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Can Indoor Residents Perceive Green and Blue Spaces in Communities as Posted Sentiments? A Verification in Nanchang

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Abstract: Ecological infrastructures (EIs), such as public and urban green and blue spaces (GBSs), have been well demonstrated to benefit visitors' mental well-being. Experiences in community GBSs may also evoke positive emotions for their residents. In this study, 54 communities in Nanchang were chosen as objective sites, where landscape metrics of GBSs were remotely evaluated. A total of 2105 local residents' facial expressions (with happy, sad, and neutral emotions) were obtained from Sina Weibo. Inhabitants showed more net positive emotions (happy minus sad) in cold seasons, and females smiled more frequently than males. Newly constructed communities with houses for sale had larger areas of normalized difference vegetation index (NDVI) and built-up index compared to communities with no houses for sale. Neither the availability of houses for sale nor housing price had any effect on facial expression scores. Poisson regression revealed significant coefficients (β) of positive emotions with largeness of green space (GS) and blue space (BS). Overall, BS had a stronger contribution (β, 0.6–1.1) to residents showing positive emotions relative to GS (β, −2.45–0.89), whose area ratio of NDVI increased the frequency of showing happiness. We recommend constructing GBSs with over 0.68 km^2 of GS and over 2000 m^2 of BS per community, where the area ratio of GS should be more than 70% of the total if the goal is to evoke more happiness in residents.

Keywords: private infrastructure; green and blue spaces; human health and well-being; facial expressions; perception of satisfaction

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1. Introduction

Both urban and rural inhabitants experience stressful life events across a wide demographic spectrum [1,2]. The COVID-19 pandemic increased mental stress for a wide range of the population [3,4]. People are seeking outlets to relieve stress and to get rid of mental fatigue. It has been suggested that interacting with nature can benefit mental health by alleviating anxiety and tension [5,6]. Urban green and blue spaces (GBSs) are two major types of ecological infrastructures (EIs) that are accessible to communities [7,8]. Experiences in GBSs can promote human health and well-being by alleviating mental stress [9,10]. The benefits of GBSs in parks have attracted major public attention [11,12]. GBSs in urban communities also account for an important proportion of EIs in a city [13–15], but their benefits have received less attention.

A community is a place where its residents build interpersonal relationships with each other. It is also a place where people experience emotional attachment to their estate(s) [16]. Evidence shows that GBSs in a community improve mental health and promote attachment to the community [17,18]. Stress recovery theory (SRT) emphasizes experiencing nature to reduce mental stress and promote psychological recovery [5]. Surveys among local stakeholders, residents, and visitors revealed that community GBSs can cause people to reflect on their well-being [19,20]. However, there may be at least three queries that limit the effects of community GBSs, which would challenge these findings. They are commercial aspects of a community, sentiment assessment at reliable accuracy, and, assuming the first

two queries, the mechanism by which landscape metrics drive emotional responses. All these queries need to be addressed in a context where people's frequency of interacting with community GBSs may differ.

Housing price has an association with the socioeconomic status of residents in a community [7]. EIs in a community matter for housing price because green space has a close association with the value of a community's real estate [21]. There are several attributes of green spaces within or surrounding communities that may be determinant for housing prices. For forest structure dimensions, connected or closely spaced trees with big crowns were found to be associated with a higher property value, but fragmented or spaced green landscape was associated with a lower property value [21,22]. A large area of green space does not necessarily mean people will frequently interact with it [12]; hence, greater accessibility to green space was also associated with a higher property value [7,22]. Visual contact with green space had an even greater association with housing price compared to accessibility to green space [22]. Greater accessibility to blue space was also associated with higher housing prices [23]. Therefore, it is reasonable to speculate that people living in upscale communities have better well-being because their communities have larger areas of GBSs. However, people living in upscale communities may also experience more positive emotions when they perceived safety with neighbors [24,25]. It is still unclear how the well-being of residents living in communities with GBSs rank by housing price.

In a systematic review, Jabbar et al. [26] put forth a summary of human well-being for those who have experienced urban green spaces. Its assessment can be summed up into six categories of well-being: physical, psychological, mental, social, subjective, and environmental perceptions. For modern residents, stress is a major factor in low quality of life. Stress imposes physical and psychological pressures, which degrade health and well-being [27]. The restoration elicited by an experience in green space had been mostly assessed by self-reported scores on questionnaires [20,28]. This methodology was queried for its accuracy regarding human errors caused by mental fatigue or making overly reserved judgments [29]. In addition, many questionnaires used for evaluating green space experiences were not validated at all [30]. Self-reported scores may not be fully reliable for academic usage [31]. There is a significant labor and time expenditures in recruiting participants and completing surveys [32]. An alternative methodology was suggested and is being employed to rate facial expressions as a gauge to assess emotions [33]. Facial expression score is a sensitive parameter that reflects emotions of GBS experiencers either at subjects' unconsciousness [34–36] or with their awareness of being photographed [11,37–40]. Facial expressions can be easily obtained from social media and compiled to create a large reserve of data; hence, this method was frequently used to assess the emotions of a big group of people who were experiencing public green spaces at large geographical scales [37,41–43]. These together suggest a potential to use facial expressions as an assessment the emotions of community residents that have experienced GBSs. However, to our knowledge, there have been few relevant studies.

People debate about the mechanism of SRT. There has been an agreement on the aspects of public GBSs that can be perceived. Themes include biodiversity [41,44], microclimate [35,39,40,45], soil properties [46], municipal dimensions [37], and regional landscape metrics [11,38,42]. GBS landscapes consist of horizontal and vertical planes and are also present in private communities [47,48]. According to findings from GBSs in public parks, people experience more positive emotions in landscapes with larger areas and lower elevations [11,38,42]. This may also be the case for GBSs in communities, but relevant evidence is highly scarce. Community residents spend a large proportion of their daily time at home; hence, technically, people spend more time in closer proximity to GBSs in communities than in public parks. The largeness of GBSs can vary among communities according to housing prices. Further investigations on the facial expressions of people living in communities at different prices are needed to verify the discussed mechanisms.

This study was conducted in Nanchang, where 54 communities were targeted as study sites across a remarkable range of housing prices. Facial expressions were obtained

from people, in communities ranked at varied price categories, who took selfies at home and posted them on social media. Landscape metrics were remotely evaluated to detect their differences among communities at different prices and to evaluate the mechanism that causes people to show emotions in relation to the size of GBSs. We hypothesized that: (i) communities at higher housing prices are constructed with larger areas of GBSs, (ii) which resulted in residents smiling more. We also assumed that (iii) the largeness of GBSs was the driver of community residents showing positive emotions shown on their faces.

2. Materials and Methods

2.1. Study Area and Basic Condition

This study was conducted in Nanchang (28°10′–29°11′ N, 115°27′–116°35′ E). Nanchang is the capital of Jiangxi, which contains six districts and three prefecture-level counties and accounts for an area of 195 km^2. At the end of 2021, the resident population of Nanchang was 6.44 million and the gross domestic product was RMB 0.67 billion. Due to its sub-tropical monsoon climate, the average annual temperature is 17.35 °C, and the daily temperature ranges between 40.9 °C and −15.2 °C. Annual rainfall averaged 1650 mm over 150 d. The average RH was 78.5% and annual sunlight duration ranged between 1723 h and 1820 h.

2.2. Commuinity and Property Value

A total of 54 communities were chosen in this study wherein 5 had houses for sale and 49 had no houses for sale (Table 1). Housing price was averaged from numbers published by online agencies, such as Shell Houses [49], Lianjia [50], Fang [51], and 58 City House [52]. Average housing prices ranged from RMB 6818 m^{-2} to 30,153 m^{-2}, which were categorized by price into high (>20,000 CNY m^{-2}, n = 8), medium (10,000–20,000 CNY m^{-2}; n = 39), and low (<10,000 CNY m^{-2}; n = 7). The spatial distributions of these communities are shown in Figure 1.

2.3. Landscape Metrics

The landscape metrics are green space, blue space, and the built-up space for communities in ArcGIS version 10.2 (Eris China, Shanghai, China). All landscape metrics were remotely evaluated using 30 m × 30 m resolution Landsat 8 OLI satellite images. The boundary of every community was outlined by people using geographical references from Baidu Map [53]. The area of every community was vectorized to a new shape file where the landscape metrics were extracted. Green space area was characterized as the largeness of normalized difference vegetation index (NDVI) according to an equation using bands in Landsat 8 imageries:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where *NIR* and *Red* are band 5 and band 4, respectively. Modified normalized difference water index (MNDWI) was calculated as [54]:

$$MNDWI = \frac{Green - SWI1}{Green + SWI1} \quad (2)$$

where *Green* is band 3 and SWI1, an abbreviation for short-wave infrared 1, is band 6 (1.57–1.65 μm) [55]. Normalized difference built-up index (NDBI) was calculated as [56]:

$$NDBI = \frac{Red - Green}{Red + Green} \quad (3)$$

The largeness of EIs was estimated as the areas of NDVI, MNDWI, and NDBI by the area of the community. Regarding potential errors in the outline of the grid, the total area of the landscape metrics was calculated as the sum of the areas of NDVI, MNDWI, and

NDBI, and not as the area of the outlined grid. In addition to the landscape metrics' areas, their ratios to the total area of every community were also calculated in percentage.

Table 1. Name and location of communities in Nanchang and the number of photos of inhabitants who took selfies and uploaded them to Sina Weibo in 2021.

Order	Longitude (°)	Latitude (°)	Community Name	Price [1] (Yuan m^{-2})	Category [2]	Sale Type [3]	Photo Number
1	115.83	28.70	Aux Shengshihuating	30,153	High	Sold	26
2	115.88	28.59	Baoji Isle	23,036	High	Sold	41
3	115.76	28.71	Paoli Half-hill International	22,678	High	Sold	48
4	116.00	28.69	Paoli Champagne International	20,561	High	Sold	57
5	115.88	28.68	Riverside No. I	20,426	High	Sold	49
6	116.04	28.68	Chengtai Versailles Palace	20,205	High	Sold	84
7	115.92	28.59	Zhengrong Lake Capital West Shore	20,149	High	Sold	54
8	115.89	28.60	Fengyuanchunhe	20,041	High	Sold	32
9	115.87	28.63	Guomao Sunshine	19,528	Medium	On-sale	39
10	116.02	28.68	Hanyuan Estate	19,266	Medium	Sold	45
11	115.87	28.57	Hengda City	19,110	Medium	Sold	56
12	115.98	28.71	Hengda Town	18,435	Medium	Sold	35
13	115.85	28.67	Honggu Spring Garden	17,903	Medium	Sold	42
14	115.86	28.69	Honggu Triumphant Return	17,703	Medium	Sold	51
15	115.81	28.67	Honggu New Town	17,553	Medium	Sold	17
16	115.83	28.67	Red Mountain Garden	17,346	Medium	On-sale	58
17	115.85	28.69	Hong City Bevely	16,626	Medium	Sold	30
18	115.84	28.73	Hongkelong Great Britain Union	16,486	Medium	Sold	49
19	115.91	28.57	Huiren Sunlight Garden	15,726	Medium	Sold	30
20	115.89	28.58	Jiangxi Olympic Garden	15,704	Medium	Sold	48
21	115.85	28.68	Jiangxin International Garden	15,675	Medium	Sold	53
22	115.88	28.58	Jingcheng Prefecture	15,389	Medium	Sold	39
23	115.89	28.60	Jiuli Xianghu Town	15,090	Medium	Sold	36
24	115.84	28.68	Liantai Vanille Center	14,625	Medium	Sold	34
25	115.88	28.72	Greenland Bund Residence	14,310	Medium	Sold	52
26	116.00	28.68	Greenland New Metropolis	14,262	Medium	On-sale	46
27	115.93	28.55	Dream land over water	14,205	Medium	Sold	51
28	115.85	28.68	Gentlefolk	13,600	Medium	Sold	49
29	115.93	28.51	Nanchang Hengda Oasis	13,208	Medium	Sold	25
30	115.82	28.71	Southern Day Sunlight	13,062	Medium	Sold	22
31	115.89	28.59	Safeness Xianghu Scenery	12,747	Medium	Sold	35
32	115.90	28.64	Millennium Summer Palace	12,633	Medium	Sold	13
33	115.95	28.70	Qingshan Lake Xiangyi Flower City	12,551	Medium	Sold	41
34	115.85	28.68	Century Central Town	12,459	Medium	On-sale	26
35	115.87	28.71	Godsent Great City	11,922	Medium	Sold	15
36	115.86	28.67	Wanda China Mansion	11,865	Medium	Sold	28
37	115.98	28.70	Wanke Seasonal Flower City	11,648	Medium	Sold	51
38	115.88	28.60	Great Dream Clearwater Bay	11,314	Medium	Sold	45
39	115.84	28.68	Weidong Garden	11,301	Medium	Sold	60
40	115.94	28.55	Xingzhou International	11,233	Medium	Sold	50
41	115.79	28.69	Coastal Lishui Homestead	11,164	Medium	Sold	25
42	115.94	28.52	Galaxity Shuiyue Bay I	10,828	Medium	On-sale	23
43	115.86	28.60	Yinyi Optimum City	10,479	Medium	Sold	12
44	115.92	28.65	Yu River Mingzhu Residence	10,364	Medium	Sold	39
45	115.95	28.70	Zhongda Qingshan Lake East	10,354	Medium	Sold	15
46	116.00	28.71	ZTE He-Garden	10,342	Medium	Sold	29
47	115.84	28.70	Zhongsen Honggu Premium	10,324	Medium	Sold	19
48	115.91	28.70	Forbidden City Red County	9554	Low	Sold	37
49	115.84	28.67	Mediterranean Sunlight	9463	Low	Sold	42
50	115.84	28.66	Green Lake Great City	9133	Low	Sold	45
51	115.83	28.74	Wanke Golden Realm International	8957	Low	Sold	11
52	115.80	28.59	Greenland Luzern Village	8915	Low	Sold	76
53	115.84	28.65	Liantai Xiangyu Riverside	8404	Low	Sold	42
54	115.90	28.69	Blue Day Water New World	6818	Low	Sold	28
						Total	2105

Note: [1] housing prices are presented as averages across that published by three commercial estate websites in 2021; [2] price category refers to the level of estate values: high, housing price > 20,000 CNY m^{-2}; medium, housing price of 10,000–20,000 CNY m^{-2}; low, housing price < 10,000 CNY m^{-2}; [3] Sale type refers to the merchant state of the community with houses sold out (Sold) or parts of houses that are for sale.

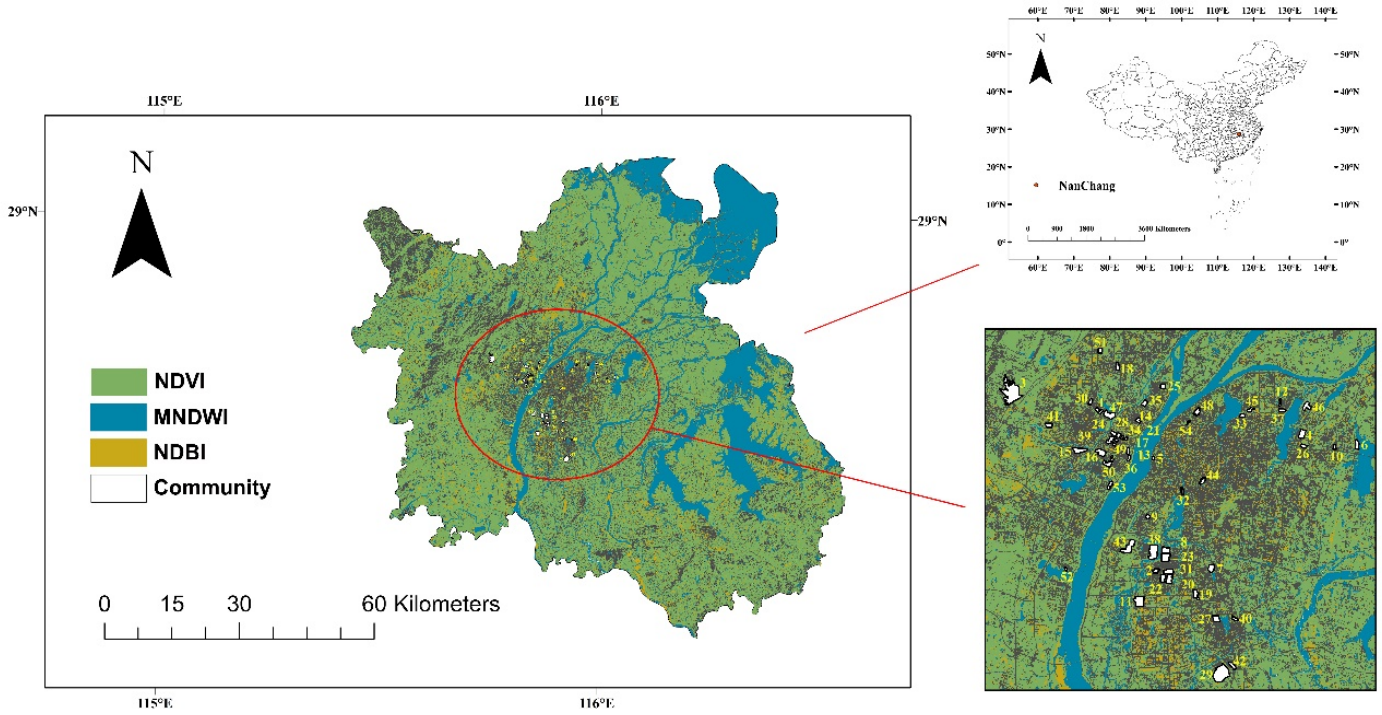


Figure 1. Location of Nanchang city in China with spatial distributions of landscape types and communities. Number of communities refers to order in Table 1. Abbreviations: NDVI, normalized difference vegetation index; MNDWI, modified normalized difference water index; NDBI, normalized difference built-up index.

2.4. Facial Photos of Community Residents

The use of facial expression data has been applied in an ethic statement and approved by the ethic board committee of College of Environment and Bioresources, Dalian Minzu University (Reference code: ES-ERC-2021-004). Sina Weibo is recognized as "Chinese Twitter" because it has a similar social interaction between or among its users as Twitter. Users can share photos showing their faces as soon as they feel emotions at a special place. This results in a pair of data: geographical information from a check-in location and the emotion assessed from users' faces. This enables analysis about the emotional responses of people, from their facial expressions, in relation to geographical factors such as location [33], municipal dimensions [37], microclimate [39,40,43], landscape metrics [11,38,42], and forest plant biodiversity [41]. Most users of Sina Weibo come from mainland China; hence this population's facial expressions were targeted as the source of data to analyze the benefits of public EIs [31,34–36,57].

In this study, photos of people's faces taken in each community were collected from Sina Weibo. Most of the photos were selfies and very few of them were taken by others. All photos had to be a portrait with locations tagged at the communities. We admit that there is some probability that a person took a photo of themself, which captured their emotions at that moment, and the person then posted the photo to Sina Weibo at a later time or a different place. The probability of this behavior may be low, so we assume it would not impact our results. All photos included only one person per shot. We processed photos with previously suggested treatments to increase the success and accuracy of recognizing and analyzing facial expressions [11,35,39,41]:

(1) All facial expressions must be fully visible and without any covers over the face.
(2) Digital decorations of the face can only be accepted if they do not change the recognition of the original face.

(3) Photos need to be rotated unless the axis of the nose was perpendicular to the horizontal line of the screen.

Photos were sent for analysis of expressions and rating of emotions using FireFACE software in its 1.0 version [38,40,46]. This version of the software can recognize emotional expressions on faces with East Asian characteristics to an acceptable extent that passes facial validation tests [31,34]. The software was trained to rate happy, sad, and neutral expressions as gauges of positive, negative, and indifferent emotions, respectively, in percentages. According to face coding theory [58], people who study facial emotions agree that a face is a complex of multiple expressions which reflect contrastingly positive (happy) and negative emotions (e.g., sad, contempt, angry). The software was trained to recognize the sum of frequencies of whether a face is about to smile (happy) or not (unhappy) and rated the total frequency of a face (100%) into proportions of happy, sad, and indifferent emotions. Given that a facial expression consists of multiple emotions [59], we assess net positive emotion (NPE) as an index by the equation [33]:

$$NPE = Happy - Sad \quad (4)$$

where *Happy* and *Sad* are scores of happy and sad emotions rated by the instrument.

2.5. Data Analysis and Statistics

This study analyzed data using SPSS 26.0 (IMB SPSS Statistics, Chicago, IL, USA). All our data passed the test for normal distribution and their variances showed no heterogeneous manners. First, data of people's facial expressions were collected in every community in Nanchang across the year 2021. Every record of facial data had to be validated according to the criterion that all emotions (happy, sad, and neutral) can be recognized. Any data with three zeros were categorized as invalid and were not used in this study. Analysis of variance (ANOVA) was used to analyze each person's facial expression in response to gender (male vs. female) and season (spring, summer, autumn, winter) by a mixed model [34,35]. Thereafter, per-person facial data were bulked by being averaged into groups in every community. ANOVA was also used to compare results about facial expression scores and landscape metrics among different communities that varied by type (sold out vs. for-sale) and price category (low, medium, high) using two-way ANOVA models. When significant effects were indicated, results were averaged and compared to either main effects (type or price category) or combined effects (type × price category). Means were compared using the Duncan multiple range test to cope with the issue of means from grouped observations having uneven numbers of replicates [42,43,46]. To detect the mechanism driving facial expression changes in community GBSs, the Poisson regression model was used to detect the most likely predictions of facial expression scores against parameters of each level at every landscape metric [33,40,43]. When significant parameters (coefficients) were estimated, they were further detected for their correlation with landscape metric size and area ratios using polynomial quadratic or linear models to characterize the critical values [40,43]. Significance was determined by confidence of probability over 95% for both ANOVA ($p < 0.05$) and Poisson regression ($ChiSq < 0.05$).

3. Results

3.1. Seasonal Variation of Facial Expression Scores of Community Dwellers in Contrasting Genders

The interaction between season and gender did not have significant effects on happy and sad scores and NPE (Table 2). Both season and gender had a significant main effect on the three types of facial expression scores and their interaction had an effect on neutral score. Happy scores changed to a significant level across different seasons (Figure 2A) and was higher in autumn and winter (~41%) than in spring and summer (34%–35%). Females had higher happy scores (~40%) than males (~37%) (Figure 2B). Sad scores did not show any significant seasonal variation in a range between 10% and 12% (Figure 2C). In contrast,

females had lower sad scores (~10%) relative to males (12%) (Figure 2D). Like happy score, NPE showed a similar trend across seasons and was higher in autumn and winter (~30%) than in spring and summer (~25%) (Figure 2E). Again, females had a higher NPE (~30%) compared to males (~20%) (Figure 2F). Neutral score was higher for males in spring (~70%) than in any other combination of season and gender (Figure 2G).

Table 2. *F* values from mixed-model analysis of variance (ANOVA) of seasonal variation (Season), gender, and their interaction (Season × Gender) on facial expression scores of community inhabitants in Nanchang.

	Source of Variance		
Tested Variables	**Season**	**Gender**	**Season × Gender** [1]
Happy	3.73 * [1]	4.09 *	2.78
Sad	1.07	5.36 *	0.94
Neutral	3.28 *	1.94	3.90 **
NPE [2]	3.55 *	5.45 *	1.88

Note: [1] asterisk number marks significance of ANOVA effect: *, $p < 0.05$; **, $p < 0.01$; [2] NPE, net positive emotion index.

3.2. Effects of Community Attributes on Scores of Facial Expressions

According to Table 3, neither property type nor price category had any significant effects on facial expression scores (Table 3). Happy score ranged between 18.44% and 69.04%. People in communities with houses for sale had a median happy score of ~40% and a mean happy score of ~45%, while those in communities with no houses for sale had a median happy score of ~34% and a mean happy score of ~38% (Figure 3A). Median happy score was about 30%, 35%, and 40% and mean happy score was about 31%, 40%, and 41% for communities at low, medium, and high prices, respectively (Figure 3B). People in communities with houses for sale and communities with no houses for sale had a median sad score of ~8% and ~11%, respectively (Figure 3C). Means of sad scores were ~9% and ~10% for communities with houses for sale and communities with no houses for sale, respectively. Median sad score was 10.3%, 11%, and 10.9% in communities at low, medium, and high prices, respectively (Figure 3D). Means of sad scores were 11.4%, 10%, and 10.1% for categories of communities at low, medium, and high prices, respectively. Regarding neutral score, people in communities with houses for sale had a median and mean of ~49%, while those in communities with no houses for sale had a median of ~55% and a mean of ~50% (Figure 3E). Median neutral score was 56%, 51%, and 49% in communities at low, medium, and high prices, respectively (Figure 3F). Means of neutral scores were 57%, 50%, and 50% at low, medium, and high prices, respectively. Median NPE was 39% and 22% for communities with houses for sale and communities with no houses for sale, respectively, while mean NPE was 31% and 29% for those respective communities (Figure 3G). Median NPE was 18%, 21%, and 27% for low-, medium-, and high-price communities, respectively, while mean NPE was 20%, 30%, and 31% (Figure 3H).

3.3. Effects of Community Attributes on Landscape Metrics

According to Table 3, the type of community had a significant main effect on the largeness of NDVI, NDBI, and total area (Area), but the price category had no effect on these parameters. The largeness of NDVI was 0.30 ± 0.30 km^2 (mean ± standard deviation) in communities with houses for sale and 0.12 ± 0.14 km^2 in communities with no houses for sale (Figure 4A). NDVI largeness ranged from 0.08 ± 0.05 km^2 to 0.15 ± 0.12 km^2 in descending order of community prices. MNDWI largeness ranged between 1650 ± 617 m^2 and 5400 ± 1158 m^2 with no responses to community type or price category (Figure 4B). NDBI largeness was 0.02 ± 0.02 km^2 and 0.09 ± 0.14 km^2 for communities with no houses for sale and communities with houses for sale, respectively (Figure 4C). Communities in the high price category have nearly no NDBI largeness and those in medium- and low-price categories have NDBI largeness of ~0.03 km^2. Communities in the medium price category

with houses for sale have higher NDBI largeness than communities with no houses for sale at any price category (Figure 4C). Again, the medium-price communities with houses for sale also have higher Area largeness than communities with no houses for sale at all three price categories (Figure 4D).

Table 3. *F* values from ANOVA of community-property effects of product-type (Type: sold vs. on-sale), price category (Category: low, medium, and high), and their interaction (Type × Category) on facial expressions of inhabitants (happy, sad, neutral etc.) and estate landscape metrics.

Tested Variables	Source of Variance		
	Type	Category	Type × Category [1]
Happy	0.38	1.33	1.01
Sad	1.53	0.16	0.62
Neutral	0.12	1.46	1.01
NPE [2]	0.63	1.15	0.98
NDVI [3]	6.15 * [4]	0.41	2.32
MNDWI [5]	1.21	0.24	2.32
NDBI [6]	11.69 **	0.62	4.31 **
Area [7]	8.07 **	0.52	3.03 *
NDVIR [8]	0.12	2.12	1.45
MNDWIR [9]	0.01	0.48	0.32
NDBIR [10]	0.14	2.07	1.43

Note: [1] Data do not support two-way ANOVA about effects of interactions; hence source of variance in Type × Category effect was evaluated by one-way ANOVA using data of combined Type and Category treatments; [2] NPE, net positive emotion index; [3] NDVI, normalized difference vegetation index; [4] asterisk number marks significance of ANOVA effect: *, $p < 0.05$; **, $p < 0.01$; [5] MNDWI, normalized difference water index; [6] NDBI, normalized difference built-up index; [7] Area, total area of NDVI, NDWI, and NDBI; [8] NDVIR, the relative area ratio of NDVI to Area; [9] MNDWIR, the relative area ratio of MNDWI to Area; [10] NDBIR, the relative area ratio of NDBI to Area.

None of the area ratios of landscape metrics had a response to community characteristic factors (Table 3). Ranges of area ratios were 83.91%–94.17%, 0.16%–0.74%, and 5.68%–18.09% for NDVI, MNDWI, and NDBI, respectively.

3.4. Regression of Facial Expression Scores against Landscape Metrics

Residents' happy scores can be regressed against the observed levels of NDVI largeness (0.02 km^2 to 0.78 km^2), while the coefficient of NDBI largeness was estimated to be 1.26 at NDBI largeness of 0.0018 km^2 (Figure 5A). The relationship between the observed levels of NDVI largeness and the estimated parameter for the happy score can be described by a polynomial quadratic equation with a U-shape curve. It was indicated that the happy score coefficient decreased as NDVI largeness increased from 0–0.38 km^2, and the lowest happy score coefficient was −2.53 (Figure 5A). The relationship between the happy score coefficient and the area ratio of NDVI can be described as linear with the slope increasing from 69.33% to 98.81% (Figure 5B).

The sad score failed to be regressed against any landscape metrics, and no results are shown. Neutral score can be regressed against both largeness (Figure 5C) and area ratio (Figure 5D) of NDVI. The neutral score coefficient was −0.43 when NDVI largeness was around 0.02 km^2, and it increased up to ~0.8 as NDVI largeness increased up to 0.08 km^2. The neutral score coefficient ranged from −0.92 to 0.43 as the area ratio of NDVI ranged from 84.51% to 98.81% (Figure 5D).

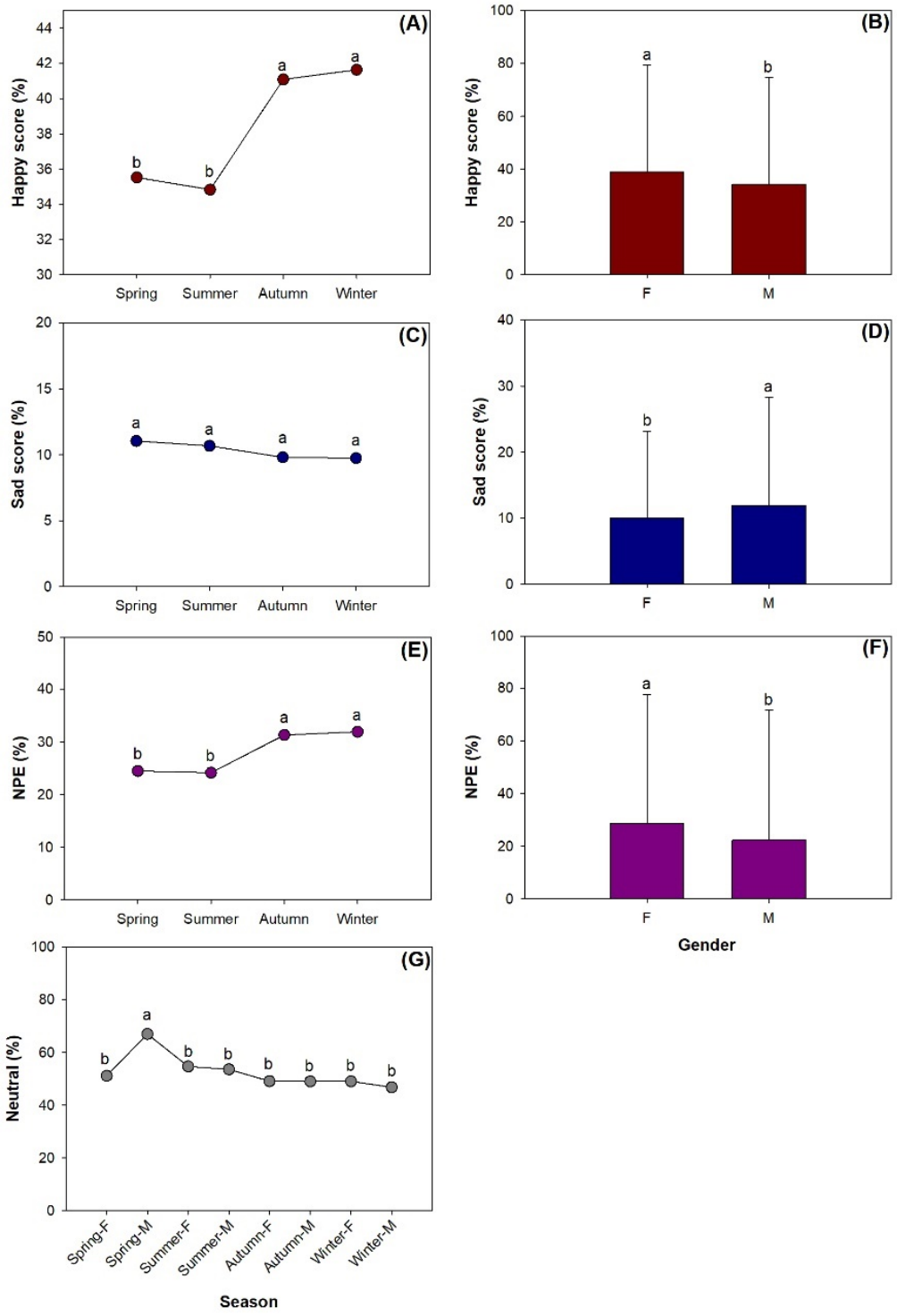


Figure 2. Dynamic changes of facial expression scores for happy (**A**,**B**), sad emotions (**C**,**D**), net positive emotion index (NPE; **E**,**F**), and neutral emotion (**G**) of community residents of differing genders (female, F; male, M) and seasonal dynamic of neutral scores for both genders. Error bars mark standard deviations; different letters label significant difference identified by Duncan multiple range test at 0.05 level.

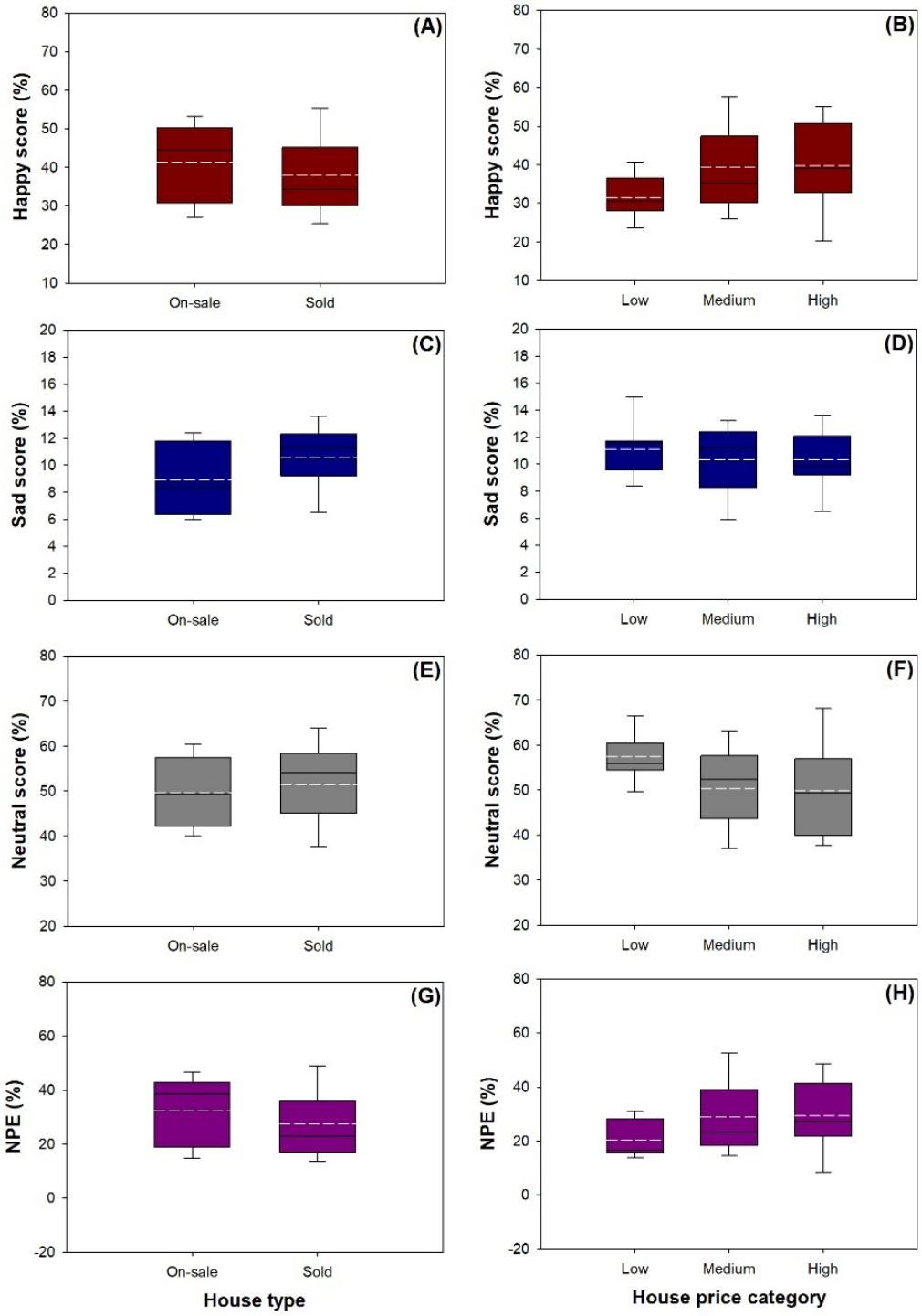


Figure 3. Whisker-box plots happy (**A**,**B**), sad (**C**,**D**), and neutral emotional scores (**E**,**F**) and NPE (**G**,**H**). A box frames the range of data in 25% (upper) and 75% (lower) quantiles attached to bars marking 5% (upper) and 95% (lower) quantiles. Within-box dash line stands for the level of median level and dashed line for the mean.

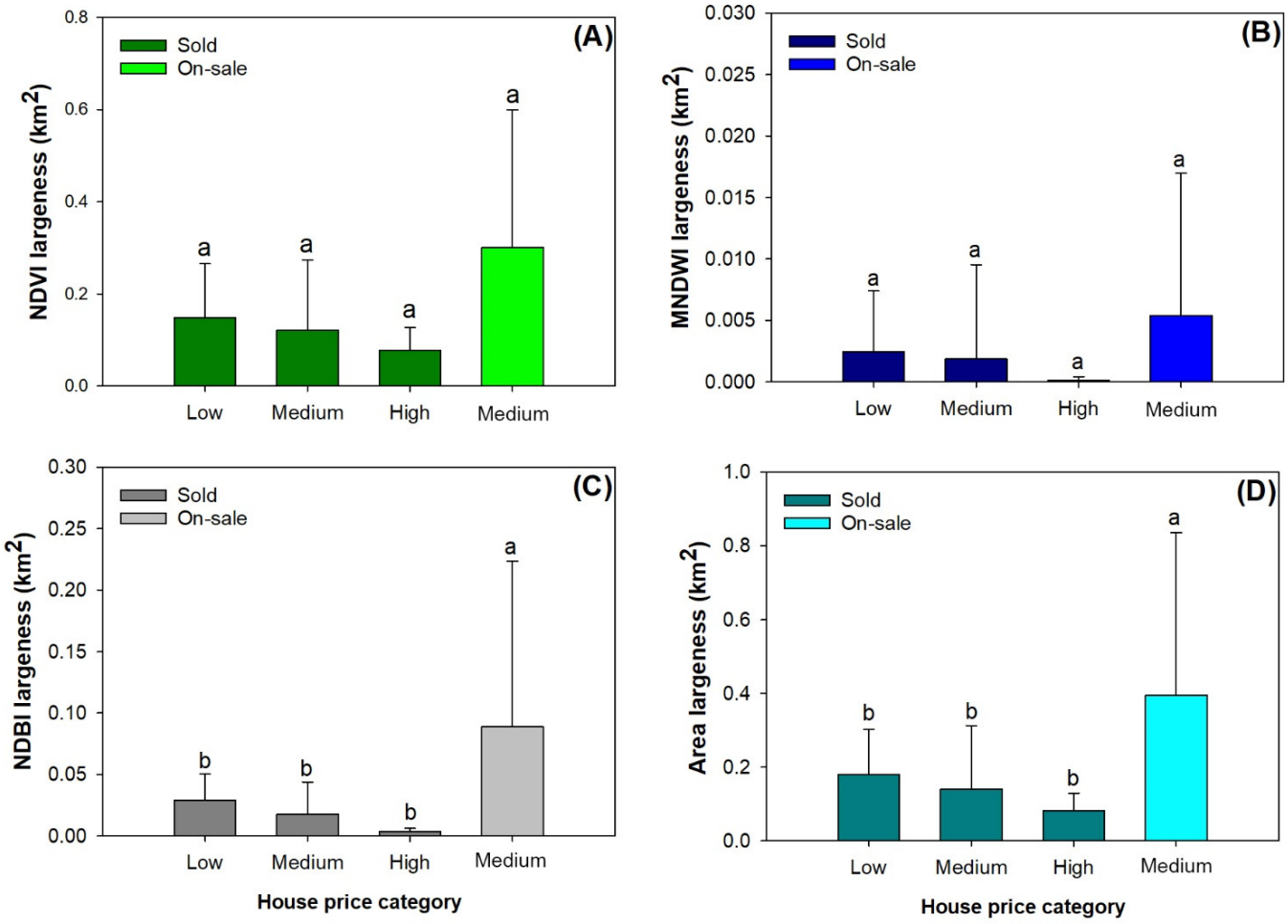


Figure 4. Landscape metrics variation in communities of largeness for NDVI (**A**), MNDWI (**B**), and NDBI (**C**) and the total area of green and blue spaces and built-up lands (Area) (**D**). Columns are means of areas and bars mark standard deviations. Different letters identify significant difference according to Duncan multiple range test at 0.05 level. Communities are classified to types of all houses sold out (Sold) and some on sale (On-sale) at price categories of low, medium, and high levels.

NPE can also be regressed against NDVI largeness with a quadratic equation (Figure 5E). It was indicated that the NPE coefficient was lowest (−3.64) when the level of observed NDVI largeness was 0.37 km^2. Meanwhile, the NPE coefficient ranged from 0.65 to 1.08 as MNDWI largeness ranged from 0 to 1800 m^2 (Figure 5G) with the NPE coefficient of 1.85 regressed against the observed MNDWI largeness of 1800 m^2. NPE can also be regressed against the area ratio of NDVI largeness, but no further relationship can be detected (Figure 5F).

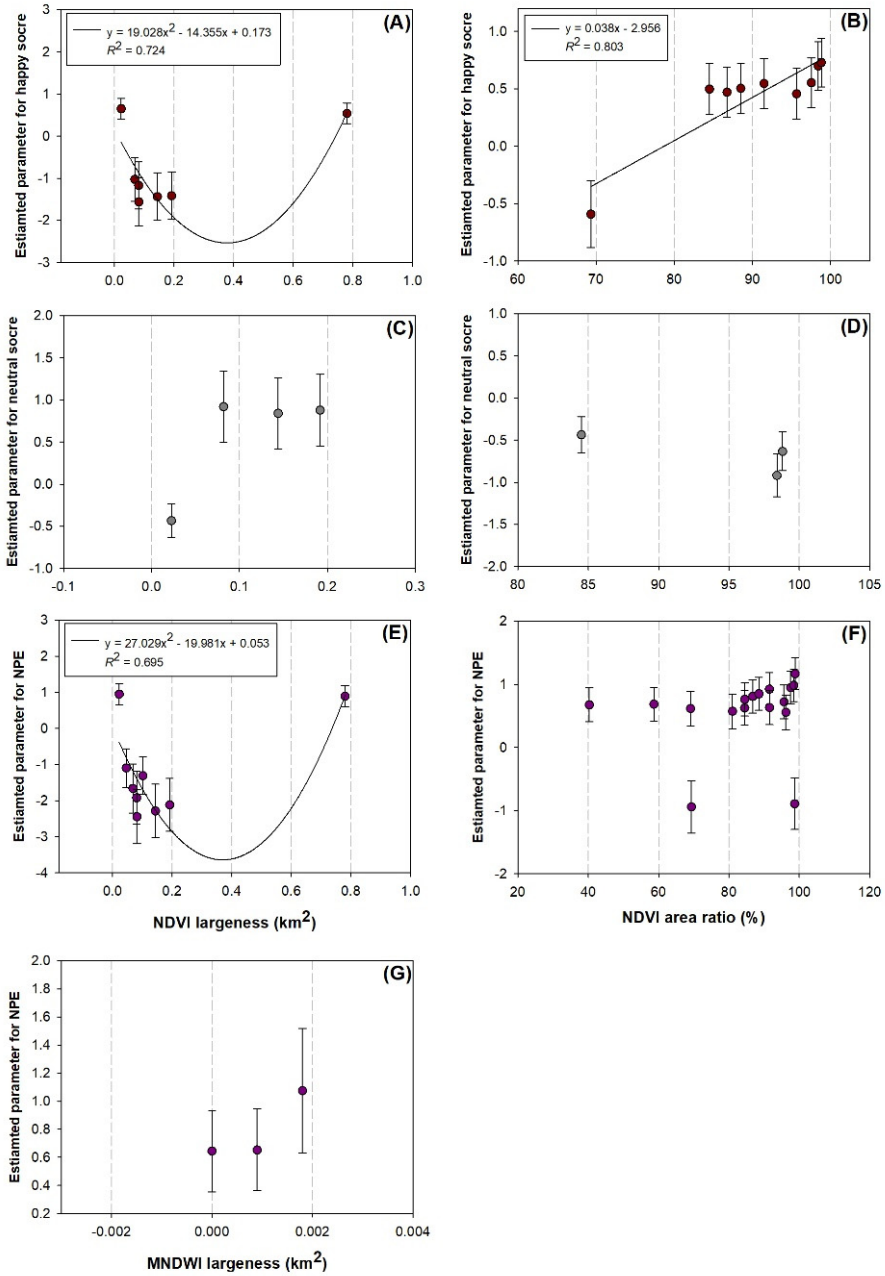


Figure 5. Poisson regression of facial expression scores for happy (**A**,**B**) and neutral (**C**,**D**) emotions and NPE (**E**,**F**) against NDVI largeness (**A**,**C**,**E**) and NDVI area ratio (**B**,**D**,**F**) or for NPE against MNDWI largeness (**G**). Dots are parameters (coefficients) estimated by maximum likelihood in Poisson models with error bars marking standard deviations against observed landscape metric largeness. Polynomial quadratic or linear equations are given based on significant correlation ($p < 0.05$) with determinative coefficient (R^2) disclosed.

4. Discussion

4.1. Landscpe Metrics in Communities of Different Attributes

We cannot accept our first hypothesis because neither the green space area nor the blue space area varied significantly by housing price. Our results disagree with previous findings that support the argument that GBS largeness is positively associated with property value and price [21,23]. There are several explanations for this disagreement, and we would like to disclose the first three that we can surmise. First, evidence that suggests an association between GBS and housing price relies on the precondition that the large landscape had

to be connected rather than fragmented [21,22]. Therefore, the reason for the association between GBSs and housing prices may be the GBS's landscape, rather than its area size. For example, Kim et al. [21] reported the positive association between green space area and housing price in Austin, TX, USA, but the objective was mostly single-family houses where having a large area of green space is difficult unless the green space was connected through multiple properties. Wu et al. [22] also reported an association between green space area and property value in China, but the green space was estimated from the respondents' perceptions of the space instead of being remotely measured. Second, GBS area tends to associate with housing prices in super large cities [7,22] where the resident population is highly dense, especially in communities that would compete with EIs for public land. The city in this study, Nanchang, only had a resident population of 6.44 million, which can be characterized as a mega-scale city [60]. It was unlikely for communities in Nanchang to compete with EIs for land. Finally, sufficient accessibility to and visual contact with GBSs may be the key reason for the association between the size of GBSs and housing prices [7,22,23]. Most of our communities were constructed with evenly distributed GBSs scattered around buildings; hence residents should also have an even chance to access and make visual contact with nature in their communities.

Among the three categories of housing prices, only the medium price category (10,000–20,000 CNY m^{-2}) had a significant difference in NDBI largeness between communities with houses for sale and communities with no houses for sale. In our study, communities with no houses for sale were built earlier than those with houses for sale. Newly constructed communities were mostly located in the suburbs and have a denser residential population and larger area (Figure 1; Table 1). The residents in this type of community did have even access to experiencing GBSs, but most of the communities' houses were all sold out. Older communities were mostly located in early developed regions of the city center, e.g., around areas of downtown beside the river where the space to introduce more trees or wetlands was limited. Therefore, we can conclude that the null difference in GBSs among communities in the region was due to a limited space that prevented the construction of EIs for old communities and buildings for new communities.

4.2. Facial Expressions of Residents in Communities of Different Attributes

We also cannot accept our second hypothesis. None of our facial expression scores showed any responses to the type of community. The second hypothesis was put forth based on the first hypothesis and SRT theory. As we discussed above, the null difference in GBSs among communities led to another null difference in facial expressions. Furthermore, the failure to find significant differences in facial expression scores can also be explained by three possibilities. First, it has been reported that facial expression scores reflect people's desire to rent houses, not to buy them [61]. Technically, we cannot distinguish between the proportions of people who are tenants or house-owners. The websites, from which housing prices were collected, indicated a much lower number of records for renting than for buying. People who already bought houses may not be sensitive to changes in housing prices and thus, their facial expressions may not be affected by housing prices. Second, positive emotions were reported to be the result of people feeling safe inside their neighborhood [24,25]. These results were mainly obtained from streets where crimes were frequent. Buonanno et al. [62] considered that housing price is associated with residents' satisfaction only when the threat of crime can be perceived. Most of our communities had high security, so it was rare for residents in communities of any price to think about crime. Finally, facial expressions may mean many things when there are no stimulations that strongly influence the respondent's perceptions. In the open spaces on public lands, unobvious geographical stimulations appear to trigger emotional responses at only large geographical scales, such as national [37,41] or provincial [11,33,39,42]. Although we studied 54 communities, they were all located in a single city. Facial expression patterns may be more uniform in people living in the same city than in people living in different cities. We suggest future works to test the facial expressions of residents in communities

of China on a larger geographical scale, which may result in significant responses among community attributes.

Our data on facial expression scores showed that people tend to show more positive emotions in colder seasons (autumn and winter), but there was no trend in showing sadness across seasons. Changes in the facial expressions of GBS experiencers by season were reported to be driven by microclimates [43]. On this basis, springtime in Nanchang can be characterized as a mild microclimate ruled by the sub-tropical monsoon climate. People start to think about work during this season, as Chinese New Year passes and a new year commences. Thinking about work resulted in a low level of positive emotions in spring. Summer is hot with extremely high temperatures in Nanchang, which drove people to show more negative emotions on their faces. Autumn is mild again, so people felt better about the temperature. Winter is the season when people like to smile according to traditional Chinese manners. The dynamic change in happy score and NPE instead of sadness was also reported in Wei et al. [36]. Our results also revealed a difference in gender in which females smiled more than males, which had also been reported in other works [33,39,42]. Since we employed Sina Weibo as the source of our photos, females tend to smile more frequently than males. Overall, it was unlikely for demographic factors to impact results about the perceptions of community GBSs.

4.3. Facial Expressions Exposed by Perceptions of Landscape Metrics

Although we did not find how experiencing GBSs directly impacts the facial expressions of community residents, the potential effects of perceiving NDVI largeness were revealed in the regression results. Therefore, we can accept our third hypothesis because the results showed a positive relationship between NDVI area ratio and the estimated coefficient of happy score. The results also showed a NDVI largeness over 0.48 km^2 while MNDWI generated positive contributions to the NPE coefficient. Studies on public lands also revealed that people show more positive emotions when they perceive larger areas of green [11,38] and blue spaces [42]. Our study's subjects were in a community setting, which has more complicated facilities than public GBSs. Therefore, although residents can perceive their experiences with GBSs in their communities, these perceptions were not strong enough to drive their facial expressions. It was also reported that microclimates may not always cause people to show emotions either in urban forests [40] or beside wetland waters [43]. A sole effect of the area ratio of NDVI was to evoke happy faces, which may be because people were more likely to show satisfaction when interacting with greenery in sunlight [35]. This was also supported by the findings of Wu et al. [22], who argued that it is more important for people to see greenery for feeling satisfied in their communities. Higher proportions of green light can also promote the perception of satisfaction by promoting physical well-being [45].

By comparing coefficients for regressed NPE, we found that the size of blue space had a greater contribution (0.65–1.85) than the size of green space (−2.45–0.89). Therefore, perception of the size of blue space increased the frequency in which community residents showed positive emotions, while the perception of the size of green space decreased this frequency unless the area of green space was larger than 0.37 km^2. However, communities with an EI landscape that has green space covering rate over 70% will still impair the will to expose positive emotions. Again, we suggest future works to study more communities in a larger area, which will identify the joint effects of GBSs in this study.

4.4. Policy Implications

In this study, accumulated knowledge about the perceptions of visitors in public GBSs was tested in community GBSs. Our findings about landscape metrics and their associations with facial expressions provide a theoretical guide for policy decisions in real estate. The size of GBSs in these communities can be referred to by urban planners to increase the possibility of evoking happiness in residents. Although it is common to believe that living in communities at higher housing prices evokes more happiness, the findings in this study

would differ because there was very little difference between communities at different housing prices. Our study can be taken as a novel trial with important conclusions, but this study can be extended to subtropical cities in other regions. Our findings may be agreed to or queried in other countries with more types of houses, so the suggestions for local policy decisions will be different accordingly. Anyway, no matter the conclusion of future studies, the module established in this study will be extended by more scholars.

4.5. Limits of the Current Study

There are limits to this study. First, the use of photos of facial expressions as a source of data suffers from uncertainties. People may post selfies that show a projection of what they think they should show and share with others rather than what they truly feel. Second, subjects in this study are limited to residents living in objective communities. The population of people posting their photos should be extended to a larger group that includes more types of people. Finally, we did not find a direct relationship and our findings were mainly derived from potential effects. As a unique study on community GBSs, our results need more relevant studies to demonstrate the validity of the findings in this study.

5. Conclusions

In this study, Nanchang was taken as a pilot city to study the facial expressions of residents in communities with different GBSs. Most findings about the emotions of people who experience GBSs in public parks cannot be verified in our study. Attributes of communities (houses for sale vs. no houses for sale and housing price) did not affect either facial expressions or landscape metrics. Only built-up area was higher in communities with houses for sale than in communities with no houses for sale at the price range of 10,000–20,000 CNY m^{-2}. The size the of blue space had a stronger contribution to residents showing positive emotions than the size of the green space. We recommend green space be established in an area over 0.38 km^2 per community with a ratio of green space area to total area over 70%. As our study was conducted in the subtropical city Nanchang, our conclusions are also recommended for reference in other studies of subtropical cities.

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