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Emotional Perceptions of Thermal Comfort for People Exposed to Green Spaces Characterized Using Streetscapes in Urban Parks

Benlu Xin [1,2], Chengfeng Zhu [1,2], Jingjing Geng [1,2,*] and Yanqi Liu [3,*]

[1] School of Business and Management, Jilin University, Changchun 130012, China; xinbl@jlu.edu.cn (B.X.); zhucf20@mails.jlu.edu.cn (C.Z.)
[2] "Lce and Snow Tourism Resorts Equipment and Intelligent Service Technology" Ministry of Culture and Tourism Key Laboratory, Changchun 130012, China
[3] School of Business Administration, Jilin University of Finance and Economics, Changchun 130117, China
* Correspondence: gengjj22@mails.jlu.edu.cn (J.G.); 114075@jlufe.edu.cn (Y.L.)

Abstract: Thermal comfort is a key determinant ruling the quality of urban park visits that is mainly evaluated by equivalent meteorological factors and lacks evidence about its relationship with emotional perception. Exposure to green space was believed to be an available approach to increase thermal comfort, but this argument still needs verification to confirm its reliability. In this study, about ~15,000 streetscapes were photographed at stops along sidewalks and evaluated for green view index (GVI) and plant diversity index in five urban parks of Changchun, Northeast China. The faces of visitors were captured to analyze happy, sad, and neutral scores as well as two net positive emotion estimates. Meteorological factors of temperature, relative humidity, and wind velocity were measured at the same time for evaluating thermal comfort using equivalent variables of discomfort index (*DI*), temperature and humidity index (*THI*), and cooling power index (*CP*). At stops with higher GVI, lower temperature (slope: from −0.1058 to −0.0871) and wind velocity (slope: from −0.1273 to −0.0524) were found, as well as higher relative humidity (slope: from 0.0871 to 0.8812), which resulted in positive relationships between GVI and thermal comfort evaluated as *DI* (R^2 = 0.3598, $p < 0.0001$) or *CP* (R^2 = 0.3179, $p < 0.0001$). Sad score was positively correlated with *THI* (R^2 = 0.0908, p = 0.0332) and negatively correlated with *CP* (R^2 = 0.0929, p = 0.0294). At stops with high GVI, more positive emotions were shown on visitors' faces (happy minus sad scores, 0.31 ± 0.10). Plant diversity had varied relationships with GVI in parks depending on age. Overall, our study demonstrated that using imagery data extracted from streetscapes can be useful for evaluating thermal comfort. It is recommended to plan a large amount of touchable nature provided by vegetation in urban parks so as to mitigate micro-climates towards a trend with more thermal comfort that evokes more positive emotions.

Keywords: thermal comfort; urban park tourism; cooling effect evaluation; emotional perception; quality of life

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1. Introduction

It is nearly agreed that we are living in a warming world, which is worsening thermal comfort conditions and increasing days with thermal discomfort [1]. This impedes the achievement of sustainable development goal (SDG) 3 as it heavily impairs "good health and well-being" [2]. Under poor thermal conditions, experiencers can suffer discomfort-caused mental stress and even illness originating from heat stroke or hypothermia. In SDG 7, "Affordable and Clean Energy", thermal comfort is involved, as a poor-comfort environment is usually associated with high power consumption for cooling or heating in a built environment [3]. It is also tied into SDG 11, "Sustainable Cities and Communities", as urban heat islands are the most perceived threat against urban sustainability [4]. Land use/land cover (LULC) is determinative of land surface temperature (LST) and outdoor thermal comfort, involved in both triggering urban heat events and mitigating them [5].

To establish an available strategy to cope with thermal discomfort conditions, land use planning is important to improve the environment with better thermal comfort. The evaluation of LST is necessary on specific given land, where more quantitative results should be documented based on critical driving mechanisms and reliable parameters.

Exposure to green space ties into a high probability of thermal comfort perception, which has generally broad applicability, being more probable on urbanized lands than on barrens with sparse vegetation [6,7]. Abundant vegetative reserves embedded in green space landscapes contribute to the adjustment of thermal comfort by means of heat absorption, water transpiration, and canopy shading [6,8,9]. As a biotic element in the landscape of a city, urban forest vegetation accounts for the majority of the mitigation of thermal comfort, especially on built-up lands. The canopy is the main organ of a vegetative plant that functions to induce a thermal comfort environment. This is because the canopy ties with foliage at the highest relevance across all organs, and leaves have a higher rate of transpiration than any other tissues [10]. Aboveground vegetative parts of lawns and grasslands are also commonly seen greenery, accounting for GVI in urban green space [11]. Stomatal openness brings about the gas exchanges that carry out transpiration, which allows cool air to flow into the micro-environment immediately around the canopy [12]. This phenomenon alters thermal comfort by dually modifying air temperature and humidity, which are two key variables that are used for evaluating thermal comfort [13,14]. Wind flow is also a concomitant variable that is involved in the evaluation of thermal comfort according to the rule of power loss [15,16]. Hence, a high occupation of walkable space by vegetative canopies can impede wind flow and theoretically reduce thermal comfort, but lawns do not. These, together, suggest an uncertain relationship between GVI and thermal comfort on municipal lands with green space using data from streetscape photos. The facticity of this relationship still cannot be fully confirmed due to the insufficiency of direct evidence on urban lands.

The enrichment of plant species in green space has been identified as a key factor that can evoke perceived well-being by urban park visitors [17,18]. This effect was suspected to be accompanied by a cooling and moist atmosphere on lands near green space trees [19–21]. It was suggested that plant diversity may have at least partly contributed to the mitigation of the cooling effect provided by vegetation [22,23]. For example, a study across four seasons in Changzhou, China, indicated that both the Shannon–Wiener diversity index and tree species richness were positively correlated with the magnitude of temperature drop amplitude [22]. However, it was also found that tree diversity was not so predictive against LST in comparison with disturbance level [23]. In theory, community transpiration should have a strong reliance on tree diversity in spite of the fact that tree physiology and local climate are two forcible drivers [24]. Even if all known factors are controlled, it is still hard to draw the conclusion that plant species diversity has any solid relationship with environmental cooling. This needs to be identified in newly conducted studies for the purpose of increasing green space through urban land management.

In an urban streetscape, the vegetative parts of canopies can be totally explained as greenery visible to the public. This can be evaluated using a parameter called the green view index (GVI), which is used for evaluating the visibility of green elements in a pedestrian's visible view [25]. It is measured by extracting pixels of greenery elements from canopies and calculating their ratio to the total in an image [26]. The extraction of foliar elements is the key process, which is achieved by training a machine to recognize a prepared dataset and summing up their number in an image [25,27]. Thus, the green elements of botanic issues are mostly derived from canopies of urban forest trees and occasional leaves attached to stems and branches can hardly be recognized [28]. The use of GVI was proven to be a flexible instrument for evaluating the occupation of canopies in walkable spaces on municipal lands and tracking geographical changes [27,28]. It was suggested to be an instrument for measuring the dose of nature that pedestrians can be exposed to along a sidewalk or a road [29]. As a visibility-dependent parameter, GVI was proven to gauge green space exposure according to individuals' green space usage behaviors [30]. The bulk of streetscapes used for GVI extraction and analysis include visual hybrids of buildings and greenery, which precondition measurements for touchable green space at the community scale [31]. Continuous to these essential uses, GVI-based measurement was also to be a meter of the spatially heterogeneous distribution of green space across a city [32]. Its close relationship with canopy has been used for detecting heat mitigation effects by urban trees [33]. Depending on high-resolution images, GVI-derived streetscapes can also be taken as a source from which plant diversity can be recognized and assessed artificially [34]. These together demonstrate the merits of using streetscapes to dually evaluate canopy shade and plant diversity, which can further be used for assessing the meteorological process to perceive thermal comfort. The relationship between GVI and thermal comfort has been proven to be essential [35], which dually changed in a joint variation of 7.9–23.0% [36]. The key determinant of achievement depends on the accuracy of the dependent thermal comfort assessment.

Currently, thermal comfort is mainly evaluated using equations against equivalent meteorological factors [37]. Air temperature and humidity at touchable height are the two most concerned factors given their key contributions to human perceptions about thermal comfort. Using these two parameters, thermal comfort was initially evaluated through a variable assessing discomfort in high temperature but low humidity conditions, namely the discomfort index (*DI*) [38], which is evaluated as [13]:

$$DI = \mathrm{T} - 0.55 \times (1 - 0.01 \times \mathrm{RH}) \times (\mathrm{T} - 58) \tag{1}$$

where T is the air temperature and RH is relative humidity. People found that *DI* has a limit that cannot indicate thermal comfort ranges, hence it was modified to two further hybrid formulas, namely, temperature and humidity index (*THI*), which can be evaluated with either Equation (2) [39,40] or Equation (3) [41,42]:

$$THI = \mathrm{T} - 0.55 \times (1 - \mathrm{RH}) \times (\mathrm{T} - 14.50) \tag{2}$$

$$THI = \mathrm{T} + 0.36 \times \mathrm{T} + 41.5 \tag{3}$$

Both of these two equations were suggested being limited in defining thermal comfort temperature ranges due to not considering LST and waterbody areas assessed in the normalized difference moisture index (NDMI), hence it was suggested to be further modified to a new, updated parameter, namely, modified *THI* (*MTHI*) [13,43–45], which can be modeled by Equation (4) [45] and Equation (5) [13,43,44]:

$$MTHI = 0.10 \times [\mathrm{T} - 0.55 \times (1 - \mathrm{RH}) \times (\mathrm{T} - 14.50)] \times (2.25 + 0.67 \times \mathrm{LST}) \tag{4}$$

$$MTHI = 1.80 \times \mathrm{LST} + 32 - 0.55 \times (1 - \mathrm{NDMI}) \times (1.80 \times \mathrm{LST} - 26) \tag{5}$$

Given that TC is a type of perception of humans towards the thermal environment, the meteorological and land variables involved in Equations (1)–(5) are equivalent to this perception, but this does not mean the equivalent models are the most matching reflections of human perceptions. For a better evaluation of thermal comfort, these equivalent variables need to be challenged by new and more accurate parameters.

For urban green space visitors, their perceptions of the thermal environment have long been investigated through questionnaire surveys [46–49]. This methodology has been discouraged by several scholars due to its inevitable biases caused by subjective fatigue and social manners [50,51]. As an alternative approach, it has been recommended to capture visitors' perceptions and rate them with facial expression scores [52,53]. Its theoretical base comes from an objective rule that people can disclose real-time emotions on their faces if environmental factors are perceived as a driving hint [54–56]. This novel methodology has been identified to be flexible to predict responsive emotional perceptions of urban park environments, including exposure to green space landscape [19,57–59], air quality [60,61], micro-climate [19,20,57,62], and plant diversity [17,34]. These together suggest a probability that facial expression scores can also be taken as an instrument for detecting emotional perceptions of urban green space visitors towards the thermal comfort environment in urban parks. It will be more confirmative to detect thermal comfort in urban park environments through variable detection involving facial expression scores than any equivalent parameters.

In this study, meteorological factors were monitored in the micro-climates of five urban parks in Changchun, which were used for evaluating thermal comfort. Facial expression scores were also employed as a variable for detecting thermal comfort against micro-climates. Streetscapes were used as a source of data, which can result in data extraction about canopy shade and diversity recognition. Our goal was to examine the emotional perception of thermal comfort by rating facial expression scores against meteorological factors and vegetative variables extracted from streetscapes. We also aimed to compare this type of thermal comfort evaluation with results derived from equivalent meteorological evaluation. It was hypothesized that (1) the scenario in a park with high canopy shade and vegetative diversity can lead to a higher thermal comfort, (2) due to perceptions towards combined low temperature, moist air, and high wind velocity. It was also assumed that (3) thermal comfort evaluated by two different methodologies shared a common mechanism against meteorological factors in the same relationship.

2. Materials and Methods

2.1. Study Site and Plots

This study was conducted in temperate regions of China and Changchun was chosen as the city for data collection. Changchun is the capital city of Jilin province, which is located in areas of Northeast China [52]. Locally, the annual temperature was 4.6 °C averaged from a historical range between −36.5 °C and 40 °C. Annual rainfall ranged between 600 and 700 mm with frost-free days on 140–150 d per year. Local spring (March–May) is windy and dry continuously into a long wintertime (previous December–current February) starting from the previous year's autumn (September–November). Summer (June–August) is short because of cooling effects caused by late-spring frost [63] and early autumn chill [64]. Even so, summer is a comfortable season in Changchun due to cool nights and frequent rain events. The local resident population was about 4.45 million as of 2020, dwelling on construction lands in an area of 537 km^2 [65]. Changchun was one of four top-tier "Landscape Garden Cities in China" with the largest area of LULCs with artificial forests scattered in urban parks, public gardens, and street GSs [65].

Five urban parks were chosen as study sites in Changchun (Table 1). They are all recommended for visiting by professional agencies over three rating-star levels. Although Nanchu Park has not been recommended with any rating stars, it is one of the oldest parks in China, with local forests established over 80 years ago [66]. Nanhu Park, located in the center of Changchun, attracts visits from a large population during the daytime [49,53,67]. The locations of parks in the municipal regions of Changchun are shown in Figure 1.

Table 1. Basic information and areal quantifications in selected parks of Changchun.

Park	Built Year	Star Rating [1]	Rating Date	Total Area (ha)	Green Space (ha)	Blue Space (ha)
Beihu Wetland Park	2012	4A	29 May 2014	792.18	0.54	113.76
World Sculpture Park	2003	5A	25 February 2017	356.86	158.31	124.74
Zoo and Botanic Park	1938	4A	15 September 2007	237.86	31.41	73.62
Jingyue Pool Park	1934	5A	14 January 2011	87.09	0.09	5.31
Nanhu Park	1935	-	-	73.58	4.95	0.72

[1] Stars are provided by ratings of recommendation for visit.

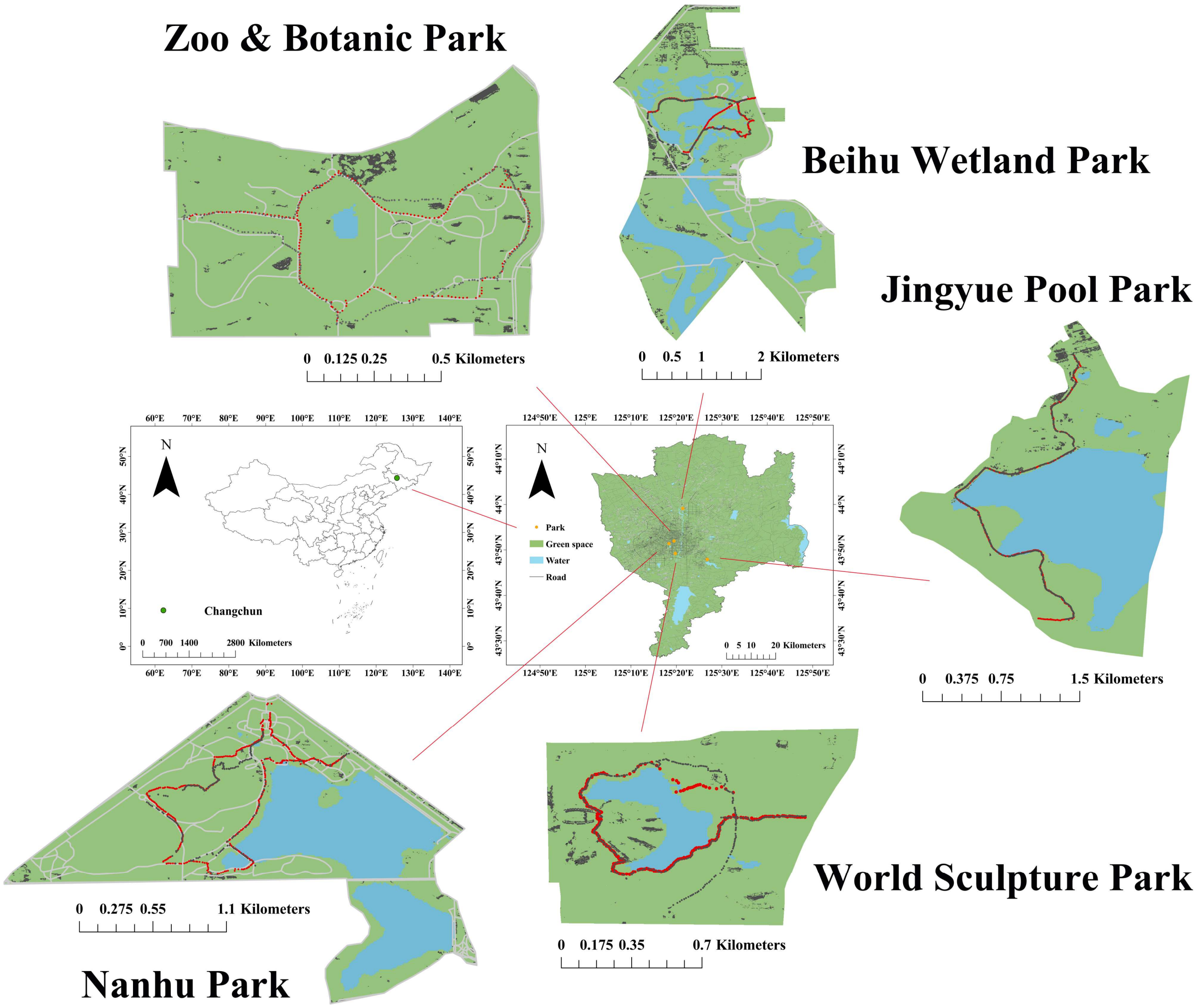

Figure 1. The spatial distributions of the five chosen urban parks for this study in Changchun. "Lines" in every park map are drawn by assembling stop positions, which are marked in red and black colors representing the first and the second days' visits, respectively.

2.2. Study Design and Layout

The time during June was chosen as the study period for data collection. This month accounts for the largest population of annual tourists and visitors in the parks of Changchun; hence, during this month, many opportunities to photograph facial photos of pedestrians in parks can be expected. Ten volunteers were recruited as data collection technicians. They were randomly separated into five pairs who were in charge of field investigations in five parks. Five pairs of technicians made investigations at the same time on the same two days, which were chosen as 12 and 25 June 2023 because they had sunny and windless weather. On the first investigating day, a technician walked from the entrance, away from which, every 5 m of walking was chosen as a stop, and streetscape photos were taken in four orientations. The other technician monitored meteorological factors at the same time as when every photo was taken. On the other day, five pairs of volunteers were rearranged to change their visits to different parks from the first day. The design and the layout of the whole experiment are shown in a technical roadmap in Figure 2.

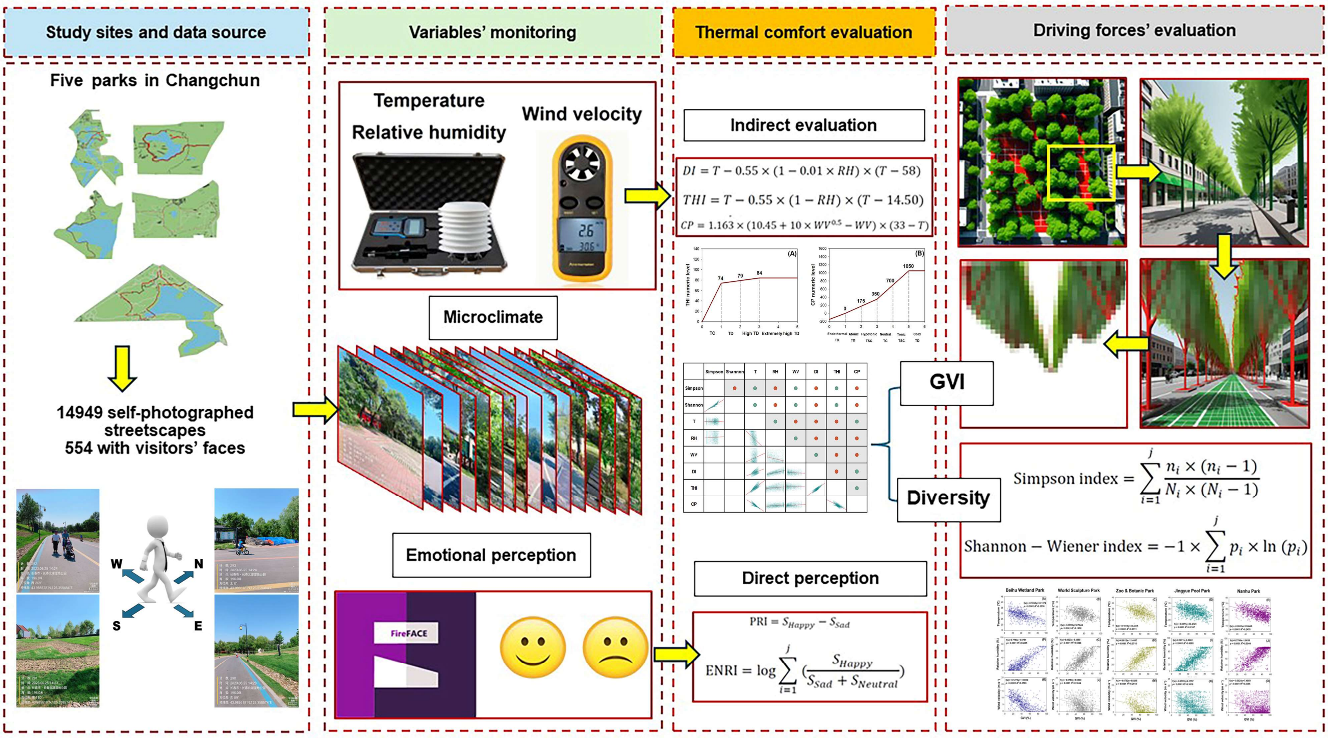

Figure 2. Technical roadmap of the whole study including processes of data collection, variable monitoring, thermal comfort evaluation, and driving force detection. Diagrams show described results in response to the section of methodology.

2.3. Meteorological Factor Monitoring

To evaluate thermal comfort using meteorological factors in micro-climates, temperature, relative humidity, and wind velocity were monitored at the same time as photographing. Wind velocity was measured using a mini LCD digital anemometer (GM8908, Benetech, Shenzhen, China) with a wind speed range of 0.1 to 30 m s^{-1} at an accuracy of ±5%. Although the anemometer can also monitor temperature, a replacement was used at a higher accuracy (−40 °C–+70 °C, ±0.2 °C) using HOBO UX100-014M (Onset Brands, Bourne, MA, USA). This can also measure RH at an accuracy of 0–100%, ±2.5%.

2.4. Photographing at Stops in Parks

Photos were taken by cellphone cameras that were uniformed to present watermarks with information about the order of the photo, time, location, elevation, orientational angle, and coordinates. All photos were taken at a standard proportion of 16:9 (width to length) and a resolution of 4k. These processes were repeated at stops every 5 m by walking along sidewalks. Real-time meteorological factors were recorded by handheld devices at the same time of every orientation's photographing. Micro-climates were characterized by equivalent factors of air temperature, relative humidity, and wind velocity. When a pedestrian's face was photographed, the volunteer asked for consent to use it for this study. Photos were deleted immediately if the consent was denied. Stops were chosen one by one at a walking pace. The stop could not be employed under any of the following conditions:

(i) Fully crowded by visitors in all four orientations;
(ii) The stop's location suffers unwalkability for reasons such as lane maintenance;
(iii) Excessively close to an adjacent building at a distance < 1 m;
(iv) Accessibility was impeded by the occupation of pets, which were mostly puppies.

Finally, a total of 14,949 photos were taken from five urban parks in two days and 554 of them contained visitors' facial photos with personal consent.

2.5. Facial Expression Recognization and Rating

FireFACE version 1.0 software (Hainan Guanzhong A&F Ltd., Sanya, China) was used to recognize facial expressions and rate scores of happy, sad, and neutral emotions. This approach has been used several times in previous studies and has proven to be sensitive for assessing visitors' emotions toward perceptions of urban park environments [34,59,60]. No technical thresholds were set to distinguish scores for happy, sad, and neutral emotions as they were recognized by a deep learning network pretrained by machine learning using 30,000 inputs [68] and tested to pass the matching-accuracy validation [69]. Thereafter, the net positive emotion in a photo was further calculated as a positive response index (PRI) [52,55]:

$$\mathrm{PRI} = \mathrm{S_{Happy}} - \mathrm{S_{Sad}} \tag{6}$$

where $\mathrm{S_{Happy}}$ and $\mathrm{S_{Sad}}$ are emotional scores for happiness and sadness, respectively. As PRI cannot cover the effects of a neutral score, which is an inevitable part of facial expression, another synthesized variable, namely, the emotional nonparametric relation index (ENRI), was also involved and calculated as [70]:

$$\mathrm{ENRI} = \log \sum_{i=1}^{j} \left(\frac{\mathrm{S_{Happy}}}{\mathrm{S_{Sad}} + \mathrm{S_{Neutral}}} \right) \tag{7}$$

where $\mathrm{S_{Neutral}}$ is the neutral score of the ith visitor in a photo, which was totaled by the sum of that for the jth visitor.

2.6. Thermal Comfort Evaluation

Thermal comfort was evaluated using equivalent meteorological factors in temperature and humidity perception models and a power consumption model. Temperature and humidity perception models were put forth as instances such as those in Equation (1) (*DI*) (scale: 350–1000) and Equation (2) (*THI*) (scale: 50–90). We did not choose to evaluate *MTHI* [13,43–45] because its estimate needs inputs of LST, which had to rely on 30 m resolution remote evaluation using satellite imageries, such as Landsat OLI or Sentinel products. The power consumption model can be employed using a variable, namely, the cooling power index (*CP*), which was also used and was estimated using temperature and wind velocity (WV, m s^{-1}) [15]:

$$CP = 1.163 \times \left(10.45 + 10 \times \mathrm{WV}^{0.5} - \mathrm{WV}\right) \times (33 - \mathrm{T}) \tag{8}$$

With the increase in the levels of *DI* and *THI*, the thermal environment was perceived from the comfortable range through to discomfort (Figure 3A). The scale for *CP* was between −270 and 1100, within which the thermal environment was perceived as uncomfortable when it was lower than 175 or higher than 1050 (Figure 3B).

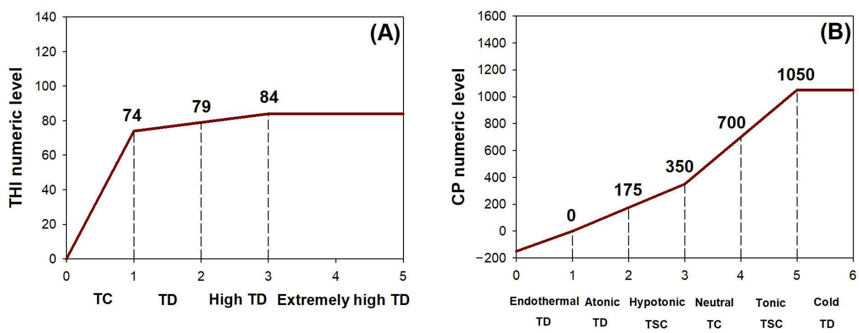

Figure 3. Characterizations of thermal comfort (TC), thermal sub-comfort (TSC), and thermal discomfort (TD) following temperature increase for *THI* (**A**) and *CP* (**B**). Data for constructing figure cells (**A**) and (**B**) are derived from previous studies of [15,71], respectively.

2.7. Data Extracted from Streetscapes

Streetscape photos were used for extracting GVI data for vegetative elements in canopies, lawns, and grasslands (Figure 2). In this study, greenery was recognized using an existing DeepLabV3+ model run through deep learning in Python ver. 3.6 (Python Software Inc., Beaverton, ON, USA). This model was established in a study by Sun et al. (2023) [34] and was trained by groups of 2000 streetscape photos downloaded from online maps using the Pycharm project (Pycharm, Praha, Czech Republic) and validated across groups (initially over 5000 photos added to 5000 newly inputted ones from this study). It was validated to have a high recovery of the matching rate at 93.75% [34], which is higher than many other GVI projects [72,73].

For photos already evaluated for GVI, an academic group of professionals in botanic science was invited to identify the vegetative species therein [34]. The five volunteers were recruited again to check plant species in the field if they were not sure from reading the photo. Genera and species names were recorded for all plants that can be seen in a photo, and their numbers were totaled by the four photos per stop. Overall, tree species mainly included *Betula platyphylla* Sukaczev (1911), *Fraxinus mandschurica* Rupr., *Juglans mandshurica* Maxim., *Populus davidiana* Dode, *P. alba* var. *pyramidalis* Bunge, *Picea jezoensis* var. *microsperma* (Lindl.) Cheng et L. K. Fu, *P. koraiensis* Nakai, *Pinus koraiensis* Sieb. et Zucc., *P. sylvestris* var. *mongolica* Litv., *P. tabuliformis* Carr., 1867, *Prunus sibirica* L. 1753, *P. davidiana* (Carr.) C. de Vos ex Henry, *P. padus* L. 1753, and *Salix alba* L. Shrubs were mainly *Acer ginnala* Maxim., *Berberis ferdinandi-coburgii* Schneid., *Cornus alba* L., *Liriodendron tulipifera* L., and *Ulmus pumila* "jinye". Herbaceous plants included *Carex hirta* L., *Cynodon dactylon* (L.) Pers., *Hosta plantaginea* (Lam.) Aschers., *Lolium perenne* L., *Trifolium repens* L., *Plantago asiatica* L.

Plant diversity was evaluated by equations of the Simpson index [74] and Shannon–Wiener models [22]:

$$\text{Simpson index} = \sum_{i=1}^{j} \frac{\mathrm{n}_i \times (\mathrm{n}_i - 1)}{\mathrm{N}_i \times (\mathrm{N}_i - 1)} \tag{9}$$

$$\text{Shannon–Wiener index} = -1 \times \sum_{i=1}^{j} \mathrm{p}_i \times \ln(\mathrm{p}_i) \tag{10}$$

where n_i is the number of the ith species in photos of a stop and N_i is the number of all species, and p_i is their ratio of n_i to N_i per photo. Both indexes were evaluated across photos per stop up to a total number of j. The Simpson index is flexible in indicating diversity driven by changes in dominant species, and the Shannon–Wiener index is more precise in predicting the evenness of diverse species [75].

2.8. Data Processing and Statistics

Data were analyzed using SAS ver. 9.4 software (SAS Statistics Inc., Cary, NC, USA). The total data pool comprised two sets of data, which were detailed to be data from all stops (n = 14,949) and those from selected stops with visitors' faces (n = 554). All meteorological and equivalent thermal comfort evaluation data passed normal distribution with homogeneous variance. Pearson correlation was used to detect relationships between pairs of parameters among meteorological and equivalent thermal comfort variables. An initial examination indicated that neither plant diversity indexes showed significant relationships with any of the meteorological factors, but GVI can be related to most of them. Hence, relationships between GVI and meteorological factors were plotted by observed data and fitted by curves to reveal correlation details. These correlations were detected separately by data variation among parks to detect common responses. For data from selected stops, however, the abovementioned data plus facial expression scores (happy, sad, and neutral scores and PRI and ENRI values) were all pooled together for correlation detection among any pairs of variables, summing data together across five parks. As the data of facial expression scores all failed to pass normal distribution, they were all transformed by ranking to generate distribution-free patterns [19,53]. Multivariate linear regression was used to detect combined driving forces of meteorological factors plus GVI and diversity indexes on thermal comfort evaluation values (*DI*, *THI*, *CP*), using data separately for all stops and selected stops. In addition, multivariate linear regression was also employed to detect driving forces for facial expression scores.

3. Results

3.1. Data Characteristics

DI data from all stops were averaged to 631.69 ± 105.50 (mean ± standard deviation) ranging from 357.72 to 1005.22 with a coefficient of variance of 0.17 (Figure 4A). For *DI* from selected stops, the mean was 625.46 ± 104.35 with a coefficient of variance of 0.16.

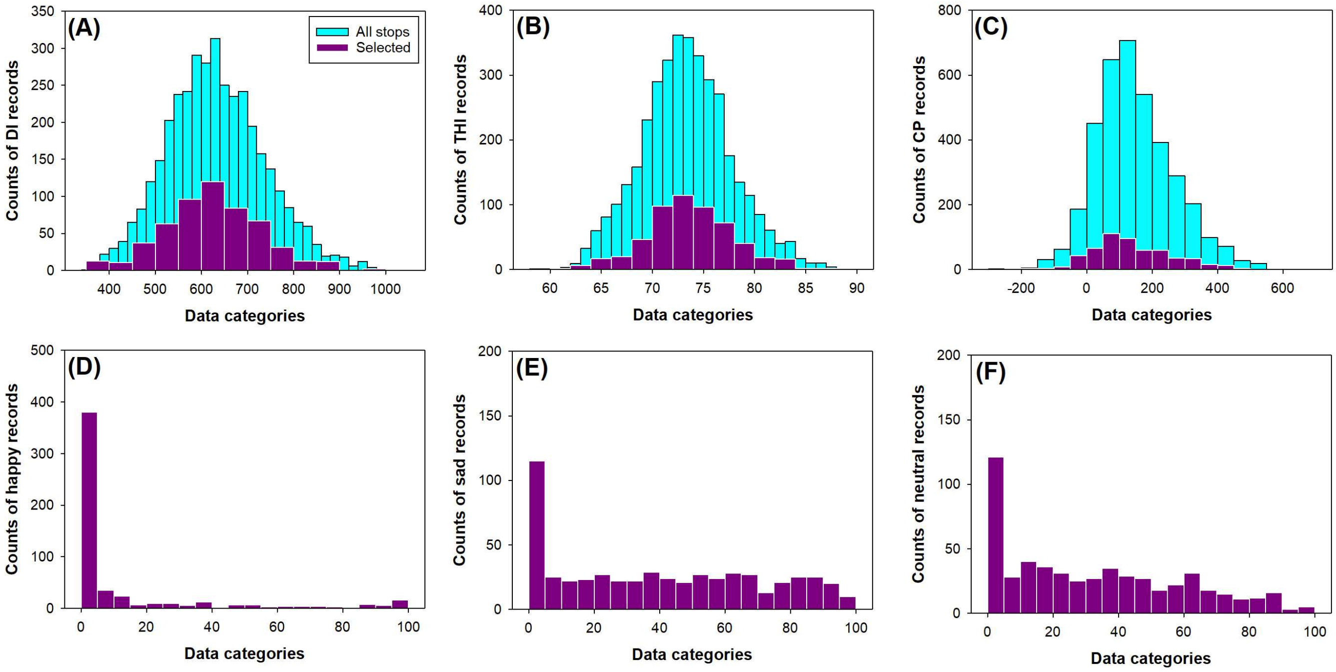

Figure 4. Histograms of thermal comfort evaluations by equivalent meteorological factors (*DI* (**A**); *THI* (**B**); *CP* (**C**)) for data from all stops or selected stops, where visitors were recorded for their happy (**D**), sad (**E**), and neutral (**F**) scores. Data categories are listed as raw records from the lowest level of observation to the highest level.

Data of *THI* from all stops ranged between 58.49 and 89.01 with an average of 73.34 ± 4.41 and a coefficient of variance of 0.06 (Figure 4B). When data were extracted from selected stops, *THI* had a mean of 73.62 ± 4.30, ranging between 61.43 and 89.01. During these changes, the increase in *THI* indicated perceptive changes from thermal comfort to thermal discomfort with the increase in temperature (Figure 3A).

Data of *CP* from all stops ranged from −272.41 to 650.96 with an average of 148.06 ± 118.55 and a coefficient of variance of 0.80 (Figure 4C); *CP* data from selected stops ranged between −212.95 and 490.52 with a mean of 135.02 ± 123.07 and a coefficient of variance of 0.91. These changes in *CP* indicated perceptions from thermal discomfort to thermal comfort (Figure 3B).

Happy, sad, and neutral emotions had the highest scores of 99.94%, 97.88%, and 97.41%, respectively (Figure 4D–F). Their means were 12.91 ± 25.34%, 39.92 ± 31.01%, and 32.62 ± 27.15% with coefficients of variance of 1.96, 0.78, and 0.83, respectively. Data of PRI ranged between −97.78% and 99.92% with an average of −27.00 ± 46.65% and a coefficient of variance of −1.73. ENRI ranged between −3.99 and 3.70 with an average of −1.05 ± 1.41 and a coefficient of variance of −1.35.

3.2. Correlation Using Data from All Stops

For data from all stops, none of the equivalent thermal comfort evaluation variables had significant correlations with diversity indexes (Figure 5). Both *DI* and *THI* had positive relationships with temperature and humidity but negative relationships with wind velocity. *CP* had a negative relationship with temperature but a positive relationship with humidity and wind velocity. The Simpson index had a negative relationship with temperature and a positive relationship with relative humidity, but the Shannon index did not correlate with either of them. Wind velocity did not correlate with either diversity index, but it had a positive relationship with temperature and a negative relationship with humidity.

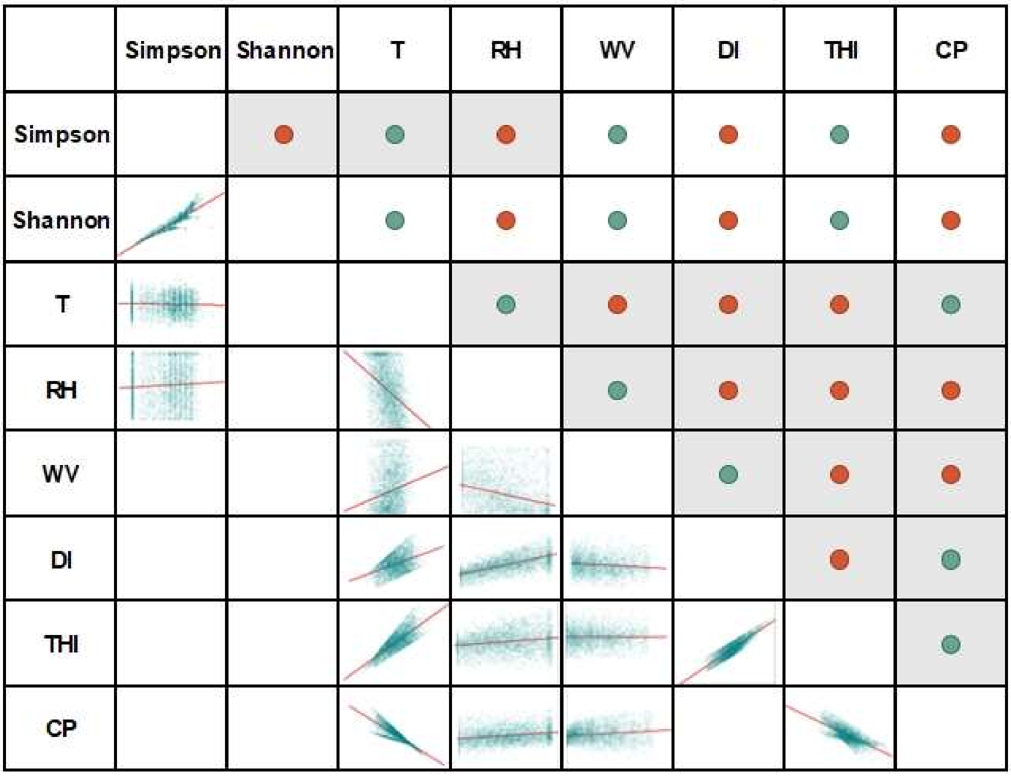

Figure 5. Heat map of Pearson correlations between pairs of variables among plant diversity index (Simpson and Shannon), meteorological factors (temperature, T; relative humidity, RH; wind velocity, WV), and equivalent thermal comfort evaluations (*DI*, *THI*, *CP*) at all stops across all five parks. Colors of dots indicate correlation results according to *R* values: positive ($R > 0$) and negative ($R < 0$) correlations are marked by red and green colors, respectively. Only significant correlations are fitted by curves (red full lines) over raw data (dots in cyan color).

Data of GVI showed no relationships with *THI* for data from all stops. Instead, GVI showed positive relationships with equivalent thermal comfort evaluation variables (Figure 6). Data from all stops also showed that GVI had negative relationships with temperature (Figure 7A–E) and wind velocity (Figure 7K–O) in all five parks. However, GVI showed positive relationships with relative humidity in the five parks (Figure 7F–J). However, relationships between GVI and diversity indexes varied among different parks (Figure 8). In detail, GVI had negative relationships with Simpson and Shannon indexes in Beihu Wetland and World Sculpture parks (Figure 8A,B,F,G), but it had positive relationships with two diversity indexes in Jingyue Pool Park (Figure 8D,I). In addition, GVI had a positive relationship with the Simpson index in the Zoo and Botanic Park (Figure 8C). No relationship was detected to be significant between GVI and diversity in Nanhu Park (Figure 8E,J).

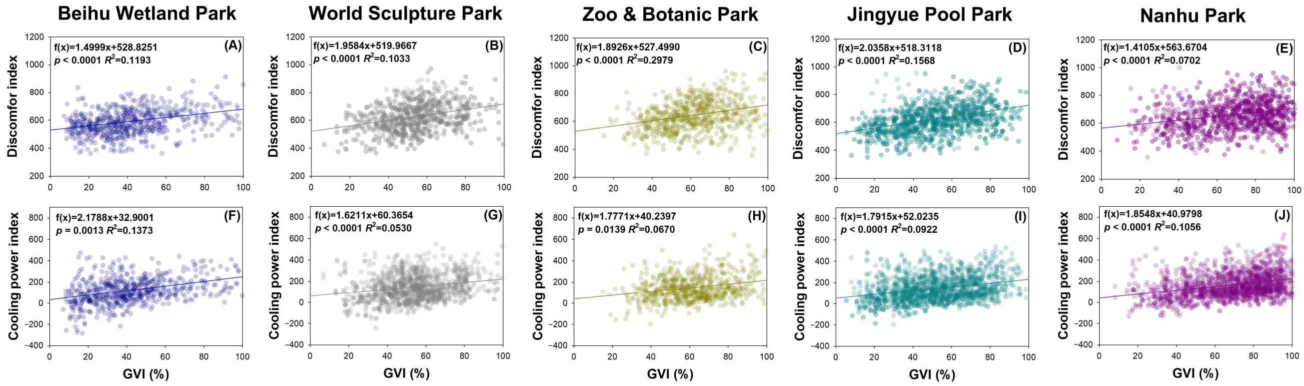

Figure 6. Relationships between GVI and equivalent thermal comfort evaluation variables (*CP* (**A**–**E**); *CP* (**F**–**J**)) drawn by plots using raw data from all stops fitted by linear correlation curves separately from five parks in Changchun.

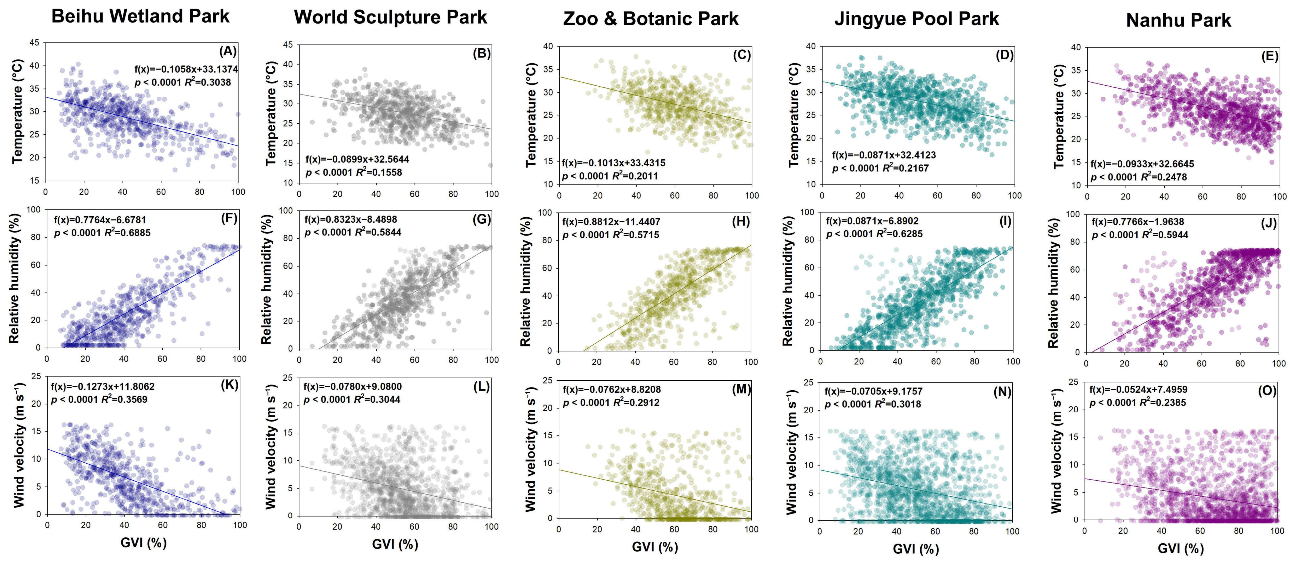

Figure 7. Relationships between GVI and meteorological variables (temperature (**A**–**E**); relative humidity (**F**–**J**); wind velocity (**K**–**O**)) drawn by plots using raw data from all stops fitted by linear correlation curves separately from five parks in Changchun.

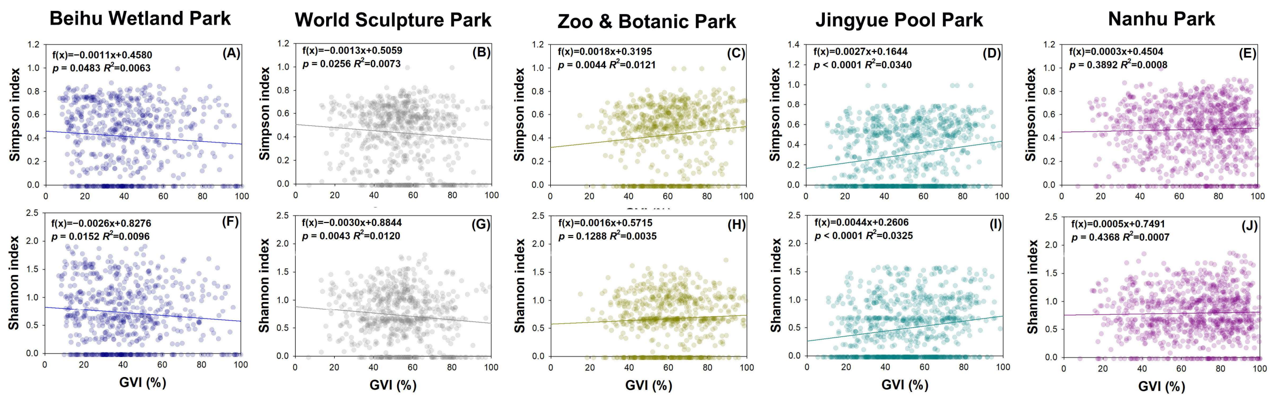

Figure 8. Relationships between GVI and plant diversity indexes (Simpson index (**A**–**E**); Shannon index (**F**–**J**)) drawn by plots using raw data from all stops fitted by linear correlation curves separately from five parks in Changchun.

3.3. Correlation Using Data from Selected Stops

Both the Simpson and Shannon indexes showed positive relationships with sad score (Figure 9). In contrast, GVI showed no relationship with sad score, but GVI had positive relationships with happy, PRI, and ENRI scores. Temperature showed a positive relationship with sad score, and it had negative relationships with PRI and ENRI. RH had no relationship with sad score, but it had positive relationships with happy score, PRI, and ENRI. Wind velocity had no relationship with any facial expression scores.

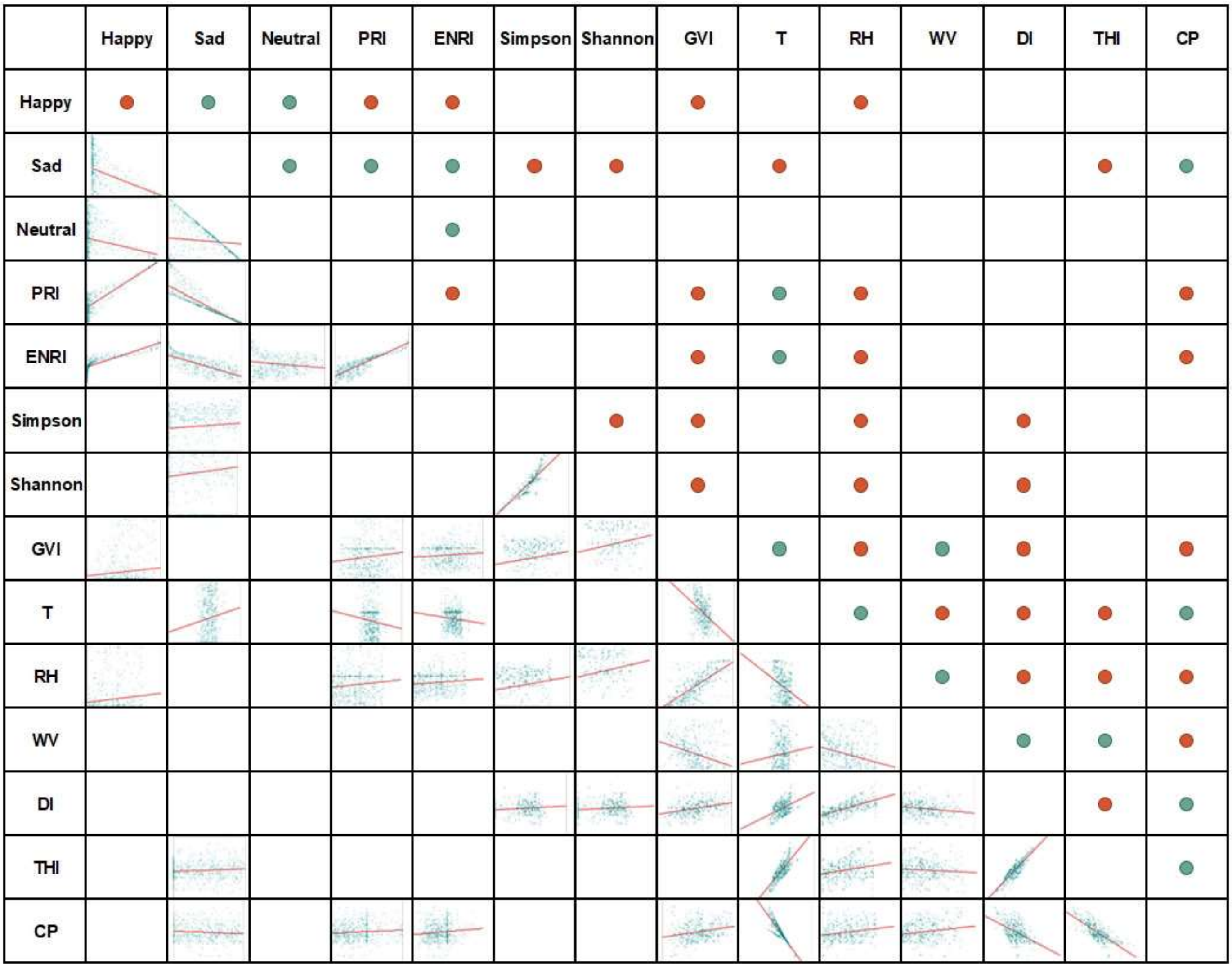

Figure 9. Heat map of Pearson correlations between pairs of variables among facial expression scores (happy, sad, neutral, PRI, and ENRI), plant diversity index (Simpson and Shannon), meteorological factors (temperature, T; relative humidity, RH; wind velocity, WV), and equivalent thermal comfort evaluations (*DI*, *THI*, *CP*) at selected stops across all five parks. Colors of dots indicate correlation results according to *R* values: positive ($R > 0$) and negative ($R < 0$) correlations are marked by red and green colors, respectively. Only significant correlations are fitted by curves (red full lines) over raw data (dots in cyan color).

Both GVI and diversity indexes had positive relationships with DI and GVI had a positive relationship with *CP*. Temperature and relative humidity had positive relationships with *DI* and *THI* and their relationships with wind velocity were negative. In contrast, temperature had a negative relationship with *CP* and wind velocity had a positive relationship with *CP*.

Temperature and wind velocity had negative relationships with GVI. In contrast, air humidity had positive relationships with GVI and two diversity variables. GVI also showed positive relationships with the Simpson and Shannon indexes.

3.4. Driving Force Analysis Using Multivariate Linear Regression

For data from all stops, the GVI and Simpson index showed no contributions to three thermal comfort equivalent parameters (Table 2). Temperature showed strong positive contributions to *DI* and *THI*, while relative humidity showed tiny positive contributions to these two parameters. Wind velocity and Shannon index showed negative contributions to these two parameters with parameter estimates higher from the Shannon index than that from wind velocity. In contrast, temperature and relative humidity showed negative contributions to *CP* with a positive contribution provided by wind velocity.

Table 2. Multivariate linear regression of equivalent meteorological variables for thermal comfort evaluation parameters against combined independent variables for data collected from all stops or from selected stops.

Variable	*DI* [1]	*THI* [2]	*CP* [3]
		All stops	
Intercept	−167.49 ± 2.27 *** [4]	35.68 ± 0.12 ***	895.76 ± 6.22 ***
GVI	- [5]	-	-
Shannon	−1.09 ± 0.53 *	−0.06 ± 0.03 *	-
T [6]	22.36 ± 0.07 ***	1.19 ± 0.00 ***	−28.67 ± 0.20 ***
RH [7]	4.76 ± 0.01 ***	0.13 ± 0.00 ***	−0.13 ± 0.04 **
WV [8]	−0.23 ± 0.06 ***	−0.01 ± 0.00 ***	9.34 ± 0.16 ***
		Selected stops	
Intercept	−122.82 ± 6.41 ***	38.06 ± 0.34 ***	944.64 ± 16.12 ***
GVI	−0.15 ± 0.05 ***	−0.01 ± 0.00 ***	−0.21 ± 0.10 *
Shannon	-	-	-
T	20.82 ± 0.19 ***	1.11 ± 0.01 ***	−29.87 ± 0.46 ***
RH	4.89 ± 0.05 ***	0.13 ± 0.00 ***	-
WV	-	-	8.47 ± 0.40 ***

[1] *DI*, discomfort index; [2] *THI*, temperature and humidity index; [3] *CP*, cooling power index; [4] results are means ± standard error with significance at critical values: *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$; [5] -, no detected driving parameters; [6] T, temperature; [7] RH, relative humidity; [8] WV, wind velocity.

Again, temperature and relative humidity also showed positive contributions to *DI* and *THI* for data from selected stops (Table 2). Wind velocity showed a positive contribution to *CP*, which received a negative contribution from temperature.

Among all physical factors, only relative humidity, GVI, and Shannon index showed significant contributions to facial expression scores (Table 3). Relative humidity showed positive contributions to happy score and ENRI. GVI generated a negative contribution to sad score and its contribution to PRI was positive.

Table 3. Multivariate linear regression of facial expression scores of visitors against physical factors and greenery variables in selected stops at parks.

Variables	Happy	Sad	PRI	ENRI
Intercept	8.00 ± 2.08	45.19 ± 3.81	−42.41 ± 5.37	−1.34 ± 0.12
RH	0.14 ± 0.05	-	-	0.01 ± 0.00
GVI	-	−0.20 ± 0.07	0.31 ± 0.10	-
Shannon	-	7.12 ± 2.64	-	-

4. Discussion

4.1. The Estimate of Thermal Comfort Using Facial Emotion Scores

As a novel approach, facial expressions were employed in this study as an instrument to estimate thermal comfort. This was achieved based on the theoretical basis that thermal comfort is a perception of humans towards experiences in a thermal environment. Humans have a nature to perceive more negative emotions in accordance with declines in psychological well-being when thermal discomfort is experienced [76,77]. In contrast, when a comfortable environment is perceived, most people will stop or reduce the exhibition of negative emotion, but rare few of them will replace perceptions about negative emotions with positive sentiments. In the context of human emotions of environmental perceptions, the face shows a mixture of expressions from positive, negative, and indifferent emotions [67,69,78]. The decline in negative emotions was usually accompanied by the switch of more neutral emotions than visible smiles. Hence, a mixed model synthesizing multiple emotional scores is more recommended than any monocultural model for the estimate of thermal comfort. The variable PRI is a commonly used mixed model that equals the difference between happy and sad scores [63,69,78]. This model concerns net changes between positive and negative emotions, but it fails to involve the indifferent emotion. The variable ENRI is also a mixed model, which covers multiple changes in happy, sad, and neutral emotions [70]. Thus, ENRI may have a lower prediction than PRI for estimating the net difference between positive and negative emotions. That is why both PRI and ENRI were employed in this study.

4.2. Difference in Thermal Comfort Evaluations between Two Methodologies

Among all equivalent parameters, *DI* failed to have any relationship with facial expression scores. Instead, *THI* showed a positive relationship with sad score, although the slope was very low. *CP* showed a negative relationship with sad score, and its relationships with PRI and ENRI were both positive. Increasing values in *DI* and *THI* with that in temperature covered a range of thermal perception switching from comfort to discomfort with results on the contrary for values in *CP*. Therefore, the abovementioned changes together indicate that thermal comfort evaluation by equivalent meteorological factors can synchronize to that evaluated by facial expression scores. This can happen only when it is accepted that sadness disclosed on the face was the only expressional response to the perception of thermal comfort ruled by LST. Furthermore, changes in sadness also charged responses of net emotion expressions (PRI and ENRI) to show positive results when thermal comfort was perceived as the lowered power loss facing a thermal environment. It can be predicted that *DI* may lose its responsive sensitivity to indicate perceptive thermal comfort as this equivalent variable was put forth as early as 1959 [38] when the general understanding of thermal comfort evaluation was limited to an initial stage when it was unlikely to find precise coefficients of meteorological factors [13]. It was surprising that *CP* was the only equivalent variable that correlated with net positive emotional expression. The estimate of this variable needs independent variables' inputs of temperature and wind velocity (Equation (8)), but it still can indicate a positive relationship with air humidity and precisely indicate contradictions against *DI* and *THI* in our given data spectrum. From the perspective of power loss with a thermal discomfort perception, a fluent wind flow can take away heat from the skin, function to decrease surface temperature, and evoke the mitigation of sadness perception [15,79]. In previous studies, wind flow was also found to be a necessary factor that induces positive emotions of visitors in green spaces with degraded ecological states in subtropical forests [57]. In urban green space in Japan, it was also indicated that low wind velocity was a limit that impeded the psychological responses of people to perceive thermal comfort [80]. Overall, we can accept our hypothesis that thermal comfort evaluations through equivalent meteorological factors using the *CP* model and facial expression scores about sadness can agree with each other.

4.3. Vegetative Effects on Thermal Comfort for People Exposed to Green Space

It has long been found that thermal comfort can be increased in scenarios of green space exposure with vegetative shade through field investigation and simulations [7,81]. In our study, results were estimated as a parameter of GVI with data extracted from streetscapes. We found that GVI showed contradictive effects on thermal comfort according to its dually positive relationships with *DI* and *CP* for both pools of data either from all stops or in selected stops. These were caused by negative relationships between GVI and temperature or wind velocity and a negative relationship with relative humidity. However, for data in selected stops, a high magnitude of GVI was detected to be a beneficial driving force that evoked positive emotions due to positive relationships of GVI with happy score, PRI, and ENRI. This means that green space exposure with more vegetation can generally evoke higher thermal comfort. According to these facial expression results, it can be speculated that the positive relationship between GVI and *CP* was more confirmative to the objective thermal comfort than the relationship between GVI and *DI*. High GVI impeded wind flow, which resulted in the negative relationship between GVI and wind velocity. This should have been a resistance to increase *CP*, but the large decrease in temperature caused by high GVI counteracted the deficiency of wind flow and led to a thermal comfort perception. It was also identified that wind flow did not contribute considerably to thermal comfort as strongly as temperature [79]. It was not the first time for our study to report that an increase in air humidity can evoke benefits in comfort perceptions [19,20]. Overall, vegetation dose in touchable nature during green space exposure was a precondition of thermal comfort perception, which was achieved by temperature decline and humidity increase, although a large canopy may decrease wind flow. This endorses the acceptance of our hypothesis through findings that people with heavy vegetation exposure can perceive thermal comfort through lowered power loss, which can be shown with more positive emotions on the face. Either *DI* or *THI* were not suitable variables for evaluating thermal comfort related to vegetation-related effects.

Data about all stops suggested that the relationship between GVI and plant diversity was highly varied among different urban parks. It is interesting to find that high GVI tended to predict lower species diversity in Beihu Wetland Park and World Sculpture Park. However, high GVI may also indicate more plant species in parks with ages over 80 years as well, such as those in the Zoo and Botanic Park, Jingyue Pool Park, and Nanhu Park. These suggest that relatively newly built parks were built with fewer vegetative species than those built with a longer history. It was also suggested that plant species richness increased with urban forest establishment in China, but the increasing rate of plant species was lower than that of urban forest expansion [82]. Lower diversity in newly built urban green space is not a unique case in China [83,84].

Unlike characteristics in relationships of GVI with equivalent variables, plant diversity indexes only showed positive relationships with *DI* with no essential relationships detected with *THI* and *CP* analyzed using data from selected stops. Slopes of correlations between plant diversity indexes and *DI* were much lower than those of correlations between GVI and *DI*. As was discussed in the preceding paragraph, *DI* changes did not show any statistical relationship with emotional perceptions, suggesting that its relationship with plant diversity did not supply any essential contributions to the perception of thermal comfort. Both the Simpson and Shannon indexes failed to show any relationships with most facial expression scores, except for sad score, which was increased at stops with high plant diversity. Visitors in this study looked unlikely to enjoy their time at stops with rich plant species, which cannot be explained from the perspective of thermal comfort perception. In a previous study, it was indicated that people tended to show more sadness on their faces when experiencing urban forests with diverse tree species, but they would show more smiles or positive moods when shrub and herbaceous species were high [17]. Based on this, we surmise that visitors in our study showed sad faces in urban parks mostly because they saw visible trees of diverse species, and they were judged to be unsatisfactory.

4.4. Micro-Climate and Thermal Comfort

Air temperature was a leading factor that ruled changes in thermal comfort for visitors exposed to urban GS. Its rise led to equivalent variables' changes towards a trend that reduced thermal comfort, which was demonstrated using data of two types. High temperatures can also stimulate perceptions of sad moods to the extent that visitors cannot control the sadness on their faces. This further led to overall decreases in net positive emotions' exhibition. These changes nearly synchronized with wind velocity by contrasting effects evaluated using data of both evaluation types. That is, high wind velocity tended to decrease *THI* and *DI* but increase *CP* as well. These changes did not evoke any responses of facial expressions in similar trends. Thence, wind velocity is a factor that can increase thermal comfort in theory, but it is unlikely a perceptible element. Instead, air humidity was a factor that can be perceived as a driving force to evoke thermal comfort up to an extent with positive emotions shown. This effect was synchronized with the control of power loss assessed by *CP*. The increase in air humidity contributed to the rise of *DI* and *THI*, which indicated a rising trend of thermal discomfort. However, these changes in highly moist air just showed an upregulation of thermal discomfort, which was not accompanied by exhibitions of emotional changes on faces. Overall, the coexistence of low temperature and high air humidity were critical combined driving forces that essentially evoked thermal comfort perceived by visitors in urban parks.

4.5. Limits of This Study

In spite of the profound results shown in our study, they can still be improved if the existing limits are overcome. Firstly, the use of facial expressions as a tool for evaluating thermal comfort was the key approach in this study. This has technical meaning because it is the nature of human beings to show sadness on their face if discomfort is perceived. Although a person may not always show smiles if thermal comfort is perceived, he/she may be evoked to show positive emotions by experiencing really comfortable environments. These can all make sense for most people, but serious validation is necessary to endorse the theoretical basis. The use of facial expressions as a proxy for estimating thermal comfort totally needs more theoretical bases to demonstrate the mathematic support for their relationship. Secondly, the variable *MTHI* was not tested in our study due to the limits of special areas in the five chosen parks. It would be better to involve this parameter as it engages thermal comfort at a higher precision than *THI*; hence the employment of *MTHI* may lead to more reliable results. Larger parks are suggested to enable tests using *MTHI* as an estimate of LST needs at least grids of 10×10 m and a park's largeness may need to be at least 10 ha in area. Finally, the number of visitors involved in this study can be higher if a higher accuracy of evaluation is achieved using facial expression scores. This is strongly suggested in future works because facial expressions show many possible intentions. Only when the number of involved subjects is large enough can the technical bias of difference among individuals be eliminated.

5. Conclusions

In this study, facial expression scores were employed as a meter of the expressed emotions of visitors exposed to thermal environments in urban parks. This is the major part accounting for the novelty of this study to evaluate thermal comfort from a new angle. Sad score was the unique variable that was shown with a similar magnitude of thermal comfort evaluated by equivalent meteorological factors. The equivalent variable, *CP*, which was evaluated by synthesizing changes in temperature and wind velocity, can indicate thermal comfort with less sadness (-0.20 ± 0.07) and more positive emotions (0.31 ± 0.10). Streetscape was proven to be an available instrument through which extracted GVI ($55.58 \pm 20.91\%$) can predict dual changes in temperature and air humidity towards a trend of increasing thermal comfort. In scenarios with high GVI, equivalent thermal comfort was strengthened with more positive sentiments shown on visitors' faces. Plant diversity stimulated the presentation of sadness (7.12 ± 2.64), which was irrelevant from thermal comfort perceptions. Overall, our study demonstrated that using imagery data extracted from streetscapes can be available for evaluating thermal comfort. The implicative meaning mainly came from the use of streetscapes for analyzing the magnitude of green space exposure and thermal comfort evaluation using facial expression scores. It is recommended to plan a large amount of touchable nature provided by vegetation in urban parks so as to mitigate micro-climates towards a trend with more thermal comfort that evokes more positive emotions on visitors' faces.

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