forests

MDPI

Article

Do Emotional Perceptions of Visible Greeneries Rely on the Largeness of Green Space? A Verification in Nanchang, China

Siying Huang [1], Jinjin Zhu [1], Kunbei Zhai [1], Yang Wang [2], Hongxu Wei [2,3,*], Zhihui Xu [4] and Xinren Gu [1,*]

[1] College of Landscape Architecture and Art, Jiangxi Agricultural University, Nanchang 330045, China; hsinging@163.com (S.H.); design21c@126.com (J.Z.); zhaikunbei@163.com (K.Z.)
[2] Key Laboratory of Wetland Ecology and Environment, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Changchun 130102, China; wangyang991026@163.com
[3] University of Chinese Academy of Sciences, Beijing 100049, China
[4] Forestry College, Beihua University, Jilin 132103, China; diligence0000@163.com
* Correspondence: weihongxu@iga.ac.cn (H.W.); jiujiuyl@163.com (X.G.)

Abstract: Experiencing nature can induce the perception of happiness because of mental stress alleviation and well-being restoration. The largeness of green space may not always mean the frequency of experiencing greenery. It is arguing about the probability of positive sentiments in response to an experience of interacting with green nature. In this study, 38 green spaces were investigated in Nanchang City, China, where the green space area was evaluated by the largeness of the landscape metrics of the Normalized Vegetation Index (NDVI), and Green View Index (GVI) data were further obtained using Open Street Maps (OSM). The semantic segmentation method was used by machine learning to analyze a total of 1549 panoramic photos taken in field surveys to assess the Panoramic Green View Index (PGVI) proportion. The photos of 2400 people's facial expressions were obtained from social networks at their check-in visits in green spaces and rated for happy and sad scores using FireFACE software. Split-plot analysis of variance suggested that different categories of NDVI largeness had a significant positive effect on posted positive sentiments. Multivariate linear regression indicated that PGVI was estimated to have a significant contribution to facial expression. Increasing the amount of PGVI promoted happy and PRI scores, while at the same time, neutral sentiments decreased with increasing PGVI. Overall, increasing the PGVI in green spaces, especially in parks with smaller green spaces, can be effective in promoting positive emotions in the visitor experience.

Keywords: Baidu panoramic street view; Panoramic Green View Index; machine learning; urban green space assessment; sentiment analysis

check for updates

Citation: Huang, S.; Zhu, J.; Zhai, K.; Wang, Y.; Wei, H.; Xu, Z.; Gu, X. Do Emotional Perceptions of Visible Greeneries Rely on the Largeness of Green Space? A Verification in Nanchang, China. *Forests* **2022**, *13*, 1192. https://doi.org/10.3390/f13081192

Academic Editor: Paloma Cariñanos

Received: 10 June 2022
Accepted: 26 July 2022
Published: 27 July 2022

1. Introduction

Urban environments increase the risk of adverse effects on mental health [1]. Studies have found that contact with greenery in urban nature benefits psychological health [2,3]. Green space is positively related to active, positive emotions [4,5]. People stroll in metropolitan settings with greeneries that affect physical and mental relaxation [6,7]. Specifically, seeing green nature can lower blood pressure and the heart rate [8], reduce negative emotions (depression, anxiety, and stress) [9], and induce positive emotions [6]. It is also argued that contact with greening does not consistently promote positive emotions [10]. It is necessary to identify the correspondence of the greening effect with mental well-being as more detailed determinants. More needs to be known about the explicit mechanism that drives the perception of positive emotions.

The remotely detected multispectral image is a common data source for measuring the quantification of greening, which can also be applied to an extensive area of studies [11,12]. Previous researchers have usually used conventional greening variables to describe the natural probability of human exposure, such as the Normalized Difference Vegetation

Index (NDVI) [13,14], the green area [5,15], and the green ratio [16]. Conventional greening variables are used to evaluate the largeness of green spaces from a top-down view, which cannot assess the frequency of seeing visual greening. For example, in mountains, there is a high level of green cover, but it is difficult to encounter exact greenery from an experience therein if no path is reachable [17]. Green areas do not represent the actual exposure of visitors to greening. In addition, traditional greening indicators have the disadvantage of not being able to measure vertical greening and sub-canopy vegetation due to the tree canopy shading [18]. Therefore, it is necessary to quantify the amount of green area and the greening of human contact from visual perspectives [19] to explore the impact on emotional perception.

The horizontal view of the Green View Index (GVI) is closer to actual human exposure because visual greeneries can be accurately measured [20]. GVI data can be collected through field research photography [21,22]. They can also be obtained from online map images [23,24]. Field surveys were usually used to measure greenness for the GVI, which, however, relies on a large labor investment of a long time trapped in forests and is easily interrupted by weather [20] and wild animals [25]. Open Street Maps (OSM) is a real-view mapping service that provides users with panoramic street-view images. With the increasing requirement for big data and machine learning in recent years, OSM has been widely used as a dataset for social perception and the city environment [26,27]. Using these maps, users can get an actual browsing experience. Yu et al. used OSM to obtain the GVI to quantify street greening, in response to which visual greening was effectively distinguished [23]. Cheng et al. used OSM with eight orientations to composite panoramic photos and described accessible greening with the Panoramic Green View Index (PGVI) [28]. A panoramic street-view image can cover an angle of 360° of surrounding environments [20]. It is essential to add the PGVI to conventional greening variables, such as the NDVI and the green ratio, for assessing the nature of greening that people can actually experience along streets.

Recent studies have explored the effect of the largeness of green spaces on emotional health [29]. In large-scale planning of urban parks, people generally trust the sense that large green spaces may result in a higher frequency of inducing positive emotions through contact with nature, such as the green ratio [16,26] and the NDVI [13]. For example, Zhu [13] showed that a higher NDVI in green areas leads to a higher emotional probability and closer association with happy emotions. In addition, larger green spaces of the NDVI can alleviate negative emotions, such as fear and anger [13]. The NDVI can be classified using thresholds [30] and Jenks natural breaks classification [31,32]. Jenks natural breaks classification has the distinct advantage of being better suited to geo-mapping than the average threshold method [32]. We can use the Jenks' classification of landscape metrics to evaluate the impact of accessible greening on emotional health. Currently, a separate indication of greening does not fully describe the exposed greening [33]. Emotions are influenced not only by the largeness of green space but also by its elevation [16] and location [34,35]. Because the association of multiple space factors with emotions is not fully known, we emphasize landscape metrics, such as the NDVI, green ratio, PGVI, and elevation, to quantify greening from different perspectives and explore the effects on facial emotions.

The conventional method of assessing emotional perception is limited to questionnaires and self-reported scores [36,37]. These would lead to the uncertainty of the impact of urban forests on emotions due to subjective choices influenced by respondents [38]. In addition, the conventional way is limited by the amount of data and is labor intensive and time-consuming [39]. In recent years, some scholars have used wearable devices to investigate human emotions [40]. This method has high accuracy and can accurately measure mood changes but is limited by the device and sample size [41]. With the development of the internet and social media platforms, social network services (SNSs) have been widely used as a source of data. SNSs have a considerable number of users who can upload data voluntarily anytime and anywhere [13]. Global SNSs include Facebook, Twit-

ter [42], Instagram [43], Flickr [44], and, in China, mainly Sina Microblog [15,45]. With the increasing use of technology and software [46], researchers can extract and analyze public sentiment [15,44]. Facial expressions reflect the perception of human emotions, which can be analyzed by modern facial recognition technology [15]. There are several advantages of obtaining facial expression data from SNS photos, including more realistically exposing human emotions.

We focused on the impact of visual greeneries (PGVI) and green space areas (NDVI) on emotional expression. In this study, we tested the relationship between actually perceived greening and visitor sentiment in different green space areas in Nanchang City, China. The quantification of multidimensional greening allows for a better understanding of the emotional impact of green spaces, which can enhance the mental health of residents in the future. In this study, we came up with the following hypotheses: (1) Increasing the NDVI does not always promote positive effects. (2) Emotional expressions of visitors in public green spaces are related to the PGVI.

2. Materials and Methods

2.1. Study Area

This study took Nanchang (28°09′–29°11 N, 115°27′–116°35′ E), Central China, as a research object, as shown in Figure 1a. Nanchang is a significant city in the middle of the Yangtze River in China, with 7194.61 sq. km. According to the 2020 Chinese census, Nanchang's population is approximately 6.255 million, of which 4.884 million live in urbanized areas [47]. Nanchang has a subtropical monsoon climate [48]. It is considered one of the hottest cities in China, with an average annual temperature of 19.1 °C [49]. There are many parks and public green spaces that provide conditions for studying the effects of green vision on emotional perception.

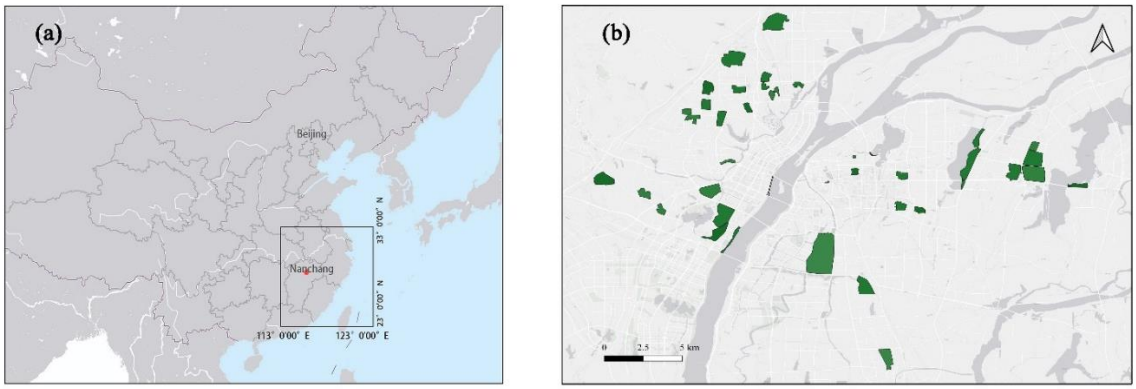

Figure 1. Location of Nanchang, China (**a**). Distribution of 38 parks in Nanchang (**b**).

The study area of this research covered a large part of green spaces in Nanchang, a total of 38 green spaces (28°33′2″–28°47′1″ N, 115°44′59″–116°4′21″ E), geographically located as shown in Figure 1b.

2.2. Data Source

2.2.1. Landscape Metric Collection

We used GIS software's un-offset satellite imagery to sketch out the boundaries of our green spaces. Recently, the sensing data for urban mapping used very high-resolution (VHR) satellite data [30]. For this study, we used Sentinel-2A, which is widely used for this purpose [31]. Because of the subtropical monsoon climate in Nanchang, the vegetation type is mainly evergreen broad-leaf forest [50]. Satellite images were used for the whole of 2020 as a data source with less than 5% cloudiness. This satellite image belongs to the type of multispectral imagery with 13 spectral bands. The greenness of the vegetation in the image is correlated with the density of the vegetation canopy. Elevations were obtained from the NASA SRTM Digital Elevation 30m dataset for a uniform period.

2.2.2. Street-View Photos Acquisition

Previous studies have used Baidu street maps to calculate the GVI [20,23], and green vegetation can be effectively distinguished from Baidu Street View images [7]. We collected street-view (SV) photos from Baidu street maps [51] with greenery in these green spaces. One stop was photographed by eight orientations of SVs at every 45° at horizontal angles. The pictures from all directions for each point were stitched together to form a panoramic photo. The pitch angle of the street-view camera was set to 0°, and its field of view was almost the same as the normal field of view of a human. Such a method of collecting and processing photographs can better reproduce the actual environment in which the observer is located. We manually removed photos with poor clarity or severe distortion by naked eye recognition. In total, we collected 9294 street photos in the study area and then made a total of 1549 panoramic images. All images were documented and labeled using their park names and photographing numbers.

2.2.3. Emotional Photos

Facial expression is an essential expression of human emotions, and the primary emotion theory in 1994 confirmed the consistency of facial expressions and basic emotions [50]. We attempted to obtain a large amount of facial expression data through an SNS platform. Sina Microblog [52] is one of the most popular SNSs in China [44], and it has a massive number of users, with 224 million daily active users in 2020 [53]. It has the function of sharing words, pictures, and videos, which are accompanied by real-time positional information. These provide a data resource for studying facial expressions. We can quantify the emotional perception of green spaces at specific locations by extracting facial expressions from images with information geo-tagging on the Sina Microblog platform. We randomly downloaded 60–100 photos from Sina Microblog in each study site of 38 green spaces from January 2020 to December 2021. All images were labeled with the date of upload, which would help to unify the data time of independent and dependent variables. We selected photos taken in public green spaces on the publicly accessible platform. In addition, we ensured the five facial features (eyebrows, eyes, nose, mouth, and ears) in the photos were clearly visible [5]. To improve facial emotion recognition accuracy, we deleted non-Asian faces, overly retouched images, and duplicate face photos to ensure that only one photo of each person was present in the data. In the end, a total of 2400 pictures of people's emotions were collected.

2.3. Data Processing

2.3.1. Landscape Metric Analysis

We used Google Earth Engine (GEE) to calculate landscape metric data. The Sentinel-2 L2A dataset has been atmospherically and radiometrically corrected and filtered to obtain cloud-free products. It can be used directly for NDVI calculations. The results of processing are derived from the Sentinel-2A image with a resolution of 10 m taken in 2020 and the composite effects of band 8 and band 4 on object classification in the vegetation area. The NDVI (Normalized Difference Vegetation Index) is an index that allows quantifying the amount of vegetation in areas. It relates to the reflected radiation in the electromagnetic spectrum's red and near-infrared (NIR) bands. The vegetation index has values ranging from −541 to 1. Its mathematical equation is as follows:

$$\mathrm{NDVI} = \frac{\mathrm{Band8} - \mathrm{Band4}}{\mathrm{Band8} + \mathrm{Band4}} \tag{1}$$

In Equation (1), Band8 is the near-infrared band and Band4 is the reflectance of red.

$$\text{Green Ratio} = \frac{\text{Green Area}}{\text{Park Area}} \tag{2}$$

As shown in Equation (2), the ratio of green space can be calculated, taking values between 0 and 1.

Elevations were determined from the NASA SRTM Digital Elevation 30m dataset and calculated mean values. As a result, we evaluated the mean values of landscape metrics that correlated with emotional perception, such as the NDVI, green area ratio, and elevation in the study area.

2.3.2. Extraction of the Panoramic Green View Index

This study used the PSPNET machine learning model based on the Tensorflow framework to extract landscape visual elements from panoramic images. The PSPNET model integrates a pyramid scene resolution network with global characteristics and has a more advanced pixel-level prediction performance [33,54]. The training model data is derived from the Cityscapes dataset [55], which identifies 19 common landscape elements that cover all park components in our investigation. On the basis of the Tensorflow framework and the PSPNET model, we extracted the identification and calculation of various environment elements through machine learning. Next, we obtained quantitative data on the visual aspects of the environment in the study area and counted the pixel percentage of the panoramic images from the landscape components, such as the sky, greenery, buildings, and roads, as shown in Figure 2.

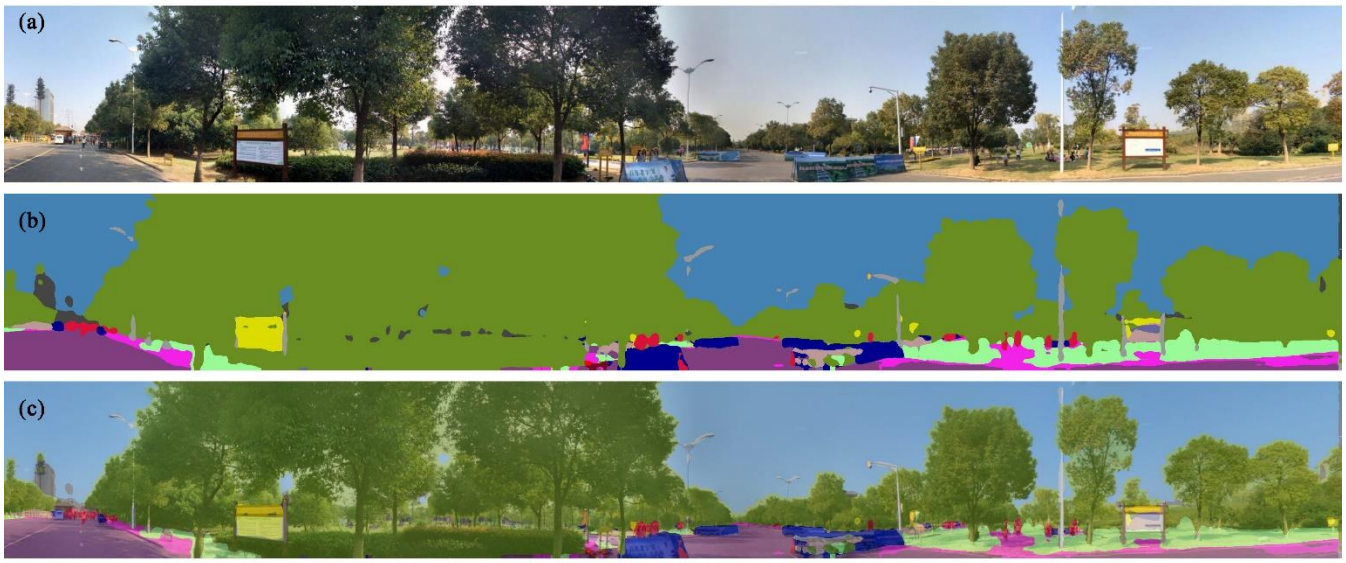

Figure 2. Extraction of landscape elements from panoramic images: (**a**) input panoramic photo, (**b**) output panorama prediction, and (**c**) overlay of input and output images.

The GVI indicates the proportion of plants in the field of view, and the PGVI shows a more comprehensive view of the proportion of plants in the 360° visual area. This study attempted to use Baidu's panoramic street view image to fully reflect the overall sight of pedestrians at a specific location and applied the PGVI to assess the greenery around the street. An example of semantic segmentation is shown in Figure 2b. The environmental factors calculated in this paper were measured from human vision and represented the visual effect of the entire 360° panorama at a specific location, and they could accurately evaluate the landscape at the site [20]. We focused on landscape elements that affect emotional perceptions, such as the PGVI. Next, we calculated the index based on the proportion of green color blocks. The PGVI can be calculated according to Equation (2). The index is higher when more planted greenery can be seen in a specific location, ranging from 0 to 1. The formula is as follows:

$$\mathrm{PGVI} = \frac{\mathrm{Area}_{\mathrm{green}}}{\mathrm{Area}_{\mathrm{all}}} \times 100\% \tag{3}$$

In Equation (2), $Area_{green}$ is the area of green vegetation in the panoramic photo, including trees, shrubs, and meadows, and $Area_{all}$ is the whole area of the picture. We estimated the PGVI at every SV in all green spaces. All PGVI data were bulked into a green space to calculate the average.

2.3.3. Facial Expression Analysis

We tried to measure emotional perception by the expressions on the visitors' faces in the green space. With the development of facial expression recognition technology, it is an effective and intuitive way of expressing human emotions [56]. Therefore, this study used an alternative method of collecting facial expressions from FireFACE v1.0 software. FireFACE software has been applied several times to measure emotional expression [4–6]. FireFACE is trained by machine learning from a dataset of 30,000 Asian faces to recognize the primary expressions of happiness, sadness, and neutrality [57]. In addition, it is applied to evaluate the emotions of Asian facial expressions with high measurement accuracy [58].

Before processing FireFACE software, we needed to rotate and crop the downloaded photos of facial expressions for accurate analysis. The nose axis of the faces in the processed images should be perpendicular to the horizontal plane [59]. The processed photos can be entered into FireFACE to obtain spontaneous expression scores of happy, sad, and neutral, as well as calculating additional indices, such as the PRI. PRI values can reveal the level of expression of positive emotions in the absence of negative emotion involvement [10,59]; the formula is shown here:

$$\text{Positive response index (PRI)} = \text{happy score} - \text{sad score} \quad (4)$$

2.4. Statistical Analysis

We used SPSS 26.0 to analyze and count the data. The facial expression data were normally distributed. The NDVI and PGVI, as essential quantitative independent variables of greenness, represented the amount of greenness in different dimensions in this study. First, we classified the data according to the calculated value range by Jenks natural breaks classification of the NDVI and PGVI into four categories to compare the differences between sites for each type of green space [31]. Second, we obtained the face expression data from Sina Microblog using FireFACE software, such as happy, sad, neutral, and PRI scores. Third, split-plot ANOVA (SPANOVA) was used to detect the effect of frequency to experience greenery (PGVI) on facial expressions in regions with different green space areas (NDVI). Since elevation is an intrinsic element of public green space, it was used as a random factor. SPANOVA was applied to detect the combined effects of the NDVI and PGVI on perceived emotions (happy, sad, neutral, and PRI scores). When the results showed significant differences, we used the Duncan test at the 0.05 significance level for post hoc comparisons to address the uneven number of replicates between the data groups [60]. In addition, the mean values of the NDVI, PGVI, green ratio, and elevation for each location were tested for correlation to compare whether there was an association between the amount of greenness in the different dimensions. Finally, we screened landscape indicators without multiple co-linearity for multivariate linear regression (MLR) to examine the effects of landscape metrics on emotional expression factors. Subsequently, we can moderately increase the positive emotional landscape elements in landscape planning.

3. Results

3.1. Landscape Elements among Different Green Spaces

The results of landscape elements in our survey are shown in Table 1. We filtered for relevant elements that had a significant effect on emotional expression. Figure 3 shows the average distribution and classification of the PGVI, NDVI, green ratio, and elevation of urban parks, which was correlated with emotional perception. Four levels of landscape elements (low, medium, high, and ultra-high) were established. The largest inter-group differences and the smallest intra-group differences were obtained among every four

groups. Thus, we can see the distribution of green space in different dimensions. As for the PGVI, it ranged from 25.2% to 89.4%, and the average value was as high as 53.7%. Figure 3a shows the distribution of the PGVI on park streets in the survey region.

Table 1. Descriptive analysis for landscape characteristics.

Variable	Min.	Max.	Mean	Std. dev.
PGVI	0.252	0.894	0.537	0.173
NDVI	0.025	0.586	0.330	0.121
Green ratio	0.020	0.767	0.247	0.191
Elevation	17.151	52.790	27.924	9.520
Water ratio	0.000	0.367	0.309	0.846
Park area	17,572.547	4,443,868.546	671,740.655	782,571.453

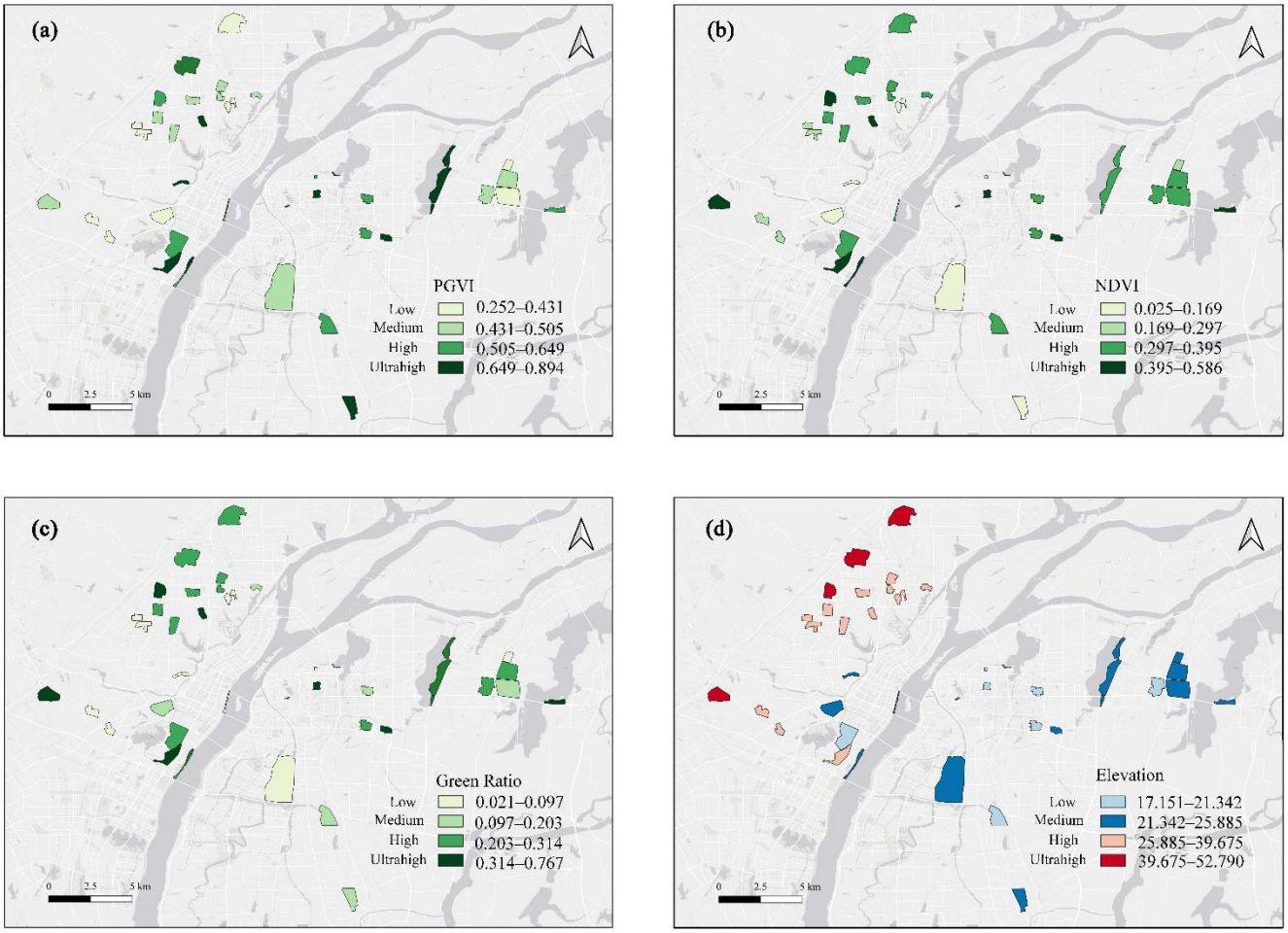

Figure 3. Mean distribution and classification of the PGVI (**a**), NDVI (**b**), green ratio (**c**), and elevation (**d**) in the 38 green spaces in the study area.

Based on the analysis results, there are differences in greenness indicators for the three green space dimensions in Figure 3. As shown in Figure 3d, the characteristics of the elevation distribution are apparent. The areas with higher elevations are mainly located in the west and north parts of the city, and elevations in the east and south are relatively lower.

3.2. Facial Expressions Analysis among Different Categories of Landscape Metrics

The statistics of happy, sad, neutral, and PRI expressions of all visitors are shown in Table 2. The mean values of sad and neutral were higher among all expressions. As shown

in Figure 3a,b, green spaces were classified as low, medium, high, and ultrahigh based on each value of the NDVI and PGVI.

Table 2. Descriptive analysis for dependent variables.

Category	Variable	Min.	Max.	Mean	Std. dev.
Dependent variable	Happy	4.511	39.866	20.173	8.483
	Sad	40.816	62.522	51.873	5.216
	Neutral	21.947	48.858	34.192	6.667
	PRI	8.203	19.155	13.290	2.512

The data for each group were tested to be normally distributed and could be analyzed using ANOVA. The first factor is the NDVI, the vertical factor of the greeneries, and the second factor is the PGVI in the horizontal view of the green space. The results of the happy, sad, neutral, and PRI expressions for all visitors are shown in Table 3. The results showed significant differences ($p < 0.05$) in happy, neutral, and PRI emotions between the different NDVI groups (Table 4). There were no significant differences in sadness among visitors in these classifications of the NDVI. The difference between neutral expression and the NDVI value was more significant than happy and PRI in the NDVI ($p < 0.001$). PGVI subgroups had no significant effect on facial emotion. The NDVI and PGVI had no interactive effects on emotional expression scores.

Table 3. SPANOVA testing effects of the NDVI and PGVI on facial expressions.

Source	DF [1]	Happy		Sad		Neutral		PRI	
		F Value	*p* Value	*F* Value	*p* Value	*F* Value	*p* Value	*F* Value	*p* Value
Intercept		1812.243	<0.001	567.118	<0.001	21631.924	<0.001	280.195	<0.001
NDVI	3	7.042	0.002	0.460	0.718	10.901	<0.001	3.322	0.048
PGVI	3	0.416	0.744	0.855	0.484	0.601	0.624	0.402	0.753
NDVI × PGVI	6	0.925	0.503	2.856	0.044	0.518	0.786	1.428	0.264

Note: [1] DF, degrees of freedom.

Table 4. Analysis of variance (ANOVA) for facial expressions among different categories of the NDVI.

Variable		Sum of Squares	Mean Square	*F* Value	*p* Value
Happy	NDVI inter-group	709.136	236.379	6.827	0.001
	NDVI intra-group	1177.242	34.625		
	Total	1886.377			
Sad	NDVI inter-group	31.605	10.535	1.397	0.261
	NDVI intra-group	256.490	7.544		
	Total	288.095			
Neutral	NDVI inter-group	522.508	174.169	8.102	0.000
	NDVI intra-group	730.884	21.497		
	Total	1253.392			
PRI [1]	NDVI inter-group	958.990	319.663	5.087	0.005
	NDVI intra-group	2136.629	62.842		
	Total	3095.619			

Note: [1] PRI, positive response.

Emotional expression scores were significantly different for NDVI groups (Figure 4). The happy scores of low and ultra-high NDVI were higher than the other two types of NDVI (Figure 4a). The positive emotion (happy and PRI) score increased with increasing NDVI, when the NDVI was greater than 16.9%. Facial expression scores of ultra-high and low NDVIs were significantly different from medium and high NDVIs. The lowest level of the NDVI had high happy and PRI scores. This was due to the fact that a low level of NDVI can also provide a high PGVI, which can promote positive emotions.

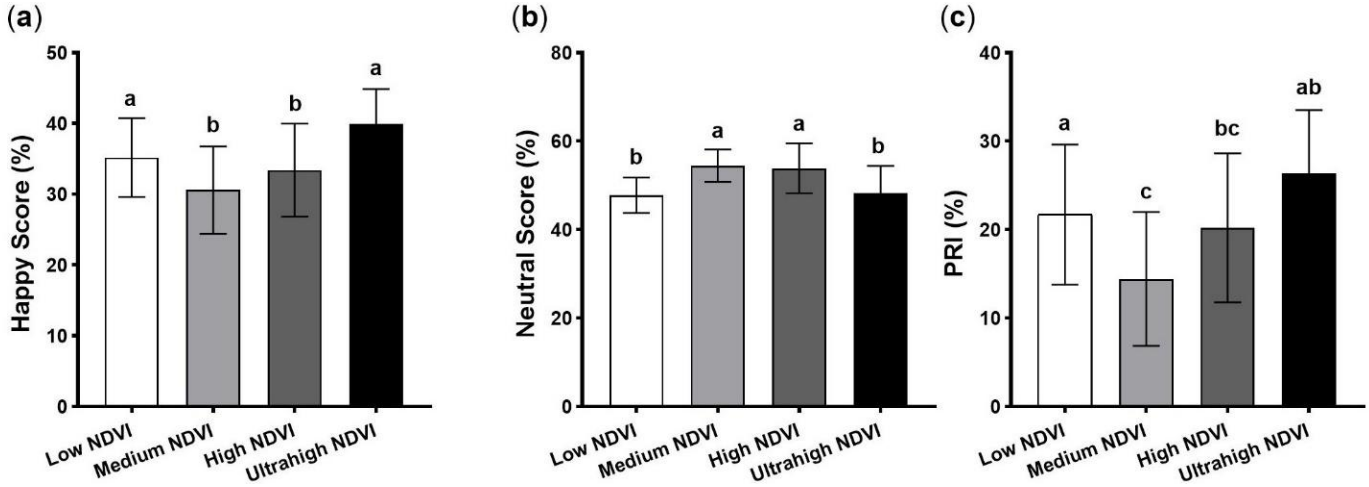

Figure 4. Differences in facial expression scores for happy (**a**), neutral (**b**), and PRI scores (**c**) on visitors' faces in different categories of the NDVI. The error bars represent standard errors, with significant differences between different lowercase letters.

3.3. Correlation Analysis of Different Landscape Metrics

Greening indexes of different dimensions were correlated, among which the green ratio had a significant positive correlation with both the NDVI and the PGVI (Table 5). The NDVI and PGVI's correlation was not significant. There was a positive correlation between the NDVI and elevation, and the higher the elevation, the higher the green vegetation cover in these target green spaces.

Table 5. Coefficients of Pearson correlation between the landscape metrics.

	NDVI	PGVI	Green ratio	Elevation
NDVI	1			
PGVI	0.182	1		
Green ratio	0.814 **	0.469 **	1	
Elevation	0.337 *	−0.245	0.269	1

Note: * $p < 0.05$. ** $p < 0.01$.

3.4. Multivariate Linear Regression of Green Space Metrics to Facial Expression Scores

We screened the independent variables for linear regression and eliminated insignificant independent variables, such as the green ratio and elevation (VIF > 4.5, $p > 0.3$). The Enter method was applied to establish MLR models to identify the factors of the NDVI and PGVI that were evaluated. The variance inflation factor (VIF) of two variables was less than 1. There were no multiple co-linear relationships in the model. According to the MLR analysis in Table 6, only the PGVI was estimated to have a significant contribution to facial expression. The NDVI had no significant effect on sentiment expressed in this study area. The conclusion of the line regression model between the PGVI and facial expression is shown in Figure 5. It can be seen that the happy and PRI indexes of the visitors were positively correlated with the PGVI of the park. The scores of positive effects increased with the PGVI. The relationship between the PGVI and neutral expression was significantly negative. Neutral scores decreased with increasing PGVI (Figure 5b).

Table 6. Multivariate linear regression of greening landscape metrics to facial expression scores.

NDVI	Variable	Parameter	SE	*p* Value
Happy	Intercept	37.532	3.682	<0.001
	NDVI	−3.186	9.224	0.732
	PGVI	16.384	6.707	0.017
Neutral	Intercept	49.900	2.995	<0.001
	NDVI	1.859	7.330	0.801
	PGVI	−15.174	5.330	0.007
PRI	Intercept	24.964	4.769	<0.001
	NDVI	−4.515	12.118	0.793
	PGVI	17.587	8.811	0.014

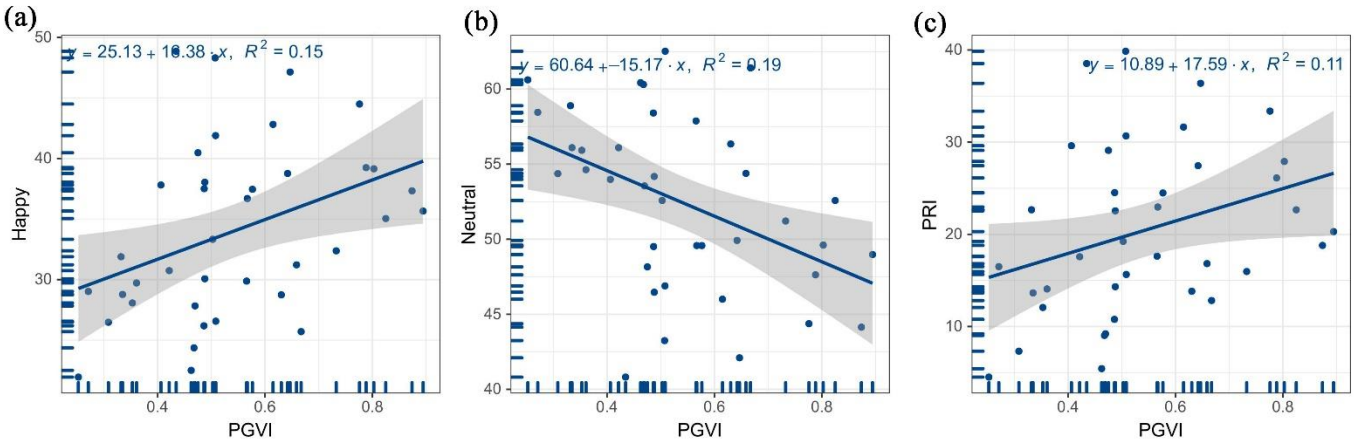

Figure 5. MLR models between the PGVI and facial expression scores for happy (**a**), neutral (**b**), and PRI scores (**c**). The gray bar represents the 95% confidence interval.

4. Discussion

Scholars have used the PGVI to describe human visual greening and explored its correlation with traditional remotely greening metrics, such as the NDVI [61,62]. However, our results were unable to demonstrate that greenness of the NDVI and PGVI were not correlated with each other. The green ratio was significantly associated with the PGVI and NDVI. Although this study focused on the NDVI and PGVI, the findings may well have a bearing on the green ratio. Furthermore, elevation had a significant positive correlation with the NDVI. The higher the elevation, the larger the area of green in the study area. However, the PGVI did not increase with the NDVI and elevation. High-value NDVIs do not mean high-value PGVIs. It can therefore be assumed that the correlation between the green space area and visual greening was related to geographic location. Bigger green space areas do not mean more greening is accessible. An implication of this is the possibility that the PGVI plays an irreplaceable role in greening quantification.

This research, conducted in the same city, excluded other factors, such as city location [33,34] and climate [4,34], from influencing sentiment perception. Different degrees of the NDVI have diverse influences on sentiment. To be specific, distinct values of the NDVI had a significant negative effect on the neutral expression. Meanwhile, NDVI groups had positive effects on happy and PRI scores. We did not find any significant difference in sadness among different green space areas. These results are in accord with recent studies indicating that experience of urban greening is not enough to cause sad expressions [63]. Neutral emotion had the most significant effect, which was higher than happy and PRI scores. A possible explanation for this might be that neutral emotion may be more responsive than sadness in public green spaces.

We also found that the PGVI had a significant effect on positive emotions. Positive sentiment increases with increasing PGVI, and neutral sentiment decreases with increasing

PGVI. The photos used for the emotion perception measurement were obtained from the photo data uploaded by users on Sina Microblog in our research. Photographs are more accurate and realistic in interpreting emotions compared to traditional questionnaire methods [38]. Due to the impact of the COVID-19 epidemic in 2020, many people were wearing face masks [33]. The chances of taking pictures of facial expressions were reduced in green spaces. To avoid data collection restrictions, we chose to analyze facial expressions from 2020 to 2021. Consistent with previous traditional methods [3], the experience in the streetscape in green spaces can promote positive emotions. These results further support the idea that green space is positively associated with positive emotions [5,16] and relieves negative emotions [64].

Another important finding was that the PGVI of green space not only promoted happy and PRI scores but also suppressed the presentation of indifferent sentiment (neutral emotions). Several reports have shown that facial expressions contain a combination of multiple emotions [65]. The PRI is different from happy scores, which stands for positive emotions and negative emotions are eliminated [62]. Two positive sentiment factors, happy and PRI, showed similar increases with PGVI increase, according to the MLR results. According to these data, we can infer that happy and PRI scores are consistent and that results of positive sentiments are reliable.

However, the results of this study were different from those of previous studies. The impact of the NDVI [13,34] on emotional perception was not significant in the study area. This interpretation differs from that of Zhu (2021), who argued that residents' positive mood usually increases with the green area and green coverage [13]. Low-green-space areas with a high PGVI promoted the presentation of positive emotions and inhibited neutral ones. The results were concordant with our hypothesis that experiencing an environment with more green areas does not always promote more positive emotions. The PGVI in urban landscaping makes a significant contribution to positive attitudes and is a strong motivator in facial emotions. Therefore, we need to focus more on enhancing the quantity and quality of the PGVI, that is, to fully optimize the positive benefits of the natural environment. In future urban green space planning and design, we need to focus on enhancing the amount of visual greenery to obtain a more positive emotional impact on urban residents.

We acknowledge several limitations. Because of the limitations of data sources for emotional expression, most emotional photos uploaded to SNSs were consciously presented. SNS messages may over-evaluate positive emotions and suppress negative ones [13]. Since people prefer to share optimistic images, users tend to upload their happy messages on SNSs [66]. We should increase the number of photos collected so that negative emotions can also be captured [16]. Emotional scores can be validated by other methods, such as field surveys [13], words, or voice expressions [67].

Machine learning semantic segmentation can better quantify the scale of green spaces from a human visual perspective. Segmented photos were collected from OSM data sources, covering a wide range and a large amount of data, but there were also several disadvantages. A camera usually takes panoramic photo collections from OSM on a mobile vehicle, and the collection time is different in different locations. Therefore, it is impossible to guarantee that the time of all PGVI sampling points is the same as that of the NDVI and expression photos. However, despite its limitations, the study certainly adds to our understanding of visual greening and emotional perception. A cross-sectional study in this paper cannot draw inferences of causal conclusions, and longitudinal studies can be conducted on their greenfield long-term effects in the future.

5. Conclusions

The greening environment can improve the sentiment and health of residents. However, quantitative data had previously been difficult to obtain. The green space landscape indicators were obtained from highly accurate remote sensing images. With the method of machine learning, we can accurately extract visual greening and facial expressions. This study set out to explore the relationship between visible greeneries and emotional

perceptions in urban green spaces. This study showed that larger green space areas (high-value NDVI) do not necessarily mean a high value of visual greening (PGVI), which is an indispensable indicator element for green quantification. Multiple regression analysis revealed that the PGVI of green space successfully reflects the actual visual greenery of visitors and has a substantial impact on visitors' emotional expression. Positive sentiment rises significantly with the PGVI. At the same time, neutral emotions decreased with an increase in the PGVI. More importantly, increasing the PGVI in areas with a low NDVI can effectively promote positive emotions in the visitor experience.

The findings of this study have a number of important implications for future practice. Government officials and designers need to focus on green areas with low-density plant cover to obtain a more significant positive emotional effect on city residents. This article provides more evidence of the relationship between indicators of urban green spaces and emotions, providing a more effective reference method for urban planning, and creating a healthier green space environment for urban green areas.

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

Funding: This research was funded by the National Natural Science Foundation of China (grant number: 31660230).

Institutional Review Board Statement: This study was carried out under the guidance of the Declaration of Helsinki and was approved by the College of Landscape Architecture and Art, Jiangxi Agricultural University (protocol code ES-2022-06-01; 1 June 2022) to use data sources for human facial expression.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors acknowledge Lingquan Meng for his assistance in facial expression analysis.

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

References

1. Ventimiglia, I.; Seedat, S. Current evidence on urbanicity and the impact of neighbourhoods on anxiety and stress-related disorders. *Curr. Opin. Psychiatry* **2019**, *32*, 248–253. [CrossRef] [PubMed]
2. Jimenez, M.; DeVille, N.; Elliott, E.; Schiff, J.; Wilt, G.; Hart, J.; James, P. Associations between Nature Exposure and Health: A Review of the Evidence. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4790. [CrossRef] [PubMed]
3. Callaghan, A.; McCombe, G.; Harrold, A.; McMeel, C.; Mills, G.; Moore-Cherry, N.; Cullen, W. The impact of green spaces on mental health in urban settings: A scoping review. *J. Ment. Health* **2021**, *30*, 179–193. [CrossRef] [PubMed]
4. Liu, P.; Liu, M.; Xia, T.; Wang, Y.; Guo, P. The Relationship between Landscape Metrics and Facial Expressions in 18 Urban Forest Parks of Northern China. *Forests* **2021**, *12*, 1619. [CrossRef]
5. Zhang, J.; Yang, Z.; Chen, Z.; Guo, M.; Guo, P. Optimizing Urban Forest Landscape for Better Perceptions of Positive Emotions. *Forests* **2021**, *12*, 1691. [CrossRef]
6. Liu, Q.; Wang, X.; Liu, J.; An, C.; Liu, Y.; Fan, X.; Hu, Y. Physiological and Psychological Effects of Nature Experiences in Different Forests on Young People. *Forests* **2021**, *12*, 1391. [CrossRef]
7. Janeczko, E.; Bielinis, E.; Wójcik, R.; Woźnicka, M.; Kędziora, W.; Łukowski, A.; Elsadek, M.; Szyc, K.; Janeczko, K. When Urban Environment Is Restorative: The Effect of Walking in Suburbs and Forests on Psychological and Physiological Relaxation of Young Polish Adults. *Forests* **2020**, *11*, 591. [CrossRef]
8. An, B.; Wang, D.; Liu, X.; Haoming, G.; Wei, H.; Ren, Z. The effect of environmental factors in urban forests on blood pressure and heart rate in university students. *J. For. Res.* **2018**, *24*, 27–34. [CrossRef]
9. Ulrich, R.S.; Simons, R.F.; Losito, B.D.; Fiorito, E.; Miles, M.A.; Zelson, M. Stress Recovery During Exposure to Natural and Urban Environments. Journal of Environmental Psychology. *J. Environ. Psychol.* **1991**, *11*, 201–230. [CrossRef]
10. Wei, H.; Hauer, R.J.; He, X. A forest experience does not always evoke positive emotion: A pilot study on unconscious facial expressions using the face reading technology. *For. Policy Econ.* **2020**, *123*, 102365. [CrossRef]
11. Gupta, K.; Kumar, P.; Pathan, S.K.; Sharma, K.P. Urban Neighborhood Green Index—A measure of green spaces in urban areas. *Landsc. Urban Plan.* **2012**, *105*, 325–335. [CrossRef]

12. Almeer, M.H. Vegetation extraction from free google earth images of deserts using a robust BPNN approach in HSV Space. *Int. J. Adv. Res. Comput. Commun. Eng.* **2012**, *1*, 134–1408.
13. Zhu, X.; Gao, M.; Zhang, R.; Zhang, B. Quantifying emotional differences in urban green spaces extracted from photos on social networking sites: A study of 34 parks in three cities in northern China. *Urban For. Urban Green.* **2021**, *62*, 127133. [CrossRef]
14. Xiao, Y.; Miao, S.; Zhang, Y.; Xie, B.; Wu, W. Exploring the associations between neighborhood greenness and level of physical activity of older adults in shanghai. *J. Transp. Health* **2022**, *24*, 101312. [CrossRef]
15. Huang, Y.; Li, J.; Wu, G.; Fei, T. Quantifying the bias in place emotion extracted from photos on social networking sites: A case study on a university campus. *Cities* **2020**, *102*, 102719. [CrossRef]
16. Li, H.; Peng, J.; Jiao, Y.; Ai, S. Experiencing Urban Green and Blue Spaces in Urban Wetlands as a Nature-Based Solution to Promote Positive Emotions. *Forests* **2022**, *13*, 473. [CrossRef]
17. Ye, Y.; Richards, D.; Lu, Y.; Song, X.; Zhuang, Y.; Zeng, W.; Zhong, T. Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices. *Landsc. Urban Plan.* **2019**, *191*, 103434. [CrossRef]
18. Ki, D.; Lee, S. Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning. *Landsc. Urban Plan.* **2021**, *205*, 103920. [CrossRef]
19. Hu, A.; Zhang, J.; Kaga, H. Green View Index Analysis and Optimal Green View Index Path Based on Street View and Deep Learning. *arXiv* **2021**, arXiv:2104.12627. Available online: https://arxiv.org/abs/2104.12627v3 (accessed on 5 May 2022).
20. Chen, X.; Meng, Q.; Hu, D.; Zhang, L.; Yang, J. Evaluating Greenery around Streets Using Baidu Panoramic Street View Images and the Panoramic Green View Index. *Forests* **2019**, *10*, 1109. [CrossRef]
21. Falfán, I.; Muñoz-Robles, C.A.; Bonilla-Moheno, M.; MacGregor-Fors, I. Can you really see 'green'? Assessing physical and self-reported measurements of urban greenery. *Urban For. Urban Green.* **2018**, *36*, 13–21. [CrossRef]
22. Yang, Y.; Lu, Y.; Yang, H.; Yang, L.; Gou, Z. Impact of the quality and quantity of eye-level greenery on park usage. *Urban For. Urban Green.* **2021**, *60*, 127061. [CrossRef]
23. Yu, X.; Zhao, G.; Chang, C.; Yuan, X.; Heng, F. BGVI: A New Index to Estimate Street-Side Greenery Using Baidu Street View Image. *Forests* **2019**, *10*, 3. [CrossRef]
24. Li, X.; Ratti, C.; Seiferling, I. Quantifying the shade provision of street trees in urban landscape: A case study in Boston, USA, using Google Street View. *Landsc. Urban Plan.* **2018**, *169*, 81–91. [CrossRef]
25. Rowcliffe, J.M.; Field, J.; Turvey, S.T.; Carbone, C. Estimating animal density using camera traps without the need for individual recognition. *J. Appl. Ecol.* **2008**, *45*, 1228–1236. [CrossRef]
26. Li, X.; Zhang, C.; Li, W. Building block level urban land-use information retrieval based on Google Street View images. *GIScience Remote Sens.* **2017**, *54*, 819–835. [CrossRef]
27. Zhang, F.; Zhou, B.; Liu, L.; Liu, Y.; Fung, H.H.; Lin, H.; Ratti, C. Measuring human perceptions of a large-scale urban regionusing machine learning. *Landsc. Urban Plan.* **2018**, *180*, 148–160. [CrossRef]
28. Cheng, L.; Chu, S.; Zong, W.; Li, S.; Wu, J.; Li, M. Use of Tencent Street View Imagery for Visual Perception of Streets. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 265. [CrossRef]
29. Akpinar, A.; Barbosa-Leiker, C.; Brooks, K.R. Does green space matter? Exploring relationships between green space type and health indicators. *Urban For. Urban Green.* **2016**, *20*, 407–418. [CrossRef]
30. Hashim, H.; Latif, Z.A.; Adnan, N.A. Urban Vegetation Classification with NDVI Threshold Value Method with Very High Resolution (VHR) Pleiades Imagery. ISPRS—International Archives of the Photogrammetry. *Remote Sens. Spat. Inf. Sci.* **2019**, *42*, 237–240.
31. Chen, J.; Yang, S.; Li, H.; Zhang, B.; Lv, J. Research on Geographical Environment Unit Division Based on the Method of Natural Breaks (Jenks). ISPRS—International Archives of the Photogrammetry. *Remote Sens. Spat. Inf. Sci.* **2013**, *3*, 47–50.
32. Creley, C.M.; Shilling, F.M.; Muchlinski, A.E. An Ecological Niche Model to Predict Range Expansion of the Eastern Gray Squirrel in California. *Bull. South. Calif. Acad. Sci.* **2019**, *118*, 58–70. [CrossRef]
33. Tong, M.; She, J.; Tan, J.; Li, M.; Ge, R.; Gao, Y. Evaluating Street Greenery by Multiple Indicators Using Street-Level Imagery and Satellite Images: A Case Study in Nanjing, China. *Forests* **2020**, *11*, 1347. [CrossRef]
34. Li, H.; Wang, X.; Wei, H.; Xia, T.; Liu, M.; Ai, S. Geographical Distribution and Driving Meteorological Forces of Facial Expressions of Visitors in Urban Wetland Parks in Eastern China. *Front. Earth Sci.* **2022**, *10*, 781204. [CrossRef]
35. Mao, B.; Liang, F.; Li, Z.; Zheng, W. Microclimates Potentially Shape Spatial Distribution of Facial Expressions for Urban Forest Visitors: A Regional Study of 30 Parks in North China. *Sustainability* **2022**, *14*, 1648. [CrossRef]
36. Zhou, C.; Yan, L.; Yu, L.; Wei, H.; Guan, H.; Shang, C.; Chen, F.; Bao, J. The Effect of Short-term Forest Bathing in Urban Parks on Perceived Anxiety of Young-adults: A Pilot Study in Guiyang, Southwest China. *Chin. Geogr. Sci.* **2018**, *29*, 139–150. [CrossRef]
37. Tyrväinen, L.; Ojala, A.; Korpela, K.; Lanki, T.; Tsunetsugu, Y.; Kagawa, T. The influence of urban green environments on stress relief measures: A field experiment. *J. Environ. Psychol.* **2013**, *38*, 1–9. [CrossRef]
38. Wei, H.; Hauer, R.J.; Meng, L.; He, X.; Liu, P.; Liu, M.; Xia, T. Assessment on Emotional Perception of Urban Forest Visitors on Rating Facial Expressions: The Spatial Difference and The Driving Force in a Case Study on Six Parks in China. *Arboric. Res. Educ. Acad.* **2021**, *16*.
39. Wei, H.; Hauer, R.J.; Guo, S. Daytime dynamic of spontaneous expressions of pedestrians in an urban forest park. *Urban For. Urban Green.* **2021**, *65*, 127326. [CrossRef]

40. Zhang, J.; Chen, M.; Zhao, S.; Hu, S.; Shi, Z.; Cao, Y. ReliefF-based EEG sensor selection methods for emotion recognition. *Sensors* **2016**, *16*, 1558. [CrossRef]
41. Ma, Y.; Yang, Y.; Jiao, H. Exploring the Impact of Urban Built Environment on Public Emotions Based on Social Media Data: A Case Study of Wuhan. *Land* **2021**, *10*, 986. [CrossRef]
42. Roberts, H.; Resch, B.; Sadler, J.; Chapman, L.; Petutschnig, A.; Zimmer, S. Investigating the Emotional Responses of Individuals to Urban Green Space Using Twitter Data: A Critical Comparison of Three Different Methods of Sentiment Analysis. *Urban Plan.* **2018**, *3*, 21–33. [CrossRef]
43. Singh, V.K.; Atrey, A.; Hegde, S. Do Individuals Smile More in Diverse Social Company?: Studying Smiles and Diversity Via Social Media Photos. In Proceedings of the 25th ACM International Conference on Multimedia, Mountain View, CA, USA, 23–27 October 2017; pp. 1818–1827.
44. Kang, Y.; Zeng, X.; Zhang, Z.; Wang, Y.; Fei, T. Who are happier? Spatio-temporal Analysis of Worldwide Human Emotion Based on Geo-Crowdsourcing Faces. In Proceedings of the 2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS), Wuhan, China, 22–23 March 2018; pp. 1–8.
45. Zhu, J.; Xu, C. Sina microblog sentiment in Beijing city parks as measure of demand for urban green space during the COVID-19. *Urban For. Urban Green.* **2020**, *58*, 126913. [CrossRef]
46. Niu, H.; Silva, E. Crowdsourced Data Mining for Urban Activity: Review of Data Sources, Applications, and Methods. *J. Urban Plan. Dev.* **2020**, *146*, 2. [CrossRef]
47. The Seventh National Population Census in Nanchang City. Available online: http://www.nc.gov.cn/ncszf/tjgb/202106/b2518d385eda494aa1d8c9467c5ae11b.shtml/ (accessed on 2 June 2022).
48. Chen, C.; Bagan, H.; Xie, X.; La, Y.; Yamagata, Y. Combination of Sentinel-2 and PALSAR-2 for Local Climate Zone Classification: A Case Study of Nanchang, China. *Remote Sens.* **2021**, *13*, 1902. [CrossRef]
49. Statistics Bureau of Nanchang, Nanchang Investigation Team of National Bureau of Statistics. *Nanchang Statistical Yearbook of 2020*; China Statistics Press: Beijing, China, 2020.
50. Levensons, R. *The Nature of Emotion: Fundamental Questions*; Oxford University Press: Oxford, UK, 1994; pp. 123–126.
51. Baidu Map. Nanchang. Available online: https://map.baidu.com/ (accessed on 1 May 2022).
52. Sina Weibo. Weibo.com: Discovering Novelties Whenever and Wherever Possible. Available online: https://weibo.com/ (accessed on 28 April 2022).
53. 2020 Weibo User Development Report. Available online: https://k.sina.cn/article_6519757211_1849b999b02001ju6q.html (accessed on 8 August 2018).
54. Zhao, H.; Shi, J.; Qi, X.; Wang, X.; Jia, J. Pyramid Scene Parsing Network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 6230–6239.
55. Cityscapes Dataset. Available online: https://www.cityscapes-dataset.com/ (accessed on 1 June 2022).
56. Jack, R.E.; Sun, W.; Delis, I.; Garrod, O.G.B.; Schyns, P.G. Four Not Six: Revealing Culturally Common Facial Expressions of Emotion. *J. Exp. Psychology General* **2016**, *145*, 708–730.
57. Wei, H.; Hauer, R.J.; Zhai, X. The Relationship between the Facial Expression of People in University Campus and Host-City Variables. *Appl. Sci.* **2020**, *10*, 1474. [CrossRef]
58. Wei, H.; Liu, P. The Accuracy Validation of FireFACE Software in Analyzing Facial Expressions of Urban Forest Visitors. *Preprints* **2020**. [CrossRef]
59. Wei, H.; Hauer, R.J.; Chen, X.; He, X. Facial Expressions of Visitors in Forests along the Urbanization Gradient: What Can We Learn from Selfifies on Social Networking Services? *Forests* **2019**, *10*, 1049. [CrossRef]
60. Liu, P.; Liu, M.; Xia, T.; Wang, Y.; Wei, H. Can Urban Forest Settings Evoke Positive Emotion? Evidence on Facial Expressions and Detection of Driving Factors. *Sustainability* **2021**, *13*, 8687. [CrossRef]
61. Li, T.; Zheng, X.; Wu, J.; Zhang, Y.; Fu, X.; Deng, H. Spatial relationship between green view index and normalized differential vegetation index within the Sixth Ring Road of Beijing. *Urban For. Urban Green.* **2021**, *62*, 127153. [CrossRef]
62. Jiang, B.; Deal, B.; Pan, H.; Larsen, L.; Hsieh, C.; Chang, C.; Sullivan, W.C. Remotely-sensed imagery vs. eye-level photography: Evaluating associations among measurements of tree cover density. *Landsc. Urban Plan.* **2017**, *157*, 270–281. [CrossRef]
63. Wei, H.; Ma, B.; Hauer, R.J.; Liu, C.; Chen, X.; He, X. Relationship between environmental factors and facial expressions of visitors during the urban forest experience. *Urban For. Urban Green.* **2020**, *53*, 126699. [CrossRef]
64. Yu, C.-P.; Lee, H.-Y.; Luo, X.-Y. The effect of virtual reality forest and urban environments on physiological and psychological responses. *Urban For. Urban Green.* **2018**, *35*, 106–114. [CrossRef]
65. Du, S.; Tao, Y.; Martinez, A.M. Compound facial expressions of emotion. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, E1454–E1462. [CrossRef] [PubMed]
66. Bij de Vaate, N.; Veldhuis, J.; Alleva, J.M.; Konijn, E.A.; van Hugten, C.H.M. Show Your Best Self(ie): An Exploratory Study on Selfie-Related Motivations and Behavior in Emerging Adulthood. *Telemat. Inform.* **2018**, *35*, 1392–1407. [CrossRef]
67. Mehrabian, A. Communication without words. In *Communication Theory*; Mortensen, D.C., Ed.; Routledge: New York, NY, USA, 2008; pp. 193–200.