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The Relationship between Landscape Metrics and Facial Expressions in 18 Urban Forest Parks of Northern China

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Abstract: Urban forests are an important green infrastructure that positively impacts human well-being by improving emotions and reducing psychological stress. Questionnaires have been used frequently to study the influence of forest experiences on mental health; however, they have poor controllability and low accuracy for detecting immediate emotions. This study used the alternative approach of facial reading, detecting the facial expressions of urban forest visitors and their relationships with the landscape metrics. Using the microblogging site, Sina Weibo, we collected facial photos of 2031 people visiting 18 different forest parks across Northern China in 2020. We used satellite imagery analysis to assess the elevation and pattern sizes of green space and blue space areas. Age and location were taken as independent variables affecting facial expressions, which were categorized as happy or sad. With increases in green space and intact park areas, people showed a higher frequency of expressing happy scores. The results showed that the forest experience frequently elicited positive emotions, suggesting that creating and maintaining urban green spaces enhance people's quality of life.

Keywords: urban forest landscape; forest therapy; facial expressions

Citation: 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. https://doi.org/10.3390/f12121619

Academic Editors: Hongxu Wei and Richard Hauer

Received: 8 November 2021
Accepted: 22 November 2021
Published: 24 November 2021

1. Introduction

More than half the world's population lives in urban areas, which studies have shown can negatively affect mental health [1]. Studies have also shown that contact with beauty and nature has physical and mental health benefits, including stress reduction [2–4]. Forest Park sustainability and visitors' park experiences and well-being depend on park managers' correlative decisions and the parks' locations [5]. People living in forest-rich areas have increased opportunities for stress-reducing experiences in natural settings [6]. Research has also shown that while age can affect park visitors' emotions and forest experiencers [7], comfortable forest environments induce positive emotions and reduce anxiety in young adults [8], middle-aged and elderly visitors, and visitors with dementia [9]. Furthermore, short-term exposure to an urban forest environment has been shown to significantly lower the heart rates of middle-aged men with hypertension and older adults [10,11]. Most previous research has used quantitative physiological measures or qualitative descriptions (e.g., questionnaires, interviews) to analyse urban parks' effects on mental health. This study tested the objectivity of previous studies' results by using an alternative measure, facial expressions, detecting the emotional responses of different types of visitors to different urban forest environments.

Optimal combinations of natural landscape elements (e.g., water, plants, topography), characteristics (e.g., location, appearance, art, and cultural elements), and park dimensions provide restorative effects that induce resilience [12] and benefit physical and mental health [13–15]. Studies have found that urban residents with ready access to higher densities of green space and vegetation were less likely to suffer from heart disease [16] and mental illness [17]. The number, size, accessibility, vegetation, and features of public green spaces can dramatically affect residents' mental health [18]. Especially conducive to relaxation are blue spaces—surface waterbodies (e.g., lakes, ponds, wetlands), surface watercourses (e.g., rivers, streams, estuaries), and other aquatic landscapes (e.g., beaches, coasts) [19]. A Finnish study found that people's favourite restorative experiences involved exercise and activity in outdoor areas, waterside environments, and extensively managed natural settings [20]. Experiencing blue spaces can improve mental health and promote physical activity [21]. Natural environments with aquatic elements evoke more positive emotions than those without blue spaces [22]. To figure the mechanism for impacts of green space and blue space on public mental health is a requisite to compare their positive effects on mental well-being and are beneficial for better choices, such as the experience to touch the nature.

This study focused on urban parks, which provide opportunities for urban residents and visitors to engage in physical activity in managed natural settings in cities and enjoy the restorative effects of nature [23]. Parks located close to residences generally have more visitors [24]. Urban parks' accessibility, area, size, and landscape style can influence visitors' impressions, activities, and mental well-being [25,26]. Brown et al. [27] found that more frequent park use was associated with park size and suitability for physical activity. Even small parks and pocket parks can positively impact visitors' mental health [28]. Parks' terrain and altitude can affect visitors' experiences. Shukitt and Bandaret reported that people's behaviours and moods differ at different altitudes; they can become more argumentative and irritable or more euphoric at high altitudes [29]. Dudek found that the terrain's slope was closely related to the aesthetics of forest landscapes; for example, tree species with high aesthetic landscape values mainly grow on high, concentrated slopes of 8–12° [30]. Thus, park visitors' emotional states can vary depending on the parks' accessibility, area, size, scale, landscape style, design features, elevation, and topography.

Geographic information systems (GIS) provide spatial decision support for forestry and park management and planning [31]. GIS data can provide valuable quantitative and timely information for mapping and assessing changes in landscapes and green spaces [32]. Stored satellite imagery can provide decades of consistent, precise, high-quality images [33] and detailed landscape pattern records at different temporal and spatial scales [34]. Data from the joint National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS) Landsat program have become increasingly critical of extensive studies on landscape dynamics [35]. The quantitative approach at a global scale relies on GIS, high-resolution digital elevation models (DEMs), and digital aerial imagery [36], which require neither public preferences nor large-scale research or measures [37] to identify and monitor precise locations over time.

Emotions can be observed through external physical expressions and monitored by measuring physiological changes and internal sensations [38]. Palermo and Rhodes wrote that "faces are probably the most biologically and socially significant visual stimuli in the human environment" [39] (p. 75), requiring us to rapidly detect, categorize, and interpret facial expressions as clues about others' emotions, behaviours, and intentions. People's facial expressions vary widely and can depend on many factors, including their emotions, social setting, environment, health, cultural background, and personality [40]. Emotional perception is usually expressed through multiple sensory channels, with crosstalk between the channels (e.g., sight, smell, touch, taste, hearing) [41]. For example, music can affect emotions (and thus facial expressions) through auditory, visual, and touch sensations [42]. Responses can be subjective, but pleasant smells induce positive emotions, and unpleasant smells induce negative emotions [43]. Therefore, perceptions of urban parks can be affected by numerous sensory perceptions, such as sights, sounds, smells, proprioception (body position), temperature, and humidity [44]. We posited that assessing park visitors' facial expressions could better clarify the influence of urban forest environments on mental health and well-being.

Traditional research has relied primarily on self-reported scores to assess visitors' emotions about the forest experience [45]. However, surveys require a significant time commitment from participants, and it can be challenging to recruit enough participants to validate the survey. We proposed an alternative method to test urban forest park visitors' psychological responses: facial reading. This relatively new technique that uses a software algorithm trained to assess emotion expressions using visual records of human faces [46]. Our method of facial emotion recognition followed four steps: (1) detecting facial images; (2) processing the photos to ensure that they were clear and without excessive modification; (3) extracting facial features; and (4) classifying the facial expressions and scoring the expressions [47]. Previous studies have demonstrated that facial reading techniques can be used to assess people's emotional states in urban forests. For example, Wei et al. [44] used facial reading technology to investigate the impact of forest experiences on visitors' emotional states. Current facial recognition technology has achieved 87% accuracy in categorizing human facial expressions by emotion [48]. The use of facial reading technology significantly contributes to the real-time detection of park visitors' facial expressions, providing a measure of their emotional responses to the park.

Our study analysed the relationship between visitors' facial expressions and urban forest landscape metrics in Northern China. We calculated the metrics of green spaces, blue spaces, park features, and park elevations to test the relationship between three expressions—happy, sad, and neutral—and the positive response index. We hypothesized that an increase in the combined green space area, blue space area, overall park area, and park elevation would arouse higher positive emotions in visitors. This study's findings will provide a useful reference for park visitors' emotional responses to urban forests to inform the design and construction of future urban forest parks.

2. Materials and Methods

2.1. Study Sites

This study focused on nine cities located in Northern China (Table 1). As the centres of China's provinces, provincial capitals have a high status and momentous influence on regional economic development, driving and promoting the development of local and neighbouring areas [49]. Hence, we selected two forest parks in nine provincial capital cities in Northern China as the research sites, randomly selecting two forest parks with different landscapes in each city. Figure 1 shows the specific geographical distribution of the studied forest locations.

Table 1. Summary of information about forest parks and the number of photos in northern China in 2020.

City	Forest Park	Coordinate	Number of Photos
Huhhot	1. Hadamen National Forest Park	41°01′ N, 111°58′ E	53
	2. Daqingshan Wildlife Park	40°88′ N, 111°62′ E	100
Taiyuan	3. Taiyuan Forest Park	37°91′ N, 112°54′ E	178
	4. Wenying Park	37°87′ N, 112°57′ E	75
Shijiazhuang	5. Century Park	38°02′ N, 114°54′ E	111
	6. Xiushui Park	38°09′ N, 114°39′ E	86
Beijing	7. Olympic Forest Park	40°02′ N, 116°39′ E	76
	8. Grand Canal Forest Park	39°88′ N, 116°74′ E	142
Tianjin	9. Pak Ning Park	39°17′ N, 117°22′ E	90
	10. Tanggu Forest Park	39°10′ N, 117°67′ E	125
Urumqi	11. People's park	43°80′ N, 87°61′ E	91
	12. Tianshan Canyon	43°49′ N, 87°44′ E	134
Shenyang	13. Beiling Park	41°85′ N, 123°43′ E	133
	14. Changbai Island Forest Park	41°75′ N, 123°39′ E	141
Changchun	15. Jingyuetan Scentic Spot	43°78′ N, 125°48′ E	180
	16. South Lake Park	43°86′ N, 125°31′ E	160
Harbin	17. Heilongjiang Forest Botanical Garden	45°71′ N, 126°65′ E	43
	18. Sun Island Park	45°79′ N, 126°60′ E	113

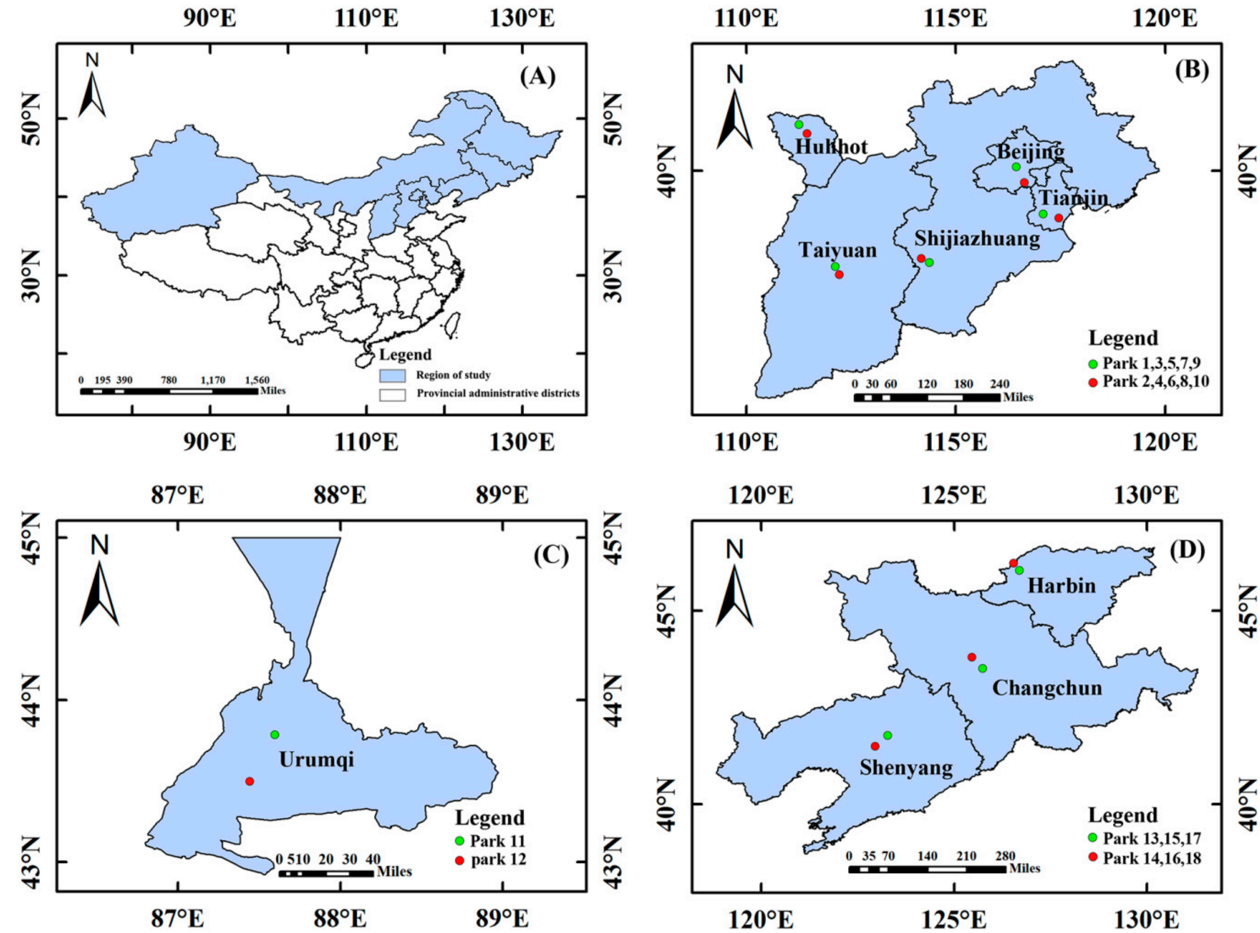

Figure 1. Distributions of study areas (**A**) in northern China. Forest park locations are labelled by green dots and red dots in north China (**B**), northwest China (**C**), and northeast China (**D**).

2.2. Data Source

2.2.1. Photo Download and Treatment

We used the microblogging site Sina Weibo (Sina Corporation, Beijing, China) as the photo data source since the information was completely accessible to the public and the photos contained geolocation data [50]. Weibo is the largest social network service (SNS) platform in China, publishing the largest number of microblogs by Chinese users [51]. The study focused on visitors with typical oriental facial features, collecting 2031 photos to test the facial emotional expression of those visitors from 1 January to 31 December 2020, from 18 different urban forest parks. Our procedures and requirements for collecting photos for academic use were in full accordance with the ethical standards of the College of Forestry, Shenyang Agricultural University, China (CF-EC-2021-001). We used the data only to categorize the facial expressions as happy, sad, or neutral; this data could only be used for academic research, not any business initiative.

We downloaded and processed the photographs following these steps. First, we collected all the microblog photographs that showed oriental faces and contained check-in (geolocation) information relevant to one of the 18 urban forest parks between 1 January to 31 December 2020. Second, we screened the collected photos to select only photos where people's facial elements (e.g., eyes, eyebrows, nose, mouth, ears) were clear and not overly decorated or covered. Third, we cropped the photos so that each photo contained only one face, with the nose axis perpendicular to the horizontal plane. Finally, we marked all the processed photos with the geolocation data, the date they were taken, and the person's age (i.e., toddler, youth, adult, old).

2.2.2. Landscape Metric Collection and Treatment

We used the ArcGIS software to accurately outline the green spaces, blues spaces, and park boundaries in the Landsat image of each forest park. We then calculated the average elevation of the park. These processes required first performing projection conversion on the Landsat data so we could accurately outline of the green spaces, blue spaces, and park boundaries. We used DEM images to randomly select multiple points on the cropped park layer to calculate the average elevation of each forest park. Finally, we studied the green space, blue space, park area, and average park height as landscape metrics.

2.3. Facial Expression Analysis

We analysed the processed photos using the FireFACE^{TM} facial recognition software, Version 1.0 (Zhilunpudao Agricultural Science & Technique Inc., Changchun, China), assigning each face a happy, sad, or neutral expression score. We also used the positive response index (PRI) as a score to assess visitors' net positive emotions [48]. We calculated this variable as the happy score minus the sad score, the visitors' immediate net positive emotions [44]. We calibrated the FireFACE^{TM} software by training it with oriental faces with deliberately posed happy, sad, and neutral facial expressions. We considered the training complete when the software could correctly identify 80% of the happy or sad faces and 85% of the neutral faces [52]. These three expressions were the only expressions used in the study's analyses because they had the highest accuracy after testing and could be matched reliably to the landscape metrics for analysis.

2.4. Statistical Analysis

We used IBM® SPSS® Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA) for our data analysis. In the analysis of variance (ANOVA) on the expression scores, the following variables were fixed effects: age (toddler, youth, middle, old) and city (Huhhot, Taiyuan, Shijiazhuang, Beijing, Tianjin, Ürümqi, Shenyang, Changchun, and Harbin). When the data did not follow a normal distribution, we ranked the expression scores according to the order of variance to make them distribution-free. In the ANOVA analysis of the landscape metric, we tested the differences in the forest parks' landscape metrics in the different cities, using the mean value ± standard deviation (SD) to express the results. When a significant effect was shown, we used the least significant difference (LSD) test with a significance level of 0.05 for comparison to prevent unevenness in the number of repetitions between the data groups. The original data used Spearman's rank correlation coefficient analysis to evaluate the relationship between the landscape metrics (independent variables) and the happy, sad, and neutral expression scores and the well as PRI (dependent variables).

3. Results

3.1. Landscape Metric among Different Northern Cities Analysis

Table 2 shows the landscape metrics of the 18 forest parks in the nine capital cities in Northern China, Figure 2 shows the mean distribution of the green spaces, blue spaces, park area, and average park elevation of each urban forest park.

We found significant differences in the green spaces, blue spaces, park area, and average park elevation among the nine cities (Table 3). The total green space in Ürümqi (53,073.25 ± 43,820.81 ha) was significantly higher than in the other cities. In terms of blue spaces, Changchun (307.94 ± 235.87 ha), Beijing (123.50 ± 59.13 ha), and Harbin (75.66 ± 45.48 ha) differed significantly from the other five cities. Changchun had the largest total blue space area, and Huhhot had the smallest (none). Ürümqi had the largest forest park area (61,895.76 ± 51,066.03 ha), and Shijiazhuang had the smallest area (45.35 ± 18.83 ha). Our calculations of the forest parks' average elevation revealed that the average park elevations in Harbin (122.25 ± 11.37 m), Changchun (233.98 ± 22.96 m), Taiyuan (781.83 ± 4.68 m), Huhhot (1378.31 ± 331.90 m), and Ürümqi (1588.03 ± 592.87

m) differed from the other four cities, but there was no significant difference between Tianjin (4.94 ± 0.30 m), Beijing (17.60 ± 13.34 m), and Shenyang (35.00 ± 2.26 m).

Table 2. Summary of information about forest parks landscape metrics in north of China in 2020.

City	Forest Park	Green Area (ha)	Water Area (ha)	Forest Park Area (ha)	Forest Park Elevation (m)
Huhhot	Hadamen National Forest Park	2970.00	none	3600.00	1832.73
	Daqingshan Wildlife Park	521.73	none	820.00	1137.47
Taiyuan	Taiyuan Forest Park	95.90	25.73	224.00	778.59
	Wenying Park	3.37	3.96	11.90	788.83
Shijiazhuang	Century Park	11.29	3.53	28.82	62.26
	Xiushui Park	38.29	10.90	66.70	84.20
Beijing	Olympic Forest Park	404.22	42.86	680.00	35.81
	Grand Canal Forest Park	546.66	166.66	713.33	7.86
Tianjin	Pak Ning Park	7.74	9.55	57.87	4.58
	Tanggu Forest Park	117.73	33.39	460.00	5.20
Urumqi	People's park	15.98	1.22	30.15	870.20
	Tianshan Canyon	89,104.68	none	103,848.54	2075.52
Shenyang	Beiling Park	233.99	26.70	356.74	37.33
	Changbai Island Forest Park	25.95	4.19	40.25	32.81
Changchun	Jingyuetan Scentic Spot	6033.38	530.00	9638.00	255.61
	South Lake Park	86.59	58.13	222.34	209.66
Harbin	Heilongjiang Forest Botanical Garden	86.34	2.16	136.00	140.63
	Sun Island Park	2126.38	103.63	3800.76	115.26

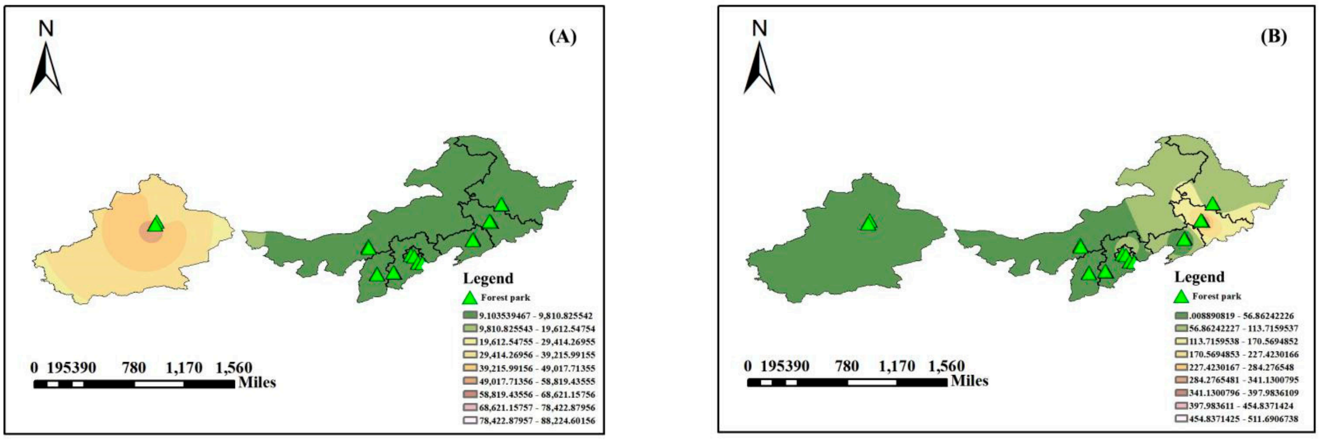

Figure 2. *Cont.*

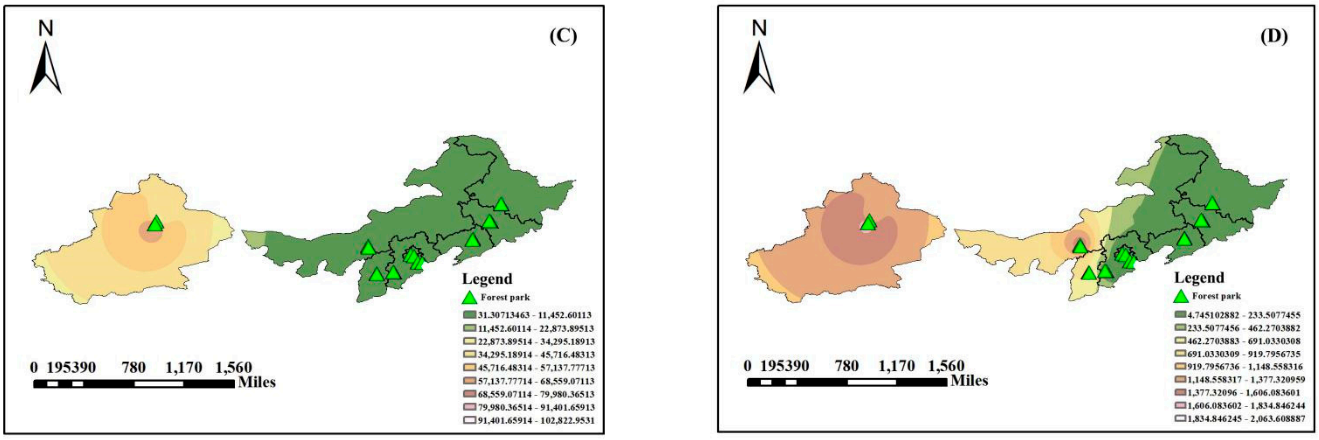

Figure 2. Mean distribution of the green area (**A**), water area (**B**), park area (**C**), and park average elevation (**D**) in northwest, north and northeast cities in 2020.

Table 3. Analysis of variance (ANOVA) of landscape metrics of green area, water area, park area and park average elevation among different northern cities.

Variable		Sum of Squares	DF [1]	Mean Square	Sig. [2]
Green area	City Inter-group	545,980,466,666.19	8.00	68,247,558,333.27	0.000
	City Intra-group	433,477,010,268.79	2022.00	214,380,321.60	
	Total	979,457,476,934.99	2030.00		
Water area	City Intergroup	24,308,520.10	8.00	3,038,565.01	0.000
	City Intra-group	20,032,288.71	2022.00	9907.17	
	Total	44,340,808.81	2030.00		
Forest-park area	City Inter-group	734,483,266,261.66	8.00	91,810,408,282.71	0.000
	City Intra-group	592,347,112,110.87	2022.00	292,951,094.02	
	Total	1,326,830,378,372.53	2030.00		
Forest-park elevation	City Inter-group	642,193,245.86	8.00	80,274,155.73	0.000
	City Intra-group	95,747,708.43	2022.00	47,352.97	
	Total	737,940,954.30	2030.00		

Note: [1] DF, degree of freedom; [2] Sig, significance, the same below.

3.2. Visitors' Facial Expressions Analysis

3.2.1. Different Ages of Visitors on Facial Expressions Analysis

We categorized the visitors as toddlers (0–5 years), youth (15–25 years), adult (30–60 years), and old (60+ years) based on their appearance and, when it was available, data were acquired from the Sina Weibo site. Table 4 shows the results of the ANOVA of all the visitors' happy, sad, and neutral expressions. The happy expression scores of the adult and old visitors were significantly higher than for toddlers and youths. There were significantly more neutral facial expressions among the toddlers and youth than the adult and old visitors. There were significantly more sad facial expressions among the old visitors than the toddler, youth, and adult visitors (Figure 3).

Table 4. Analysis of variance (ANOVA) of toddler, youth, middle-aged and old visitors on happy, sad, neutral facial expressions and positive response index in forest parks.

Source of Variance		Sum of Squares	DF [1]	Mean Square	Sig. [2]
Happy	Age Inter-group	45,251.894	3	15,083.965	0.000
	Age Intra-group	3,360,420.586	2027	1657.83	
	Total	3,405,672.48	2030		
Sad	Age Inter-group	2938.082	3	979.361	0.009
	Age Intra-group	518,526.228	2027	255.81	
	Total	521,464.31	2030		
Neutral	Age Inter-group	43,757.541	3	14,585.847	0.000
	Age Intra-group	2,437,688.961	2027	1202.609	
	Total	2,481,446.502	2030		
PRI [3]	Age Inter-group	51,707.131	3	17,235.71	0.000
	Age Intra-group	5,315,552.956	2027	2622.374	
	Total	5,367,260.086	2030		

Note: [1] DF, degree of freedom; [2] Sig, significance; [3] PRI, positive response index, the same below.

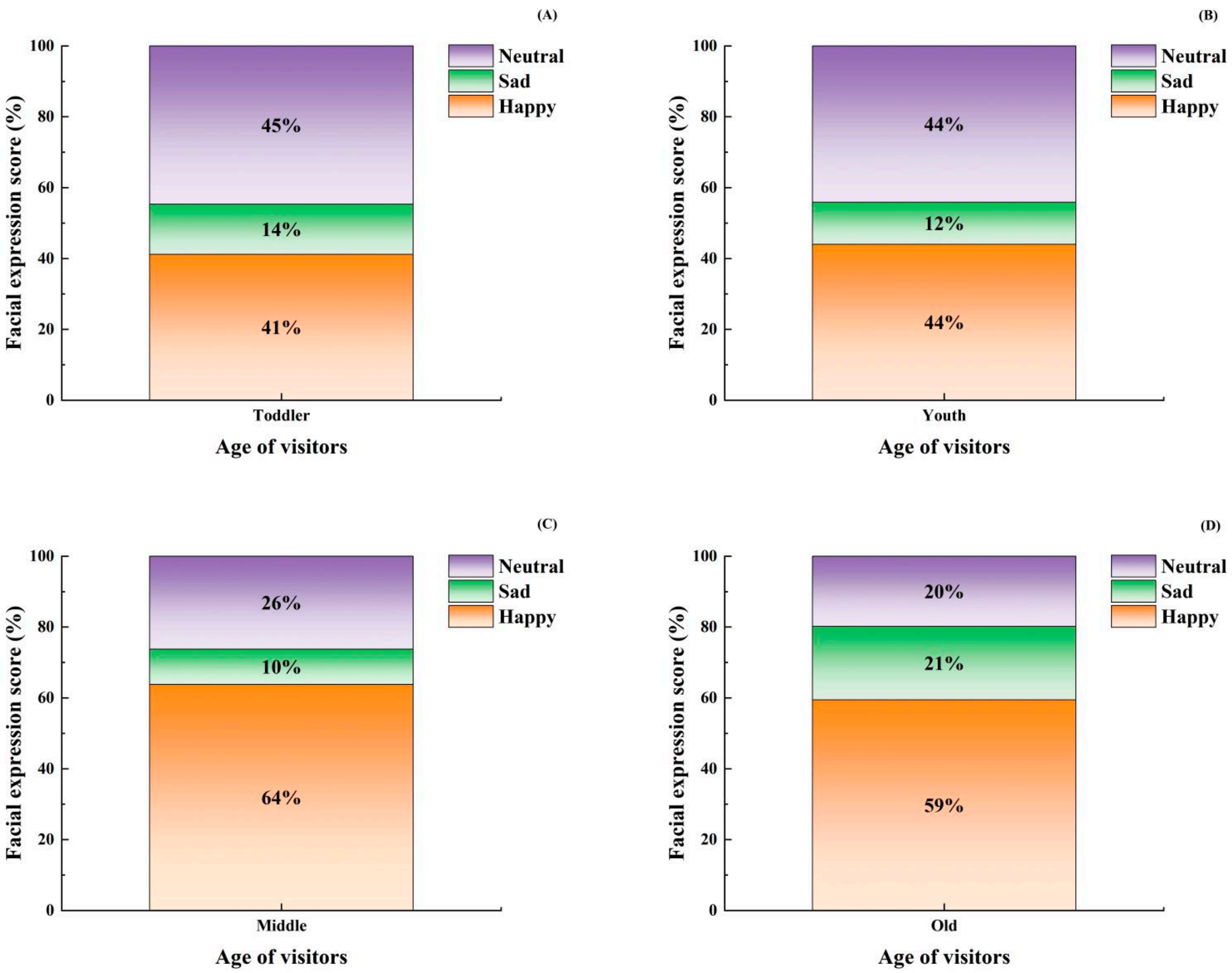

Figure 3. The neutral, sad, and happy expression scores of toddlers (**A**), youth (**B**), middle-aged (**C**) and old (**D**) visitors in northern forest parks.

3.2.2. Different Cities of Visitors on Facial Expressions Analysis

We found significant differences in the happy and neutral scores of visitors' expressions in China (Table 5). There were significantly higher happy expression scores in Tianjin than in Taiyuan, Harbin, Changchun, Ürümqi, Shenyang, and Shijiazhuang (Figure 4A). There were significantly higher neutral scores in Shijiazhuang than in Taiyuan, Beijing, Huhhot, and Tianjin (Figure 4B). There were no differences in the sadness scores between cities.

Table 5. Analysis of variance (ANOVA) of cities on happy, sad, neutral facial expressions and positive response index in forest parks.

Source of Variance		Sum of Squares	DF [1]	Mean Square	Sig. [2]
Happy	City Inter-group	55,801.983	8	6975.248	0.000
	City Intra-group	3,349,870.497	2022	1656.711	
	Total	3,405,672.48	2030		
Sad	City Inter-group	2669.126	8	333.641	0.239
	City Intra-group	518,795.184	2022	256.575	
	Total	521,464.31	2030		
Neutral	City Inter-group	40,370.52	8	5046.315	0.000
	City Intra-group	2,441,075.982	2022	1207.258	
	Total	2,481,446.502	2030		
PRI [3]	City Inter-group	74,121.697	8	9265.212	0.000
	City Intra-group	5,293,138.389	2022	2617.774	
	Total	5,367,260.086	2030		

Note: [1] DF, degree of freedom; [2] Sig, significance; [3] PRI, positive response index, the same below.

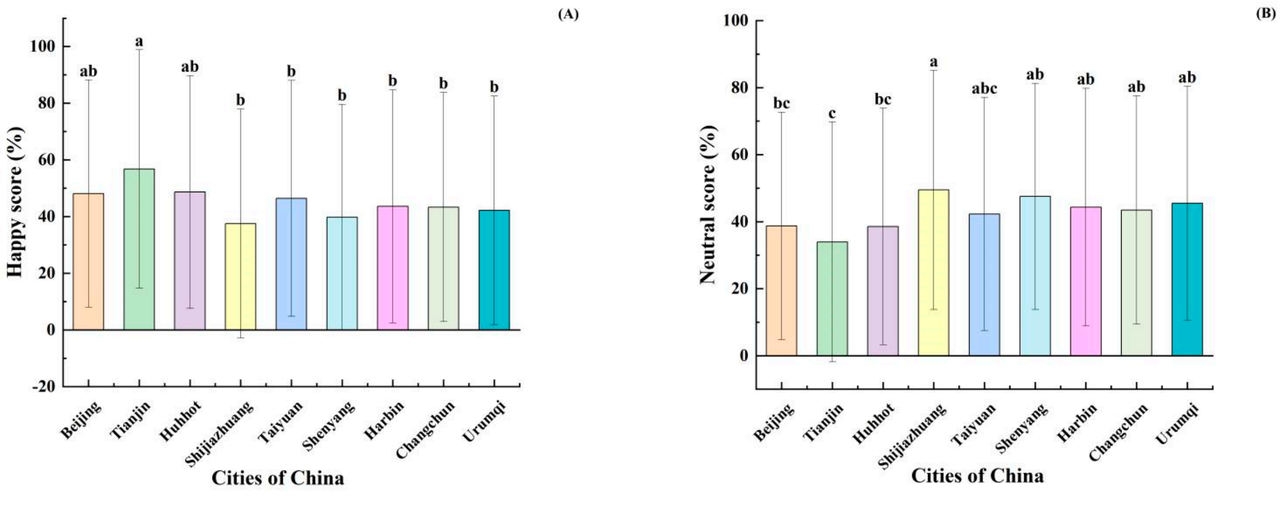

Figure 4. Happy (**A**), and neutral (**B**) scores on visitors' face in northern cities. Error bars stand for standard errors that stared from the columns (means). Different letters of a, b and c indicate significant differences of ranked scores according to LSD test at the 0.05 level.

3.2.3. Cities and Ages Interaction Analysis

We found significant differences between the variables city and age and the visitors' happy, sad, and neutral facial expressions. When the city variable interacted with age, only happiness and sadness were significantly different; however, there was no difference in the neutral expression (Table 6).

Table 6. Analysis of variance (ANOVA) with the mixed model of city, age, and their interaction on repeated measures of ranked scores about happy, sad, and neutral facial expression scores and the positive response index.

Source	Variable	III Sum of Squares	DF [1]	Mean Squares	Sig. [2]
Model	Happy	147,640.354	31	4762.592	0.000
	Sad	19,413.101	31	626.229	0.000
	Neutral	111,873.975	31	3608.838	0.000
	PRI [3]	219,572.676	31	7082.99	0.000
City	Happy	38,955.391	8	4869.424	0.002
	Sad	9424.833	8	1178.104	0.000
	Neutral	20,564.952	8	2570.619	0.027
	PRI [3]	75,966.925	8	9495.866	0.000
Age	Happy	26,088.062	3	8696.021	0.001
	Sad	2551.57	3	850.523	0.017
	Neutral	21,006.118	3	7002.039	0.001
	PRI [3]	36,141.331	3	12,047.11	0.003
City × Age	Happy	55,217.161	20	2760.858	0.028
	Sad	13,185.125	20	659.256	0.000
	Neutral	36,484.372	20	1824.219	0.060
	PRI [3]	100,695.677	20	5034.784	0.007

Note: [1] DF, degree of freedom; [2] Sig, significance; [3] PRI, positive response index, the same below.

3.2.4. Positive Response Index Analysis

Adult visitors had higher PRI scores than toddlers and youth visitors (Figure 5A). The PRI scores of visitors in Tianjin were significantly higher than in Harbin, Changchun, Shenyang, Shijiazhuang, and Ürümqi (Figure 5B). The visitors' PRI scores were positively correlated with park size (p = 0.011), indicating that people's net positive emotion levels were significantly related to the size of the park (Table 7).

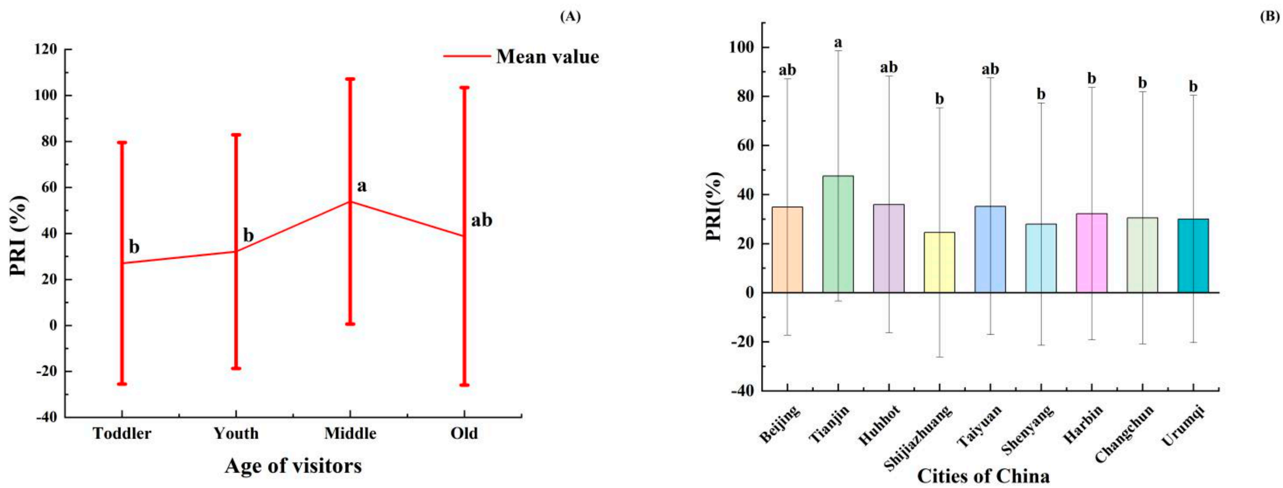

Figure 5. PRI of different ages visitors (**A**) and PRI of visitors from different cities in China (**B**). Error bars stand for standard errors that stared from the columns (means). Different letters of a and b indicate significant differences of ranked scores according to an LSD test at the 0.05 level.

3.3. Landscape Metrics and Facial Expressions Correlation Analysis

The visitors' happy scores were positively correlated with the green spaces (p = 0.019) and the park area (p = 0.001); we found the highest number of happy faces in the parks with the greenest space and overall park area (Table 7). However, there was no correlation between sad expressions and the four-landscape metrics, suggesting that visitors were not sadder because a park had less green space, blue space, or overall park area or a specific average park elevation. However, visitors' neutral expressions were negatively correlated with a green space area (p = 0.017) and overall park area (p = 0.002). This suggested that increasing vegetation coverage would not necessarily cause the number of neutral expressions to have happy (or sad) expressions.

Table 7. Coefficients from Spearman correlation between the landscape metric and three facial expressions and the positive response index of visitors therein in target forest park.

Index	Happy	Sad	Neutral	PRI [1]	Green Area	Water Area	Park Area	Park Elevation
Happy	1							
Sad	−0.731 **	1						
Neutral	−0.886 **	0.522 **	1					
PRI [1]	0.936 **	−0.882 **	−0.768 **	1				
Green area	0.052 *	−0.001	−0.053 *	0.039	1			
Water area	0.014	0.012	−0.02	0.006	0.324 **	1		
Park area	0.071 **	−0.011	−0.070 **	0.056 *	0.984 **	0.319 **	1	
Park elevation	−0.026	0.015	0.028	−0.027	0.286 **	−0.422 **	0.261 **	1

Note: * and ** mean significant correlation at $p < 0.05$ and extremely significant correlation at $p < 0.01$, respectively. [1] PRI, positive response index.

4. Discussion

4.1. The Age Effect on Facial Expressions

Thanks to the popularity of mobile devices with high-quality cameras, visitors upload more selfies than in the past [53]. More of our facial photographs originated with youths' selfies than other visitors' selfies. Artificial age assessments have also been used in studies of public sentiment during pandemics and to provide large-scale data [54]. Toddlers and youths scored relatively lower than adults and old people on happy expressions. The sadness scores were lower among adults than among the toddler, youth, and old visitors. These results suggest that the forest environments had a positive psychological effect on adult and old visitors, which is consistent with previous research [2]. Therefore, we concluded that the restorative effects of the urban forest experience extended to the elderly. The urban park activities provided opportunities for older adults to interact socially while enjoying the natural environment, enabling them to start and maintain friendships, which is known to benefit mental health [9]. Because we assessed the emotional expressions of different age groups during their urban forest park experiences using many sample photographs, our results provide empirical evidence for the improvement of mental health through urban parks.

4.2. The Discrepancy of Facial Expressions among Cities

Urbanization is the product of a combination of social, economic, and resource factors. The rapid development of cities should be based on the science of the human settlement environment to balance the environmental carrying capacity and urban development intensity [55]. In 1984, the World Health Organization (WHO) proposed establishing healthy cities to promote the healthy urban development [56]. The Healthy Cities program links cities' living conditions to citizens' health. Health and well-being are interrelated, and the environment of a healthy city can influence residents' and visitors' health and well-being. Therefore, psychological variables might be more significant for health than external variables [57]. Our results showed that parks in Tianjin, Beijing, and Harbin were strongly correlated with happy expressions; they were the highest in Tianjin. Shijiazhuang had the lowest happy expression scores. Our results suggest that visitors to northern urban forest parks showed a higher frequency of happy expressions than visitors to southern urban forest parks, which is consistent with Wei et al. [46]. Although we found no significant differences in sad expressions among the nine cities, we found the greatest number in Shijiazhuang was the most prominent.

4.3. Relationship between Landscape Metrics and Facial Expressions

Other studies have focused on specific forest landscape metrics [58]. According to Chen et al. [59], changes in the landscape scale can affect the visual quality of the visitor photos. People establish connections with the environment through psychological reactions [60]. Psychophysics quantitatively investigates the relationship between stimuli, the sensations they elicit, and the magnitude of changes in perceivable physical stimuli [12]. This study explored the impact of various urban forest park stimuli on visitors' facial expressions from the perspective of landscape metrics. We found a significant positive correlation between green spaces and happy expressions. Similarly, Gozalo et al. [61] found that large green spaces were positively correlated with frequent strolling and relaxation among urban residents. Therefore, people's urban forest park experiences might be influenced by lower normalized difference vegetation index (NDVI) scores; NVDI is a graphical indicator of the live green vegetation and tree cover density. Residents of communities with abundant green spaces tend to enjoy better mental health. One study in the Netherlands found that the positive correlation was most pronounced among senior citizens, homemakers, and those from lower socioeconomic groups [62]. More research is needed to verify the findings that green spaces induce positive emotions in visitors. Studies show that experiencing blue spaces helps reduce stress and promote social contact among the elderly [63]. Other studies support the health benefits of blue space environments [19,64]. In fact, Sonntag-Ostrom et al. [65] reported that blue spaces were the most restorative landscapes. Similarly, Nutsford et al. [66] indicated that people's psychological stress decreased when they were within 15 km of visible outdoor blue spaces. In our study, there were three forest environments without water element landscape, which may lead to less happiness of visitors.

The area and average elevation of forest parks are also crucial factors affecting park visitors' expressions. People usually prefer to visit large parks with specific facilities [67]. Another study found that a three-day trek in the highlands could improve children's negative moods [68]. We found that the park scale was positively correlated with the PRI scores. Other studies have shown that humidity, terrain slope, and the vegetation are also important factors that affect visitors' experiences [30]. Hence, when planning and constructing an urban forest park, designers should ensure that the size of the park meets the residents' needs to stay active and exercise regularly. They should also consider the aesthetic value of the park to optimize the benefits of natural surroundings.

4.4. Limitation

We studied the facial expressions of visitors in urban forest parks in nine of China's provincial capitals. Future studies should expand the scope of the target city selections and park locations to eliminate the influence of neighbourhood and inner group differences.

Second, we addressed the effect of the park environments on visitors' facial expressions, but we did not set up any other urban environment as a control group for comparison. Future studies should consider additional urban variables to allow comparisons.

Third, people generally make happy expressions when they take selfies or have their photos taken by others, which might have affected the accuracy of our assessments; visitors might have worn sad or neutral faces until they were being photographed, which could have led to inaccuracies in our analyses. Therefore, future research should try to choose randomly captured candid photos for testing rather than selfies because the expressions would be more representative than posed photos.

Fourth, our age categorizations were guesses based primarily on people's appearances. Liu et al.'s study [51] used visual assessments with the same age ranges: toddlers 0–5, youths 15–25, adults 30–60, and old people 60+; people who seemed to fall into the gaps were added to the nearest age group (e.g., someone seven years old would be classified with the toddlers). We might have misclassified the facial expressions because of the person's age or the fluidity of expression; for example, a snapshot of what we classified as a toddler's neutral expression might have been a transitional expression between happy and sad. However, there was no accurate indicator for distinguishing the visitors' ages without additional information.

Finally, we selected only green spaces, blue spaces, park area, and average park elevation as the landscape metrics; we did not include hardscapes or structures. Future studies might follow the lead of Su [69], who divided forest landscapes into coniferous forest, broad-leaved forest, mixed forest, and static water landscape spaces. Su's study found that people's expressions of excitement and relaxation were more frequent in the mixed forests than in the other three groups. Therefore, our future studies will consider the influence of the different landscape elements on visitors' facial expressions to confirm the connection between nature and benefits to mental health.

5. Conclusions

We screened and downloaded 2031 facial photographs from Sina Weibo of urban park visitors in nine provincial capitals in Northern China. We performed facial recognition on the processed photos using the FireFACE^{TM} ver 1.0 software to categorize the faces' expressions as happy, sad, or neutral. The results showed that the urban parks with the greatest number of visitors with happy expressions were the parks with the greenest space and overall area. Thus, we recommend that future urban parks should feature a high percentage of vegetation to maximize residents' experiences with managed natural spaces to improve their health and well-being.

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

Funding: This research was funded by the Liaoning Key Research and Development Program (grant number: 2020JH2/10200033, 2021JH2/10200007), the National Natural Science Foundation of China (grant number: 31771695), and the Fundamental Research Funds for the Central Universities (Program for ecology research group) (grant number: 0901-110109).

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by The Ethic Committee of Human Studies, College of Forestry, Shenyang Agricultural University (protocol code: CF-EC-2021-001; date: 2 November 2021).

Informed Consent Statement: The study was approved by The Ethnic Committee of Human Studies, College of Forestry, Shenyang Agricultural University (protocol code: CF-EC-2021-001). All photos data for this study were obtained through Sina Weibo open source. Humans were informed when they uploaded photos on this open source platform. The Ethical Approval for Human Studies was submitted to the Forests submission system.

Data Availability Statement: Not applicable.

Acknowledgments: Authors acknowledge Lingquan Meng for photos treatment.

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

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