2985	Thu 13 December 12:08:52 +0800 2018
3	What kind of a divine day is this!\n too happy bah!!! http://t.cn/8ksbSR2? (accessed on 28 September 2018)	What kind of a divine day is this! too happy bah!!!	30.54076	114.3046	Fri 28 September 21:47:16 +0800 2018
4	Waiting for two hours to faint from hunger http://t.cn/RuaKHvP? (accessed on 25 July 2018)	Waiting for two hours to faint from hunger	30.53554	114.3043	Wed 25 July 20:03:08 +0800 2018
5	Up all night, fidgeting http://t.cn/z8AU8Yt? (accessed on 19 May 2018)	Up all night, fidgeting	30.53515	114.2985	Sat 19 May 06:42:48 +0800 2018

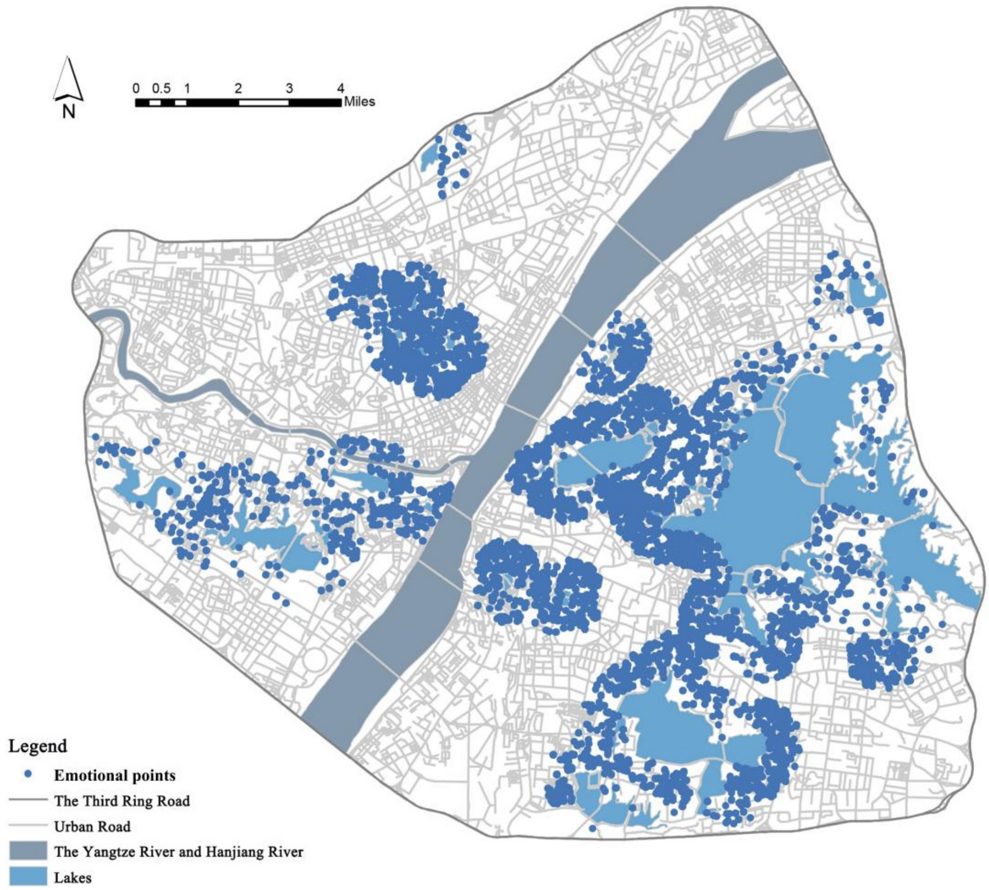


Figure 3. Distribution of emotional points in the lakefront area.

3. Methodology

3.1. Machine Learning Based on BMSV

Specific operations were performed according to the following technical procedures (Figure 4) to achieve a large-scale spatial quality assessment based on BMSV set of the lakefront area.

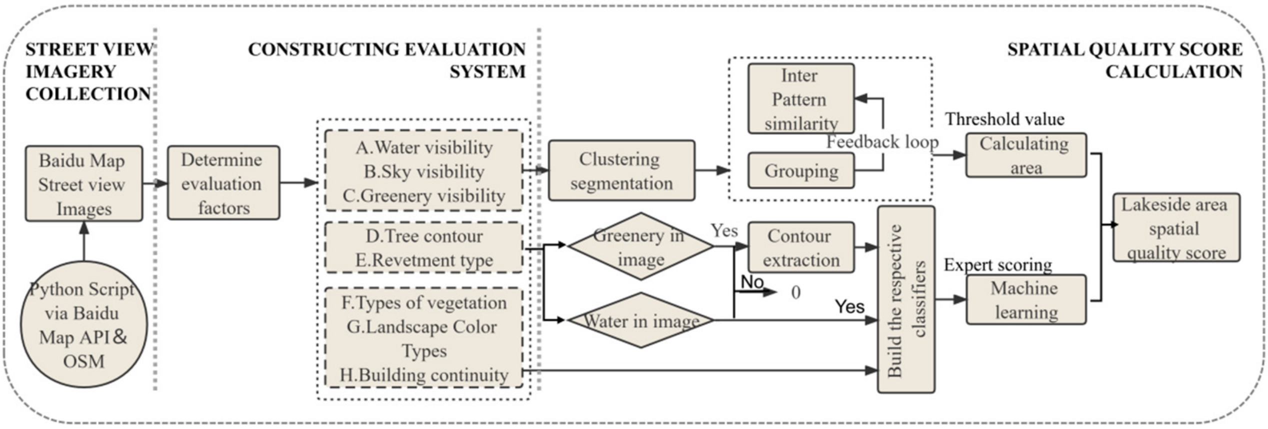


Figure 4. Technical route of evaluation index.

Street view images are rich in realism and strong information and have proven to be an efficient tool for quantitative studies of regional spatial quality. According to previous studies, there are many indicators for the evaluation of street quality from the point of view of physical conditions, which are gradually becoming more uniform. These indicators mainly include both natural and artificial elements [66]. Therefore, this study will continue with a similar idea, describing the spatial quality of the lakefront landscape in terms of both natural and artificial elements. The nature elements include greenery, water and the sky, while the artificial elements include buildings, etc. Greenery and water are among the more important elements of the lakefront landscape system and are widely used [67,68]. Therefore, the evaluation of the greenery elements of the street in this paper will be carried out in four dimensions: greenery visibility, types of vegetation, landscape color type and tree contour. The evaluation of water elements considers both water visibility and revetment type. The visibility of sky elements and the continuity of building elements on the street affect the pedestrian experience, thus being included in the evaluation system [69,70].

Finally, eight factors were developed to evaluate the spatial quality of Wuhan's lakefront landscape (Table 3). Then, seven experts with experience in urban planning, landscape architecture, and architecture were invited to rate the sample set of street view image data.

Water visibility, sky visibility, and green visibility can reflect the probability or perception of a landscape element that the public can perceive with their eyes on the streets of the lakefront; moreover, visibility affects the public's satisfaction with the surrounding urban environment and people's quality of life [4,85–88], calculated as follows:

$$WV = \frac{A_{water}}{A_0} * 100\%, \quad SV = \frac{A_{sky}}{A_0} * 100\%, \quad GV = \frac{A_{green}}{A_0} * 100\%, \tag{2}$$

where WV, SV, and GV represent water visibility, sky visibility, and greenery visibility, respectively. A_{water}, A_{sky}, and A_{green} refer to the number of pixels extracted from each image for water, sky, and greenery, respectively, and A_0 is the total number of pixels in the image.

Table 3. Evaluation system for space quality of the lakefront area.

Indicator		Explanation
Greenery	A. Greenery visibility	The extent to which pedestrians on the street perceive green landscape elements [71]; exposure to green space can improve mental health [72,73].
	B. Types of vegetation	Vertical ground stratification on the street with different species of plants, including a high mix of trees and shrubs with herbaceous plant types promoting positive emotions [74].
	G. Landscape color type	Variety of landscape colors on the street; rich colors have strong visual appeal to stimulate pedestrian sensory perception and further convey the visual characteristics of the greenery [75].
	D. Tree contour	The roughness of tree contours on the street, with rough and uneven tree contours representing a natural ecological landscape with a high sense of security [76].
Sky	E. Sky visibility	The extent to which pedestrians on the street perceive elements of the skyscape [41], with high sky visibility leading to positive emotions [69].
Water	F. Water visibility	The extent to which pedestrians on the street perceive elements of the water body landscape [77]; spatial exposure to water bodies has an impact on people's emotional, physical, and mental health [78,79].
	G. Revetment type	The type of revetment visible on the street; natural revetment has better ecological quality with less human intervention than hard-paved artificial revetment [80,81].
Building	H. Building continuity	The degree of continuity of the interface formed by the building façade on the street; a continuous building façade provides pedestrians with a sense of security, location, and identity [82,83]; it also enhances the attractiveness of the street [70,84].

A segmentation clustering algorithm was used in segmenting the street view image dataset into "water", "sky", and "greenery" to measure the public's perception of the three landscape elements, namely water, sky, and greenery, in the lakefront area. As the most popular clustering algorithm, K-means mean algorithm has the advantages of good clustering effect, simple idea, and fast clustering speed. It is unsupervised learning and generally uses Euclidean distance as a measure of similarity between data objects, where similarity is inversely proportional to the distance between data objects; the greater the similarity is, the smaller the distance is; the image can be eventually divided into K clusters based on feature similarity [89]. In this study, the K-means mean algorithm was used for cluster analysis to obtain the three targets, namely "water", "sky", and "greenery", in the street view images. The target was used to calculate the percentage of the area of each of the three parts in the image by setting the threshold. Finally, the scoring of the three scoring factors, A, E, and F, was performed according to the scoring criteria in Table 4.

Determining the spatial quality of the lakefront area is a dichotomous problem. Support vector machine (SVM), a class of generalized linear classifiers that classify binary data through supervised learning, is a common approach to solve a dichotomous problem. Therefore, the SVM classifier was used for the machine learning of the B, C, D and H factors of the whole study area's street view images based on the expert ratings of the sample set. The findContours function, a tool based on the cross-platform open-source computer vision (OpenCV) library, was used in detecting and extracting the boundary contour lines of trees in the street view images to improve the machine learning accuracy. The scores scored by experts for the tree contours in the sample dataset were used in training the classifier to score the tree contours for all streetscape points in the study area through machine learning.

Table 4. Evaluation standard for space quality of the lakefront area.

Evaluation Factors	Scoring Criteria				Weights
	1 Point	2 Points	3 Points	4 Points	
A. Water visibility	0%	(0%–5%]	(5%–15%]	(15%, 100%]	0.20
B. Sky visibility	[0%–10%]	(10%–30%]	(30%–50%]	(50%, 100%]	0.20
C. Greenery visibility	[0%–25%]	(25%–50%]	(50%–75%]	(75%, 100%]	0.20
D. Tree contour	No tree group formed	Smooth contours	Slightly uneven	Rough Contour	0.10
E. Revetment type	No revetment	Artificial revetment	Artificial and natural revetment	Natural revetment	0.10
F. Types of vegetation	0 kinds	1 kind	2 kinds	≥3 kinds	0.05
G. Landscape color type	1 kind	2 kinds	3 kinds	≥4 kinds	0.05
H. Building continuity	Low	Relatively low	Relatively high	High	0.10

After repeated tests, eight factors were given corresponding weights according to the magnitude of the relative accuracy of each factor. The factors limited by quantitative techniques were given small weights. The objective spatial quality scores of the streetscape points in Wuhan City lakefront area were obtained by weighting the eight factors. The scoring criteria and results of the eight factors are shown in Figures 5 and 6. Finally, the scores of all streetscape points were imported into Arc GIS10.7 for visualization to analyze the spatial quality distribution characteristics of the lakefront landscape.

Figure 5. Standard schematic of each factor score.

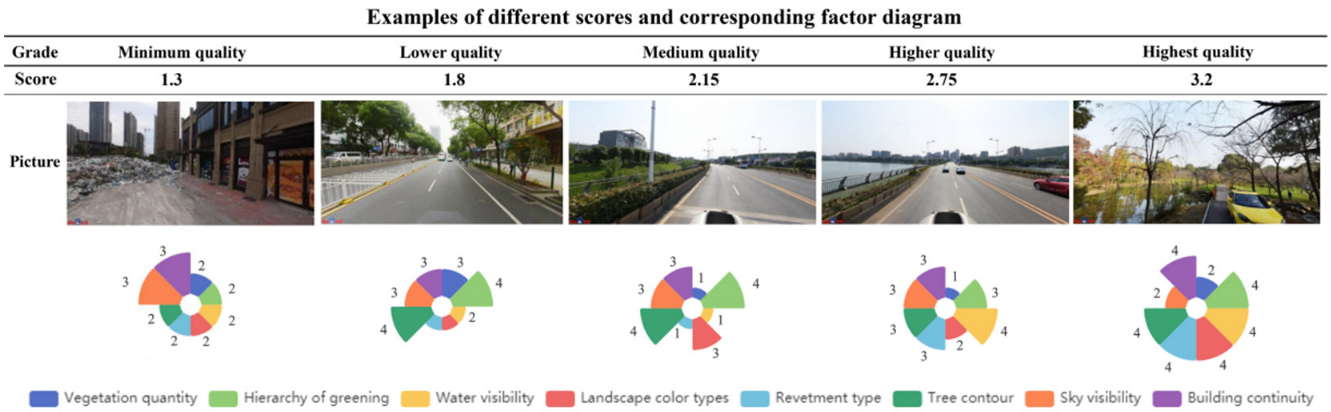


Figure 6. Schematic of grading result.

3.2. Sentiment Analysis Based on Sentiment Dictionaries

Identifying public attitudes and opinions on the lakefront landscape plays an important role in planning the future development of Wuhan's lakefront area. In this study, the textual content of microblogs was used to analyze the sentiments of microblog users. Text sentiment analysis is a tool for extracting subjective information from natural language texts [90]. It also aims to classify texts into sentiment categories, such as positive or negative, or more fine-grained categories, such as very positive, positive, and neutral [91]. Sentiment methods based on sentiment dictionaries and sentiment analysis based on machine learning are the two most common approaches in text sentiment analysis [92]. The content of microblog texts is mostly concise, with 20–30 words mostly and at most 140 words. It is also difficult to analyze based on deep context. Thus, sentiment analysis methods based on sentiment dictionaries were used in this study to collect public opinions and sentimental responses to urban lakefront spaces [93,94].

HowNet Chinese Sentiment Dictionary is a general knowledge base that describes the concepts represented by Chinese and English words; this general knowledge base also reveals the attributes of concepts and the relationships between concepts as the basic content [95], including positive sentiment words, negative sentiment words, deactivation words, and degree adverbs. In this study, the sentiment words in the Tsinghua University dictionary and *NTUSD* dictionary of Taiwan University were expanded on the basis of *HowNet* dictionary to improve the accuracy of text sentiment analysis [96].

According to the technical route shown in Figure 7, the microblog data of the lakefront area were scored following the steps of vocabulary-sentence-microblog after text segmentation. It is noteworthy that sentiment words at the beginning or end of a sentence often determine the overall color of a sentence in Chinese expression, so the weight of these emotion words is expanded to ± 1.2. Moreover, degree adverbs before the sentiment words will strengthen or weaken the sentiment tendency, so each type of degree adverb is given the appropriate weight and multiplied by the sentiment value (Table 5). Since negation reverses the sentiment tendency, the number of negatives should be judged. For an odd number, we multiply the sentiment value by -1. For an even number, we multiply the sentiment value by 1.

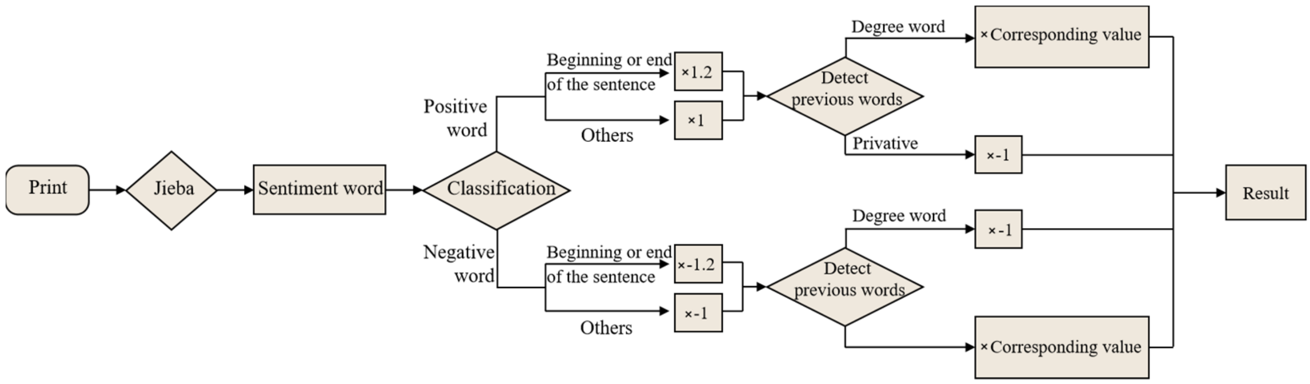


Figure 7. Flowchart of calculating emotion value of word combination.

Table 5. Weights of various words.

Words	Weights
Over, excessive, overdone, over the top	0.1
Half a bit, not much, not very, not much	0.25
Slightly, somewhat, a little	0.5
More, comparative	1.25
Really, specially, very, especially, too	1.5
Extremely, very, absolutely, very	2
No, not really, no need, no, no	−1
Positive sentiment words without degree adverbs	1
Negative sentiment words without degree adverbs	−1
Positive sentiment words without degree adverbs (sentence starters, sentence enders)	1.2
Negative sentiment words without degree adverbs (sentence starters, sentence enders)	−1.2

The sentiment value of each clause is the sum of the weights of each combination in the sentence:

$$F_q = \sum_{i=1}^{n} \left[(-1)^p f(x_i) \prod_{j=1}^{m} a_{ij} \right], \quad (3)$$

where n refers to the number of sentiment words in each clause of the microblog text, p denotes the number of negation words of the ith sentiment word, m refers to the number of degree adverbs modifying the ith sentiment word, $f(x_i)$ refers to the polarity value of the ith sentiment word, a_{ij} refers to the weight value corresponding to the jth degree adverb of the ith sentiment word, and F_q denotes the final sentiment value of the qth clause.

The average of the sentiment values of all clauses in a text is calculated as the sentiment score of that text.

$$C_n = \frac{\sum_{q=1}^{h} F_q}{h}, \quad (4)$$

where h denotes the number of clauses in a microblog text, and C_n denotes the final sentiment score of the nth microblog text.

3.3. Curve Regression

The spatial quality score and public sentiment score of each lake were imported into IBM Statistical Product and Service Solutions (SPSS) Statistics 24 software for curve estimation to explore further the relationship between objective spatial quality and subjective public sentiment. Curve estimation can solve the essential linearity problem. The curve estimation tool can be used to complete the parameter estimation of multiple models when the models close to the sample data cannot be surely determined (Table 6). This tool can also select the best model based on statistics such as the f-value of the significance test of the regression equation, the *p*-value of the companion probability, and the R2 of the coefficient of determination.

Table 6. Different models for curve estimation.

Model	Regression Equation
Linear function	$Y = b_0 + b_1 t$
Quadratic equation	$Y = b_0 + b_1 t + b_2 t^2$
Compound function	$Y = b_0 (b_1^t)$
Logarithmic function	$Y = b_0 + b_1 \ln(t)$
Cubic equation	$Y = b_0 + b_1 t + b_2 t^2 + b_3 t^3$
S curve	$Y = e^{b_0 + b_1/t}$
Inverse function	$Y = b_0 + b_1/t$
Power function	$Y = b_0 \left(t^{b_1}\right)$

3.4. Analysis of Spatial Coupling Coordination Degree

After correlation tests, the coupling coordination model was used to evaluate the level of coordinated development between spatial quality and public sentiment. The unified basic unit of spatial analysis is the basis of this research. Therefore, after repeated tests, a 150 × 150 m sized fishing grid was created to unify the analysis cells. The attributes of the original streetscape points and emotional points were connected to the fishing grid layer. The average normalized score of the streetscape points in each grid is the spatial quality score of that grid; the average normalized score of the emotional points in each grid is the public sentiment score of that grid. Grids with null values of spatial quality or public sentiment were excluded to ensure the accuracy of the calculation.

The spatial coupling coordination model, which can analyze the level of coordinated development between two elements, is widely used in environmental science [97,98]. This model involves two indicators. One of them is the coupling degree, which indicates the degree of interaction and mutual influence between two elements [99]. The coupling degree can hardly reflect the overall effectiveness and synergy between elements; thus, a coupling coordination model was further constructed with the coordination degree to evaluate the degree of coordination between spatial quality and public sentiment in different lakefront areas [100]. Before data calculation, the spatial quality and public sentiment indicators were normalized by the maximum–minimum method to eliminate the influence of the magnitude. The model can be mathematically described as follows.

$$X_i = \frac{SQ_i - min(SQ_i)}{max(SQ_i) - min(SQ_i)} \tag{5}$$

$$Y_i = \frac{PS_i - min(PS_i)}{max(PS_i) - min(PS_i)} \tag{6}$$

$$C_i = \sqrt{\frac{X_i * Y_i}{[(X_i + Y_i)/2]^2}} \tag{7}$$

$$T_i = \alpha X_i + \beta Y_i \tag{8}$$

$$D_i = \sqrt{C_i * T_i} \tag{9}$$

where X_i is the normalized spatial quality score of the *i*th grid, Y_i is the normalized public sentiment score of the *i*th grid, C_i is the coupling degree of the *i*th grid, T_i is the comprehensive coordination index of the *i*th grid, and D_i is the coupling coordination degree of the *i*th grid. The α and β in the formula are the weights of spatial quality and public sentiment, respectively. $\alpha = \beta = 0.5$ was taken as the spatial distribution of spatial quality and public sentiment, considering that they are equally important in this study. The specific grading of coupling degree and coupling coordination degree was set according to the data distribution characteristics (Table 7).

Table 7. Classification of coupling degree and coupling coordination degree.

Degree	Coupling Degree Classification	Coupling Coordination Degree Classification
0.0–0.2	Extremely uncoupled	Extreme uncoupling coordination
0.2–0.4	Moderately uncoupled	Moderate uncoupling coordination
0.4–0.5	Barely uncoupled	Bare uncoupling coordination
0.5–0.6	Barely coupled	Bare coupling coordination
0.6–0.7	Moderately coupled	Moderate coupling coordination
0.7–0.8	Strongly coupled	Strong coupling coordination
0.8–1.0	Extremely coupled	Extreme coupling coordination

The original five levels of spatial quality and public sentiment were reclassified into high and low after comparing them with the mean of the two cutoff values of the neutral order to determine further the type of coupling coordination between the two sets of data for each grid. Moreover, the spatial quality score and public sentiment score of each grid were assigned with the attributes of high and low, respectively. If each grid is high, then the matching degree field of that grid is given the attribute of high space quality–high public sentiment (HH). By analogy, the grids in the lakefront area are classified as HH, high space quality–low public sentiment (HL), low space quality–high public sentiment (LH), and low space quality–low public sentiment (LL).

4. Results

4.1. Spatial Distribution of Spatial Quality and Public Sentiment in the Lakefront Area

We can understand the spatial distribution of spatial quality and public sentiment score in the study area through machine learning and emotion analysis tools. As shown in Table 8, the spatial quality score was divided by the natural breakpoint method into five categories: high, relatively high, neutral, relatively low, and low. The public sentiment score was divided into positive, relatively positive, neutral, relatively negative, and negative.

Table 8. Score distribution of spatial quality and public sentiment.

Score Distribution of Space Quality					
Grade classification	Low 1.6–2.025	Relatively low 2.025–2.225	Neutral 2.225–2.425	Relatively high 2.425–2.625	High 2.625–3.175
Data number	2176	4285	5558	3036	1368
Average score	1.94	2.13	2.32	2.52	2.76
Ratio	13.25%	26.09%	33.84%	18.49%	8.33%
Score Distribution of Public Sentiment					
Grade classification	Negative [−10, −6)	Relatively negative [−6, −2)	Neutral [−2.2]	Relatively positive (2, 6]	Positive (6, 10]
Data number	3261	13,007	211,551	59,640	31,441
Average score	−8.74	−3.47	0.30	3.82	8.73
Ratio	1.02%	4.08%	66.34%	18.70%	9.86%

The spatial distribution of spatial quality and public sentiment of the lakefront landscape were depicted according to the geographic coordinate information of streetscape points and emotional points (Figure 8). Based on the kernel density analysis of the total point data and the graded point data of spatial quality and public sentiment, respectively, the streetscape points and emotional points of each graded segment are all concentrated around the series of lakes in Wuchang District and Hankou District, whereas the number of points distributed in the lakes of Hanyang District is small.

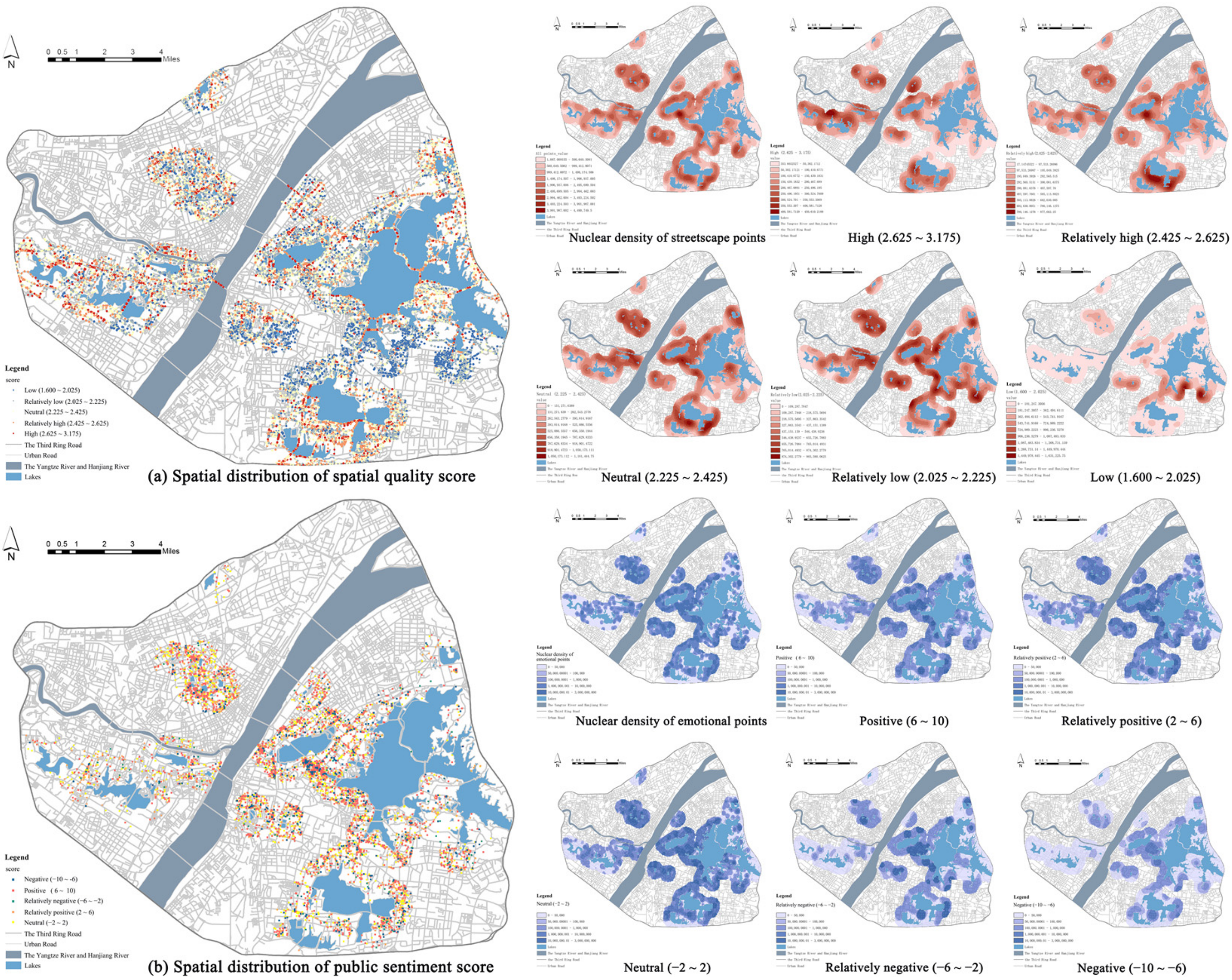


Figure 8. Spatial distribution of spatial quality and public sentiment (see Figure A1 in Appendix A).

In the spatial dimension, the hot and cold spots of spatial quality are distributed in a contiguous pattern, whereas the hot and cold spots of public sentiment are distributed in multiple clusters (Figure 9). In particular, the hot spots of spatial quality are mainly distributed in the buffer zone between the north and south of Hanyang District, Wuchang District, and the east and west of Hankou District, whereas the cold spots are concentrated in the lakefront area in the middle of Wuchang District. By contrast, no similar distribution of public sentiment exists. Its hot spots are scattered in the lakefront area of Simei Pond-Sha Lake in Wuchang District, the southeast side of the lakefront area of South Lake, and the central part of the lakefront area of the series of lakes in Hankou District, whereas the cold spots are mainly distributed in the periphery of the lakefront area of East Lake, Ziyang Lake–Shai Lake in Wuchang District, and the series of lakes in Hankou District.

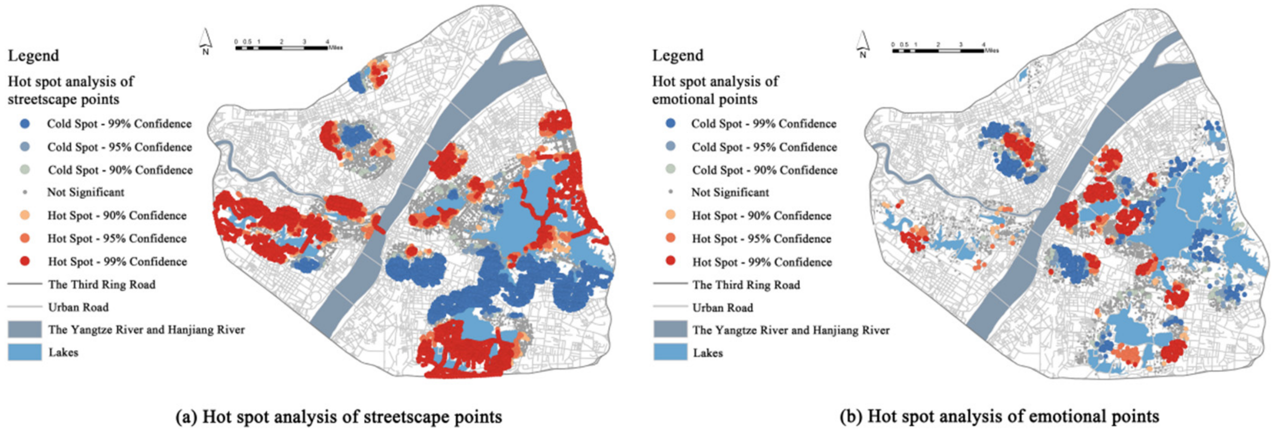


Figure 9. Hot spot analysis results of streetscape points (**a**) and emotional points (**b**).

4.2. Spatial Distribution of Spatial Quality and Public Sentiment in the Lakefront Area

Given the noticeable geographical differences in the spatial distribution of the spatial quality and public sentiment of lakefront landscape, each lakefront landscape must be analyzed and characterized separately. The five levels of spatial quality and five levels of public sentiment in each lakefront area are displayed on a three-dimensional map (Figure 10). Obvious difference characteristics can be observed. For example, the grading situation of spatial quality is more remarkable than the grading situation of public sentiment. The different characteristics of spatial quality and public sentiment are more prominent at all levels of the lakefront, such as East Lake, South Lake, and Sha Lake in Wuchang District.

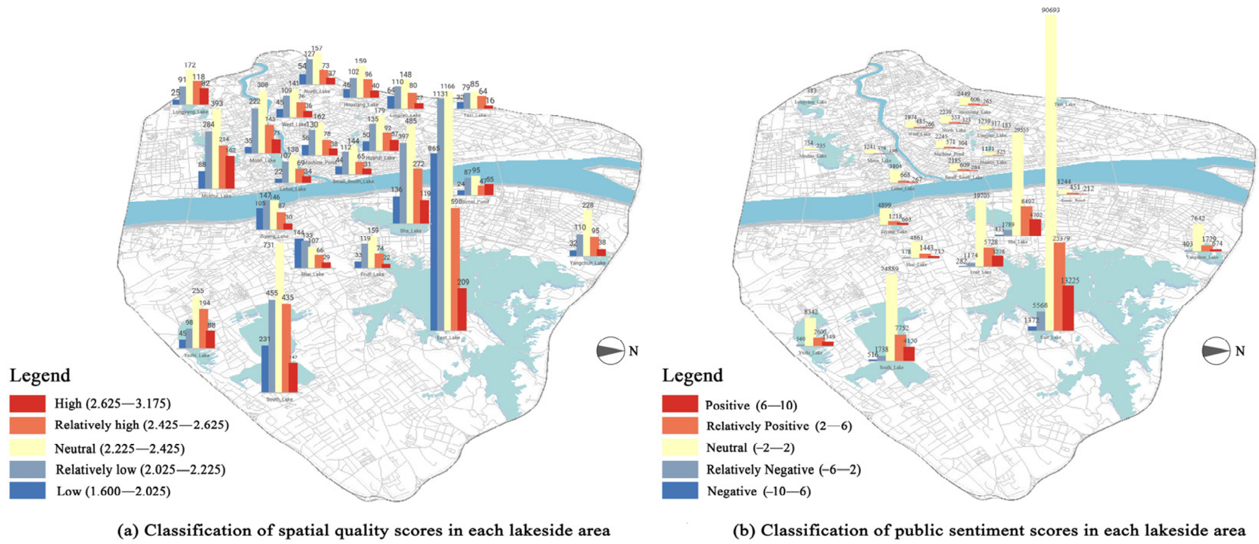


Figure 10. Classification characteristics of spatial quality (**a**) and public mood (**b**) in each lakefront area.

The average space quality score and public sentiment score of each lake were calculated separately and compared with the mean scores of the entire study area to explore further the sub-lake characteristics. The average spatial quality score for all streetscape points in the study area was 2.306, and the average public sentiment score for all emotional points was 1.529. Lakes with scores higher than the overall average were labeled "above average (AA)". On the contrary, lakes with scores lower than the overall average were labeled as "below average (BA)". On this basis, the difference between the spatial quality of each lake and the public sentiment score was compared with the mean of the difference in the lakefront area to classify the lakes into two categories. The lakes above the mean of the difference were labeled as "AA", and those below the mean of the difference were labeled as "BA". In addition, the spatial quality score and the public sentiment normalized score of each lakefront area were used to calculate the coupling degree and coupling coordination to characterize the similarity and difference characteristics of each lakefront area (Table 9).

Table 9. Characteristics in spatial quality and public sentiment in each lakefront area.

Lakes	Average Sentiment Sore	Sentiment Category	Average Street View Score	Street View Category	Difference	Coupling Degree		Coupling Coordination Degree	
East_Lake	1.536	AA	2.238	BA	BA	0.708	SCD [1]	0.736	SCCD [2]
Fruit_Lake	1.675	AA	2.298	BA	BA	0.948	ECD [3]	1.101	ECCD [4]
Houxiang_Lake	1.278	BA	2.305	BA	AA	0.961	ECD	0.890	ECCD
Huanzi_Lake	1.583	AA	2.317	AA	BA	0.993	ECD	1.128	ECCD
Lingjiao_Lake	1.597	AA	2.269	BA	BA	0.922	ECD	0.989	ECCD
Longyang_Lake	1.752	AA	2.397	AA	BA	1.000	ECD	1.390	ECCD
Lotus_Lake	1.060	BA	2.322	AA	AA	0.000	/	0.000	/
Machine_Pond	1.506	BA	2.287	BA	AA	0.982	ECD	1.004	ECCD
Moon_Lake	1.705	AA	2.323	AA	BA	0.984	ECD	1.213	ECCD
Moshui_Lake	1.642	AA	2.352	AA	BA	1.000	ECD	1.245	ECCD
North_Lake	1.516	BA	2.287	BA	AA	0.979	ECD	1.008	ECCD
Sha_Lake	1.619	AA	2.305	BA	BA	0.979	ECD	1.116	ECCD
Shai_Lake	1.486	BA	2.208	BA	BA	0.000	/	0.000	/
Simei_Pond	1.790	AA	2.353	AA	BA	0.993	ECD	1.330	ECCD
Small_South_Lake	1.382	BA	2.305	BA	AA	1.000	ECD	0.940	ECCD
South_Lake	1.630	AA	2.320	AA	BA	0.987	ECD	1.152	ECCD
Tazi_Lake	1.624	AA	2.285	BA	BA	0.957	ECD	1.071	ECCD
West_Lake	1.485	BA	2.297	BA	AA	0.994	ECD	1.022	ECCD
Yangchun_Lake	1.150	BA	2.322	AA	AA	0.753	SCD	0.735	SCCD
Yezhi_Lake	1.617	AA	2.393	AA	BA	0.991	ECD	1.322	ECCD
Ziyang_Lake	1.482	BA	2.248	BA	AA	0.880	ECD	0.831	ECCD

[1] SCD: Strongly uncoupled degree; [2] SCCD: Strong coupling coordination degree; [3] ECD: Extremely coupled degree; [4] ECCD: Extreme coupling coordination degree.

The data show that the differences of the lakefront landscape of each lake are apparent, among which 9 lakes have mean scores of spatial quality higher than the average value, 12 lakes have mean scores of public sentiment higher than the average value, and 8 lakes have differences higher than the mean of difference. According to the results of coupling degree and coupling coordination degree, the vast majority of the lakefronts belong to extremely coupled degree and extreme coupling coordination degree, with values of more than 0.8. This finding indicates that high similarity and high coordination consistency exist between spatial quality and public sentiment in most of the lakefront landscapes. This interaction relationship is benign and demonstrates a high level of mutual promotion. However, the evaluation results of East Lake and Yangchun Lake are low, indicating that the coupling degree and coupling coherence of these two lakefront areas may have obvious spatial heterogeneity, which needs further analysis.

4.3. Potential Impact of Spatial Quality and Public Sentiment in the Lakefront Area

The vast majority of lakefront areas in the study area show a high degree of coupling and coupling coordination. This finding suggests a strong correlation between spatial quality and public sentiment. Several studies have shown that the physical urban environment [75,101,102], including the street environment [103–106], can have a direct or indirect impact on the public sentiment state through its characteristics. Therefore, spatial quality and public sentiment data for each lakefront area were used for curve estimation to explore their potential correlations and coupling relationship characteristics.

In particular, positive sentiment (6 to 10 points) and relatively positive sentiment (2 to 6 points) were uniformly defined as active emotion (2 to 10 points) to avoid offsetting positive and negative emotions within each lakefront. Moreover, negative sentiment (−10 to −2 points) and relatively negative sentiment (−6 to −2 points) were defined as passive emotion (−10 to −2 points). The active and passive emotion values for each lake were calculated and simulated separately with the spatial quality score and the mean scores of the eight factors of the streetscape in the SPSS software for separate curves (Figure 11). Among all the fitted results, the inverse function simulates the best results with high confidence. The correlation matrix between the variables fitted by the inverse function is shown in Figure 12.

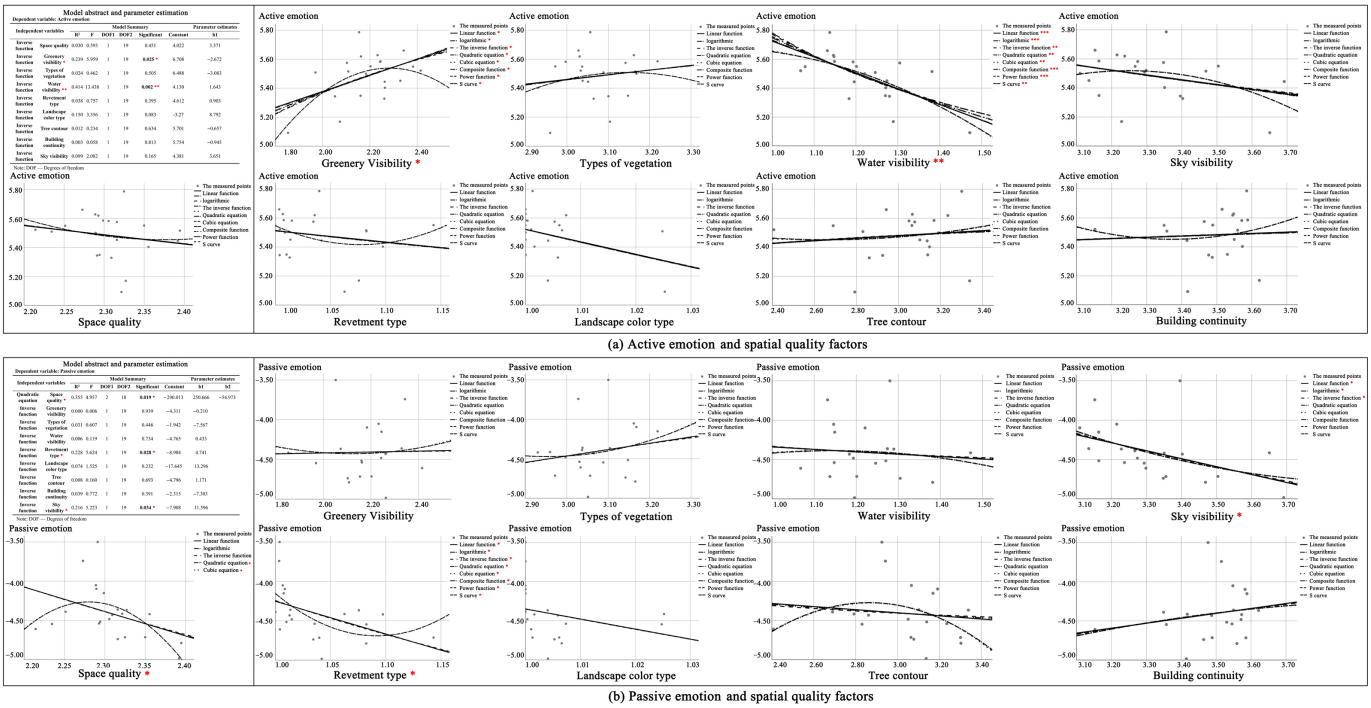


Figure 11. Curve estimation results (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, see Figure A2 in Appendix A).

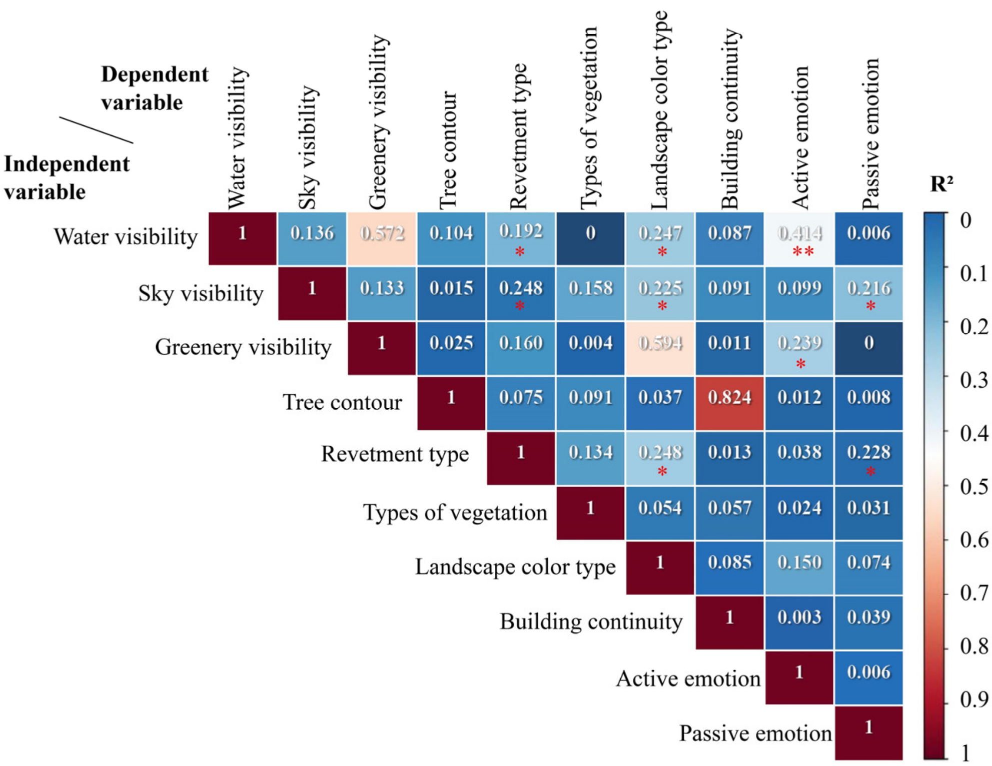


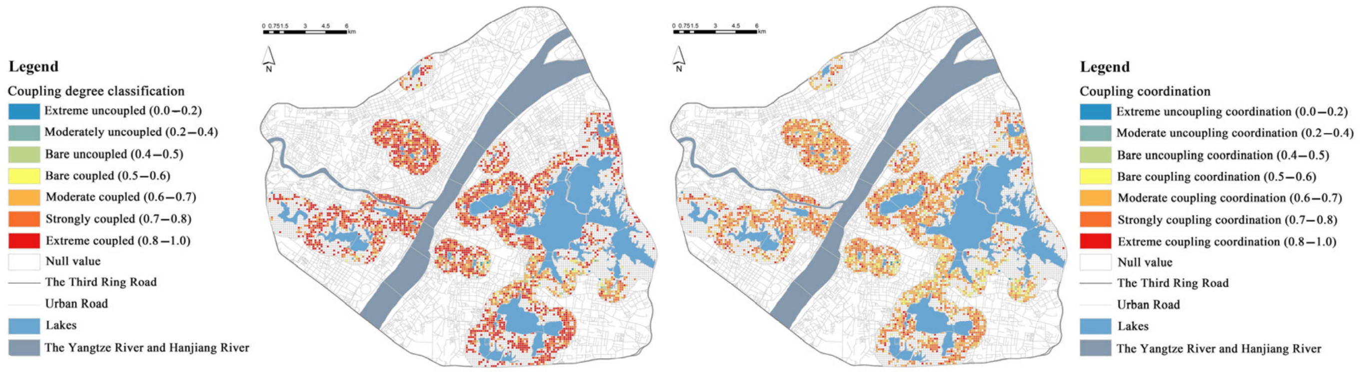
Figure 12. Correlation matrix of the variables. The color indicates the magnitude of the coefficients between the variables (** $p < 0.01$, * $p < 0.05$).

The results show that the quality of the lakefront landscape is negatively correlated with passive public emotion at the 95% significance level and explains 35.5% of the diminished passive emotion. However, it is not significantly correlated with active public emotion. This finding indicates that the good spatial quality of the lakefront landscape can alleviate passive public emotion. In particular, green visibility in streetscape elements is positively correlated with active public emotion at the 95% significance level and can explain 23.9% of enhanced positive emotion in the lakefront area. Water visibility is negatively correlated with active public emotion at the 99% significance level and can explain 41.4% of weakened active emotion in the lakefront area. Sky visibility and natural revetment are negatively correlated with passive public emotion at the 95% significance level. Sky visibility explains 21.6% of the weakened passive emotion in the lakefront, and the natural revetment explains 22.8% of the weakened passive emotion in the lakefront. In other words, high green visibility, high sky visibility, and natural revetment have a significant positive effect on public sentiment, whereas high water visibility has a negative effect on public sentiment.

4.4. Coupling Coordination Evaluation of the Spatial Quality and Public Sentiment in the Lakefront Area

The above conclusions can reveal the similarity and correlation between the spatial quality and public sentiment of the Wuhan lakefront landscape. However, geographical differences exist in this relationship. Coupling degree, coupling coordination degree, and type of coupling and coordination at the scale of fishing network were analyzed in turn to measure further the type of coupling and coordination between spatial quality and public sentiment in the study area.

The results of the geographic distribution of coupling degree and coupling coordination degree are roughly similar (Figure 13). The junction zone of Shai Lake lakefront and East Lake–South Lake lakefront shows an evident contiguous clustering distribution of low coupling and low coordination. This observation indicates that the degree of association and coordination state of spatial quality and public sentiment in this area is poor. This finding can also explain the poor coupling and coordination of East Lake and Yangchun Lake in the previous study. These areas are the zones where the old city of Wuchang historically developed to the east along Luoyu Road. Nowadays, mixed distributions of old and new residential land, commercial land, and educational land can be found. The combined results of hot spot analyses of streetscape points and emotional points indicate that concentrated and continuous distribution of cold spots of spatial quality exists. However, scattered hot and cold spots of public sentiment also exist with apparent differences in geographical distribution, which may weaken the coordination between the two. By contrast, the lakefront areas of Yangchun Lake, Simei Pond, and South Lake–Yezhi Lake junction zone in Wuchang District, the lakefront areas of Moon Lake–Lotus Lake junction zone and Moshui Lake–Longyang Lake junction zone in Hanyang District, and the lakefront areas of Houxiang Lake–North Lake junction zone in Hankou District have high coupling and coupling coordination. With regard to land use, these places are often the locations of urban scenic areas, high-class residential communities, universities, and urban green areas, such as Yellow Crane Tower Park, Guishan Scenic Area, Hanzheng Street, Central China Agricultural University, and Zhongnan University of Economics and Law.



(a) Spatial distribution of coupling degree (b) Spatial distribution of coupling coordination degree

Figure 13. Spatial distribution of coupling degree and coupling coordination degree between spatial quality and public sentiment.

The judgment of coupling coordination type can portray the spatial matching degree of spatial quality and public sentiment of the Wuhan lakefront landscape. The original five-level classification of the two sets of data was redivided into two categories according to the mean value of the two dividing values of the neutral classification. The attributes of the coupling system type of each grid were judged in turn, and the number of each type of grid was counted with respect to its actual area (Table 10). The number of LH-type grids in the study area accounts for the largest proportion, whereas the number of HL-type grids accounts for the smallest proportion. This finding indicates that the Wuhan lakefront landscape should focus on improving spatial quality to bring a superior aesthetic experience.

Table 10. Distribution of coupling coordination type between spatial quality and public sentiment in lakefront area.

Category	HH	HL	LH	LL
Area (m^2)	19,351,898.81	8,092,936.89	33,566,663.21	12,531,893.63
Share (%)	26.31	11.01	45.64	17.04

The four types of fishing grid, HH, LL, HL, and LH, were visualized in Arc GIS 10.7. The distributions of the four coupled coordination types differed remarkably and showed a multigroup cluster-like distribution (Figure 14). In particular, HH and LL show a multigroup cluster-like distribution. LH also has a tendency of contiguous clustered distribution, whereas the distribution of HL is not obvious. The areas matched by HH are consistent with the areas of high coupling and high coupling coordination, indicating that the spatial quality and public sentiment of these areas are at a high level and mutually reinforcing at a high level. The distribution areas of HL are few and contrast with the contiguous clustering of LH in the lakefront areas close to urban centers. This finding indicates that the construction of the Wuhan lakefront may lack consideration of streetscape elements, and its physical spatial quality must be optimized.

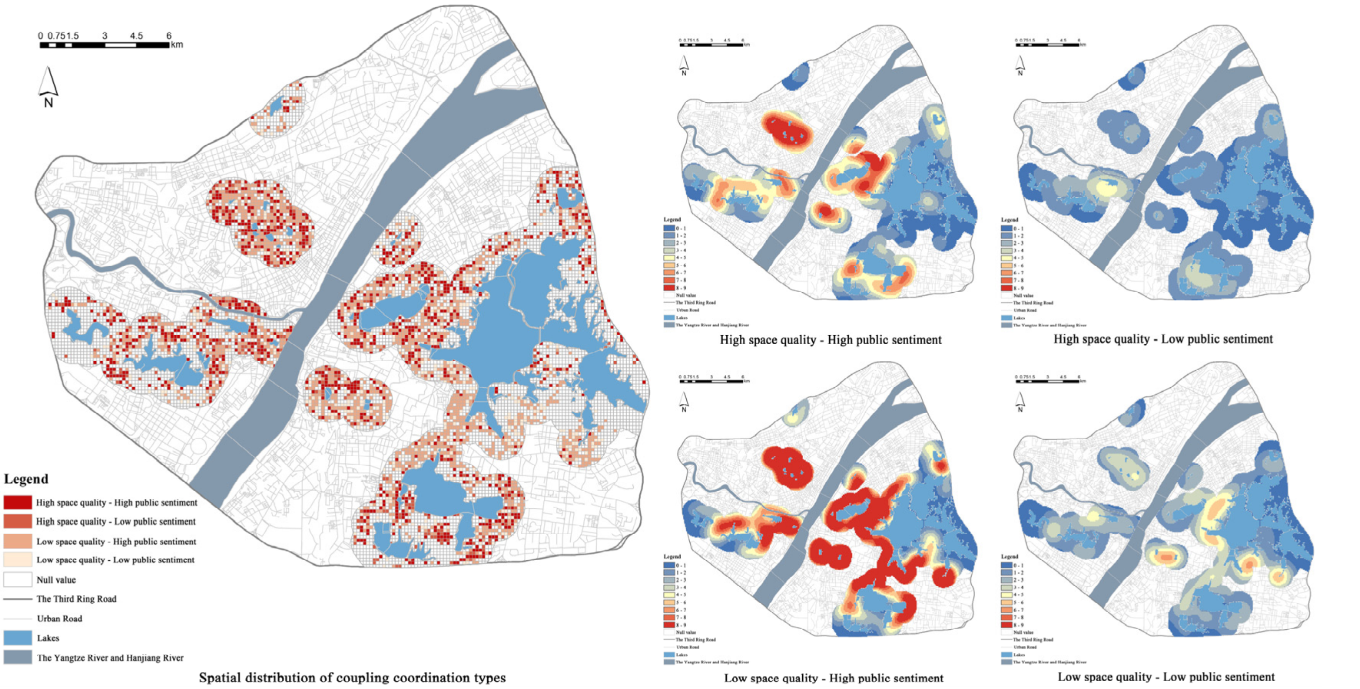


Figure 14. Spatial distribution of coupling coordination type between spatial quality and public sentiment (see Figure A3 in Appendix A).

5. Discussion

Urban lakes have natural and social functions [10]. They are also an important part of urban open spaces with far-reaching impacts on urban development [107]. In previous studies, much attention has been paid to the ecosystem health of lakes [108,109]. As an important place for active public socialization [110], comprehensive landscape quality in lakefront areas profoundly affects public physical and mental health [111]. However, objective assessment of spatial quality does not necessarily imply the same subjective assessment [112,113]. Moreover, two aspects must be evaluated comprehensively: (a) whether the environment has a good objective basis; (b) whether the people are satisfied with the environment. In this study, Wuhan City, famous for its lake resources, is taken as an example. Multisource big data are also used to assess and describe quantitatively the distribution characteristics and coupling coordination between spatial quality and public sentiment in the lakefront area based on Baidu street view images and microblog text data on a large scale from a human perspective, to explore the influence of street view elements on public sentiment, and to characterize the type of coupling coordination between subjective and objective assessments.

A remarkable geographical difference exists between spatial quality and public sentiment evaluation results of the 21 lakefront areas in Central Wuhan. Further exploration revealed the intrinsic linkage of this difference. Spatial quality can remarkably alleviate passive public emotion. In particular, lakefront areas with high green visibility can strengthen active public emotion, and lakefront areas with high sky visibility and natural revetment can improve passive emotion. High green visibility and natural revetment imply a good ecological environment, which is beneficial to the public's physical and mental health. In comparison, open skies can reduce depression and make people feel happy. A lakefront with high water visibility weakens active public emotion but does not remarkably correlate with passive public emotion. This finding is different from previous studies, probably because the indicator of "water visibility" in the present study refers to the perception of water bodies by vehicle passengers on traffic roads in the lakefront area. The higher the visibility of water bodies is on traffic streets, the closer the traffic roads are to the water bodies, i.e., a large proportion of land traffic in the lakefront area is close to the lake, resulting in a considerable negative impact on the lake. Therefore, the considerable visibility of water bodies on traffic-oriented streets has a certain degree of weakening on the active emotion but does not have an impact on the passive emotion.

The four types of coupling coordination between the spatial quality and public sentiment of the lakefront landscape show multigroup distribution on the map. The HH-matched areas are basically highly coupled with high coupling coordination. These areas are often urban parks and green areas, scenic areas, universities, and high-class neighborhoods. The LL-matched areas are consistent with those with low coupling and low coupling coordination. The probable reason is that the rapid expansion of land and large population concentration in the ancient city of Wuchang to the east historically led to imperfect planning of the area, immature ecological landscape construction, and poor environmental management and maintenance. However, the addition of supporting facilities and functional mixing of the plots have slightly improved the public sentiment in some areas. Therefore, the spatial quality of these areas is in low harmony with the public mood. HL is slightly distributed, but LH is concentrated and densely distributed in the lakefront areas close to urban centers. This finding indicates that the ecological landscape construction of some lakefront streets in Wuhan is neglected. Given the impact of space quality on public sentiment, the construction department should strictly plan and manage the lakefront landscape, actively solve the problems that hinder the development of lakes, and bring a superior aesthetic experience to the public.

The spatial quality of most areas is highly coupled with public sentiment. This study identifies the specific effects of individual streetscape elements on public sentiment, reminding planners that they can effectively improve the lakefront landscape by targeting the level of some particular elements. For example, planners can improve the spatial quality of the lakefront landscape by increasing greenery visibility, sky visibility, and revetment naturalness of the lakefront streets, reducing the negative impact of land traffic on active public emotion, enhancing active public emotion, and alleviating passive emotion, ultimately achieving the effect of improving the comprehensive quality of the lakefront landscape.

This study could provide meaningful insights into academic research and practical experience in the field. The optimization of the lakefront landscape should first and foremost harmonize the relationship between man and nature. The results of this study show that adequate vegetation, wide skies and natural barges of water on the lakefront streets not only create a natural and human landscape conducive to an improved microclimate, but also optimize the public sentiment state in the lakefront. Although in recent years, Wuhan has developed a series of lake protection policies to strengthen lake management and lakefront area management, such as the Wuhan Lakes Protection Regulations and the Wuhan Lakes Protection Master Plan, today some of Wuhan's lakefront landscapes are still not at a good level, and city managers continue to pay insufficient attention to lakefront streetscapes. Therefore, planners should be wary of the destruction of natural landscapes caused by urban overdevelopment. The natural landscape elements of the lakefront streets should be preserved and optimized as far as possible, and efforts should be made to reconcile the contradictions between the different types of land use in the lakefront area. In addition, it is important to actively listen to public opinion and feedback in order to create a positive effect where spatial quality and public sentiment develop in harmony and promote each other.

6. Conclusions

The article characterizes the spatial quality and public sentiment distribution of Wuhan's lakefront landscape through machine learning of street view images and sentiment analysis of microblog text. Based on the coupling and coordination analysis, the type of coupling and coordination between the two is determined, and the key areas of the lakefront landscape that need to be optimized and improved are identified. The main findings are as follows: (1) There are significant geographical differences in the distribution of spatial quality and public sentiment in Wuhan's lakefront area. Hot and cold spots of spatial quality are distributed in a contiguous pattern, while hot and cold spots of public sentiment are distributed in multiple clusters. (2) There is a strong coupling coordination and correlation between spatial quality and public sentiment. The good quality of the lakefront landscape space can explain 35.5% of the passive emotion reduction. High green visibility, high sky visibility and natural revetment have a significant positive effect on public sentiment, and high visibility of water has a negative impact on public sentiment. (3) There is significant spatial heterogeneity in the types of coupled coordination. The distribution of HH regions coincides with regions of high coupling coordination and the distribution of LL regions coincides with regions of low coupling coordination. HL is less distributed while LH is concentrated and densely distributed in the lakefront area near the city center. With these findings, this study can help planners identify key areas for lakefront landscape enhancement.

This study improves on the shortcomings in the current comprehensive quality assessment of Wuhan's lakefront landscape and provides a reference for future policy practice. At the same time, it avoids the disadvantages of traditional research methods, which have few data points, high costs and low efficiency. It enables large-scale automatic assessment of spatial quality and public sentiment with the help of machine learning, sentiment analysis and other technologies. The coupled coordination evaluation can identify the HL, LH and LL areas between spatial quality and public sentiment of the lakefront landscape, where the future lakefront landscape needs to be improved. Due to the specificity of the research subject, the methodological framework and analysis process in this study can be used as a reference for the study of lakefront landscapes in other cities, with policy and practical guidance.

However, there are limitations to this study. For example, Baidu Street View images are in-car images and data are still missing for some areas that are inaccessible to street view vehicles. Moreover, the street view images are not fully representative of the pedestrian visual experience and may affect the overall rating. Furthermore, Sina Microblog users are mostly young people, which has an impact on the statistical accuracy of public sentiment in lakefront area. Therefore, in future research, we will use more advanced techniques to combine in situ observations with geographic big data, including complementary data from areas inaccessible to the street view vehicles to improve data on the spatial quality of the lakefront landscape. The microblog text will also be analyzed in more depth to extract a more accurate picture of public attitudes towards the lakefront area.

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Appendix A

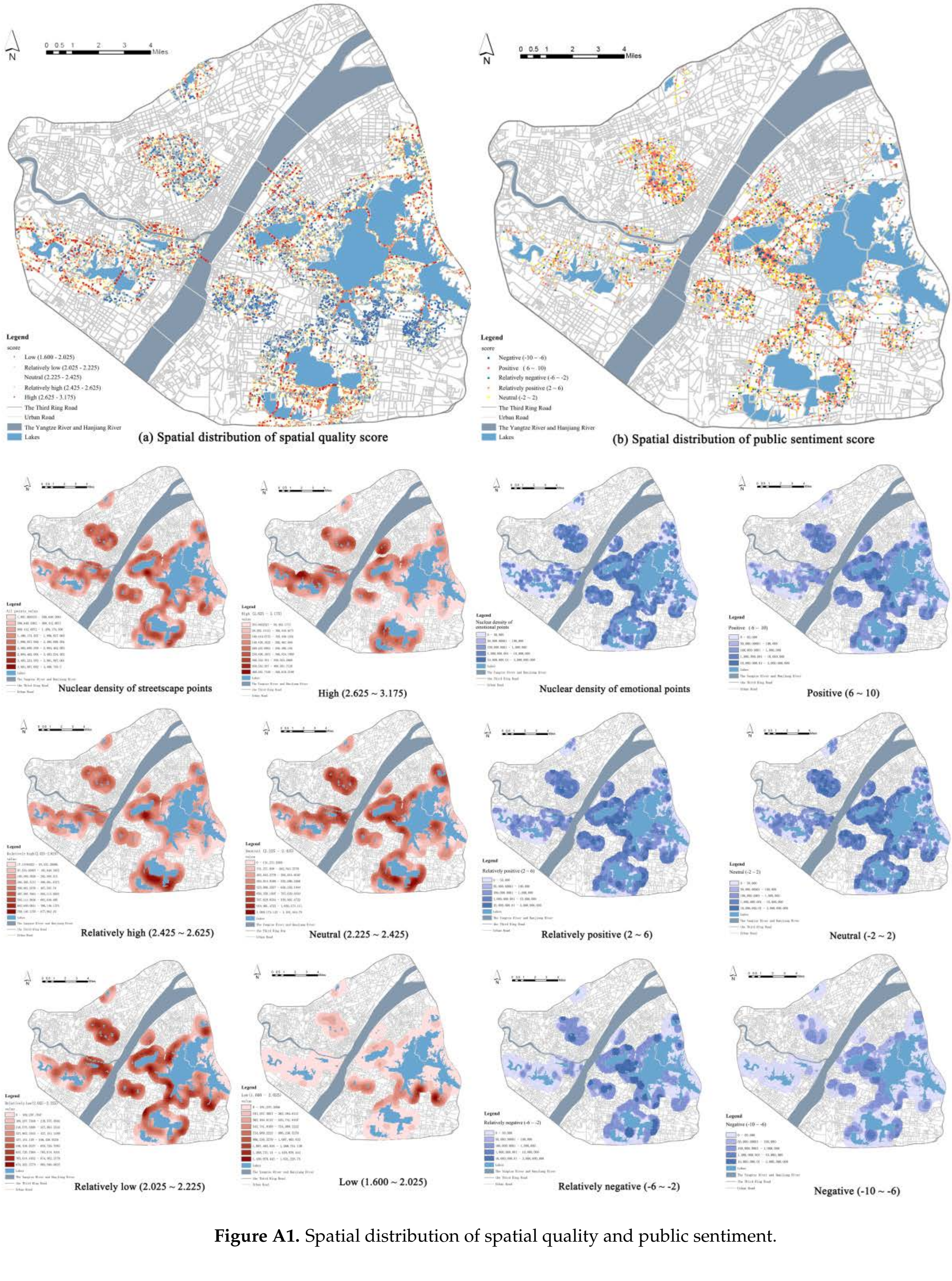


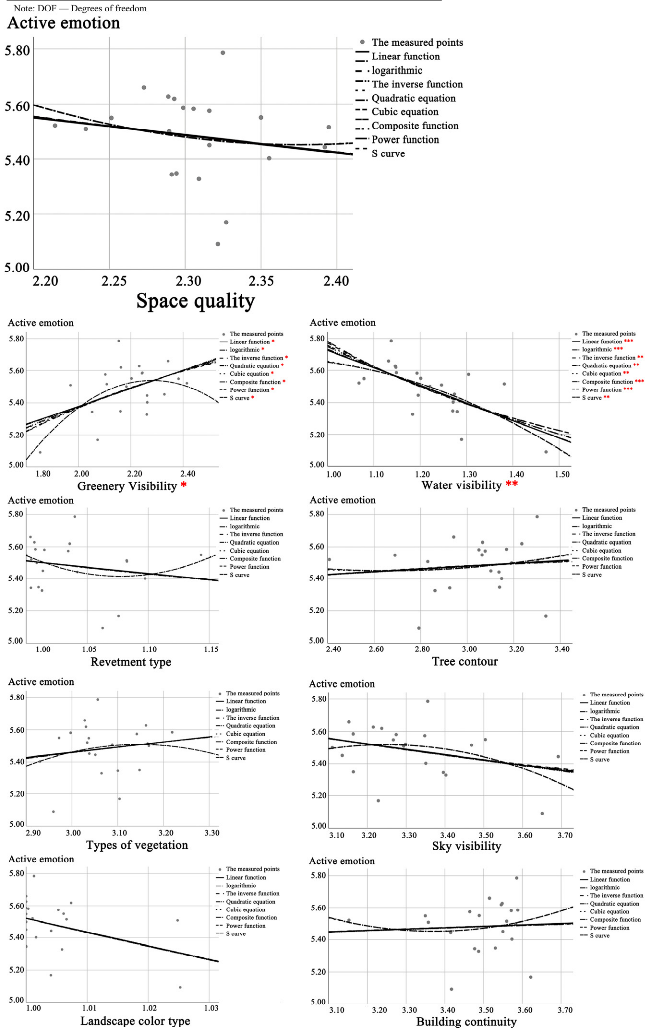
Figure A1. Spatial distribution of spatial quality and public sentiment.

Model abstract and parameter estimation

Dependent variable: Active emotion

Independent variables		Model Summary						Parameter estimates
		R^2	F	DOF1	DOF2	Significant	Constant	b1
Inverse function	Space quality	0.030	0.593	1	19	0.451	4.022	3.371
Inverse function	Greenery visibility *	0.239	5.959	1	19	**0.025** *	6.708	−2.672
Inverse function	Types of vegetation	0.024	0.462	1	19	0.505	6.488	−3.083
Inverse function	Water visibility **	0.414	13.438	1	19	**0.002** **	4.130	1.643
Inverse function	Revetment type	0.038	0.757	1	19	0.395	4.612	0.903
Inverse function	Landscape color type	0.150	3.356	1	19	0.083	-3.27	8.792
Inverse function	Tree contour	0.012	0.234	1	19	0.634	5.701	−0.657
Inverse function	Building continuity	0.003	0.058	1	19	0.813	5.754	−0.945
Inverse function	Sky visibility	0.099	2.082	1	19	0.165	4.381	3.651

Note: DOF — Degrees of freedom



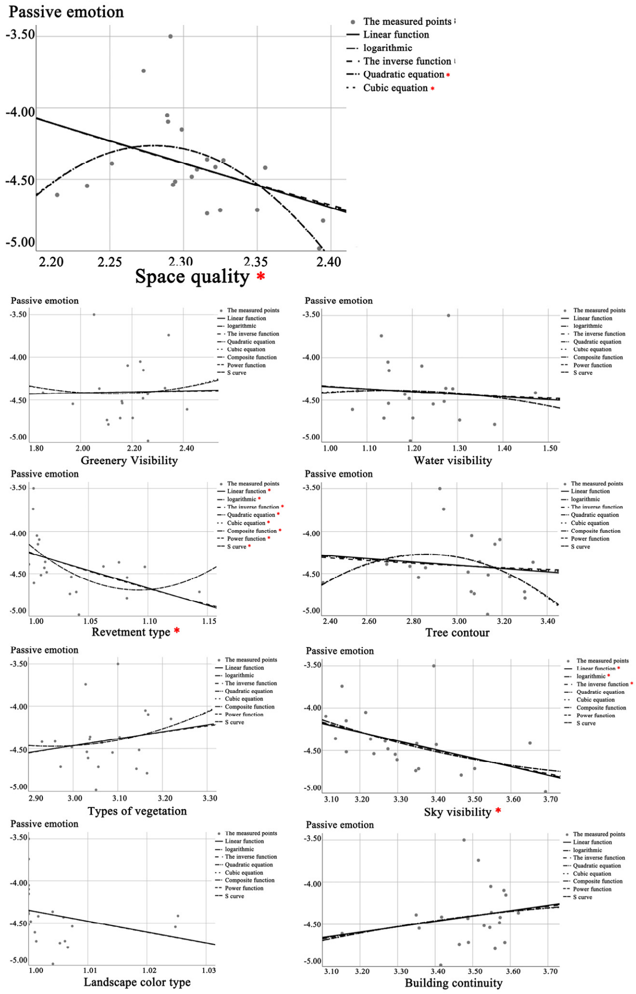
(a) Active emotion and spatial quality factors

Model abstract and parameter estimation

Dependent variable: Passive emotion

Independent variables		Model Summary						Parameter estimates	
		R^2	F	DOF1	DOF2	Significant	Constant	b1	b2
Quadratic equation	Space quality *	0.355	4.957	2	18	**0.019** *	-290.013	250.666	-54.973
Inverse function	Greenery visibility	0.000	0.006	1	19	0.939	-4.311	-0.210	
Inverse function	Types of vegetation	0.031	0.607	1	19	0.446	-1.942	-7.567	
Inverse function	Water visibility	0.006	0.119	1	19	0.734	-4.765	0.433	
Inverse function	Revetment type *	0.228	5.624	1	19	**0.028** *	-8.984	4.741	
Inverse function	Landscape color type	0.074	1.525	1	19	0.232	-17.645	13.296	
Inverse function	Tree contour	0.008	0.160	1	19	0.693	-4.796	1.171	
Inverse function	Building continuity	0.039	0.772	1	19	0.391	-2.315	-7.303	
Inverse function	Sky visibility *	0.216	5.223	1	19	**0.034** *	-7.908	11.596	

Note: DOF — Degrees of freedom



(b) Passive emotion and spatial quality factors

Figure A2. Curve estimation results (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$).

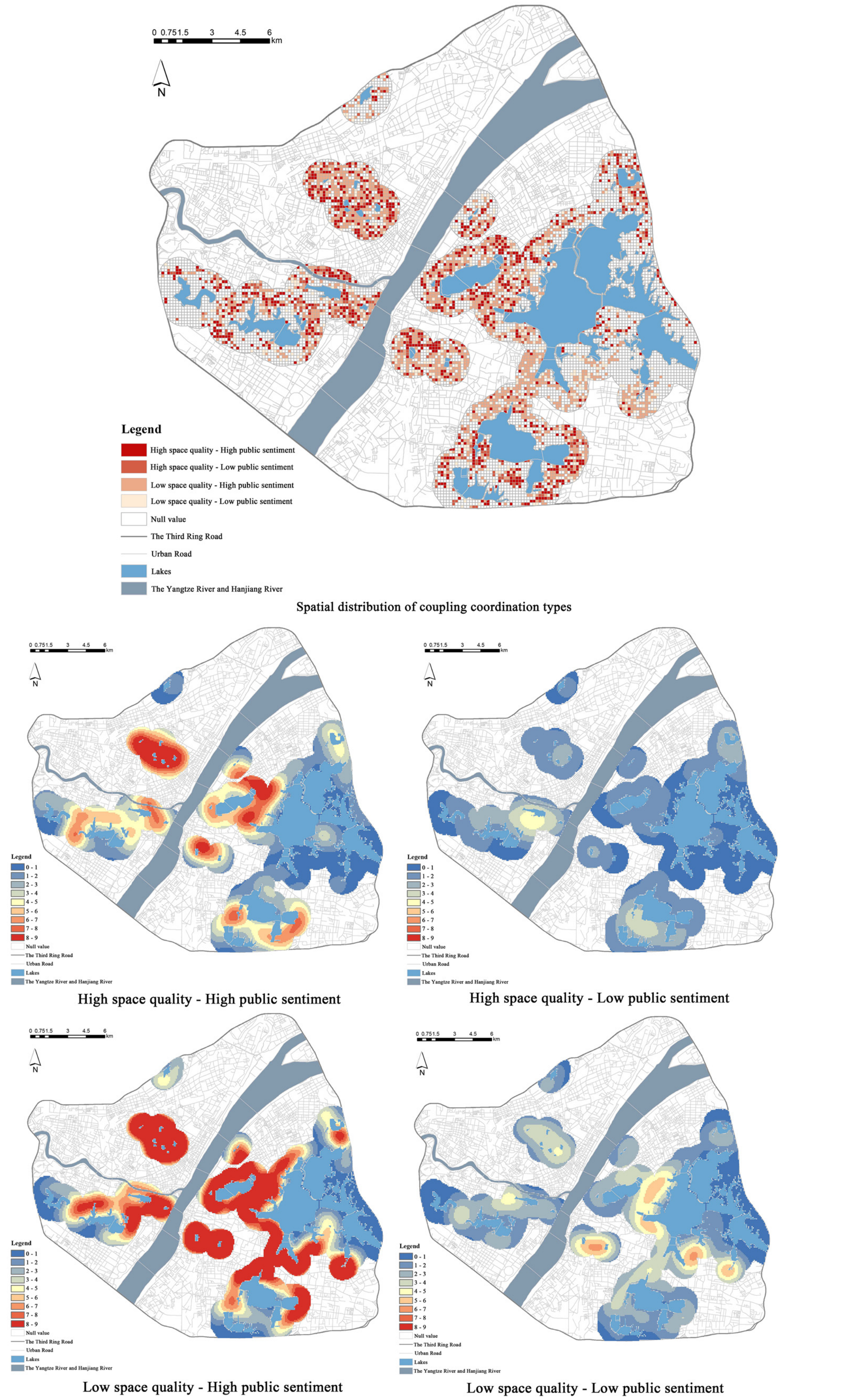


Figure A3. Spatial distribution of coupling coordination type between spatial quality and public sentiment.

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