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Exploring the Relationship between the Sentiments of Young People and Urban Green Space by Using a Check-In Microblog

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Abstract: Green spaces have a positive impact on the mood of urban residents. However, previous studies have focused primarily on parks or residential areas, neglecting the influence of green spaces in different socioeconomic locations on public sentiment. This oversight fails to acknowledge that most young individuals are exposed to places beyond their homes and parks throughout the day. Using web crawlers, we collected 105,214 Sina Weibo posts from 14,651 geographical check-in points in Hangzhou, Zhejiang Province. We developed a mixed ordered logistic regression model to quantify the relationship between public sentiment (negative/neutral/positive) and the surrounding green space. The findings are as follows: (1) the correlation between GVI and public sentiment is stronger than that between public sentiment and NDVI; (2) among different socioeconomic regions, residential areas are associated with lower levels of public sentiment, while parks are associated with higher levels; and (3) at a scale of 1000 m, an increase of 1% in GVI significantly improves public sentiment regarding transportation hubs, with a regression coefficient of 0.0333. The relationship between green space and public sentiment is intricate and nuanced, and it is influenced by both public activities and spatiotemporal contexts. Urban green space planners should consider additional factors to enhance the effectiveness of green space in improving public sentiment.

Keywords: urban green space; social media; sentiment; GVI; NDVI

check for updates

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1. Introduction

In the context of global urbanization, it is projected that the urban population will surpass 60% of the total population by 2050 [1]. As cities expand due to population influx, natural landscapes such as forests, grasslands, and wetlands are gradually being replaced by impermeable surfaces, such as concrete and asphalt [2], thereby limiting opportunities for urban residents to engage with nature. This urban lifestyle results in reduced public interaction with the natural environment and can have detrimental effects on mental health, including depression, anxiety, and loneliness [3]. Young individuals in China face a particularly high risk of depression. According to the China Emotional Health Development Report (2021–2022), the prevalence of depression among individuals aged 18–24 and 25–34 is significantly greater than that among individuals aged 35 and older [4].

An increasing body of research indicates that exposure to green spaces is associated with mental health benefits for urban residents [5], as well as a reduced risk of certain types of mental illnesses in the general population [6]. Studies investigating the relationship between greening and mental health rely only on remote sensing data and may not accurately capture the level of public perception of greenery [7,8]. Green view index (GVI) has been proposed as a more suitable measure for capturing public perceptions of green spaces, with previous studies confirming a close relationship through physiological measures [9], questionnaires [10], and GPS activity diaries [10]. However, comparative studies examining the impact of GVI and normalized difference vegetation index (NDVI) on public sentiment are still lacking, given the limitations of traditional methods, namely their passive and static characteristics and small sample sizes [11,12].

In urban areas, the public receives natural and cultural ecosystem services from nearby green spaces through various mechanisms [13]. Biophilicity-derived stress reduction theory (SRT) [14] and attention restoration theory (ART) [15] suggest that natural environments meet the psychological needs of the public; in addition, physical activity [16], social interaction [17], and environmental regulation [18] may also mediate psychological benefits. Inequities in access to green spaces remain [19]. Previous studies on green spaces and health have proposed improvement strategies for residential and park green spaces aimed at vulnerable groups, such as elderly people and young children [20,21]. However, most young adults face greater work-life pressures [22], and their little available leisure time [23] significantly affects their activities in residential and park green spaces. Additionally, the attractiveness of green space quality [24,25] and epidemic lockdowns [26] also affect public access to green spaces.

Social media is commonly regarded as an active platform for younger people to express themselves [11]. Previous research utilizing social media data to analyze public sentiment towards green spaces has predominantly focused on green park areas [12,24,27–29] or residential areas [29]. For instance, sentiments expressed in parks located outside Manhattan in New York City were found to be greater than those expressed in internally located parks [28]; inadequate cleanliness reduces the utilization of green spaces by the public [29]; and visitors' sentiments towards comprehensive and heritage parks were significantly more positive than those towards community parks [27]. These studies have validated the utility of geotagged social media data for investigating the relationship between public sentiment and urban green spaces.

Recent research has substantiated disparities in public sentiment across diverse environments, with individuals exhibiting greater happiness levels in natural landscapes than in densely urbanized areas [30]. Furthermore, the influence of tree canopy coverage on public sentiment varies depending on the type of land use and the urban functional zone [12]. Notably, vague functional zones and land use categories offer limited insights into location backgrounds, as most adults tend to visit destinations associated with socioeconomic factors. Consequently, acknowledging the significance of the impact of green spaces on public sentiment among different socioeconomic contexts is crucial; however, no comparative studies have been undertaken thus far.

Therefore, in this paper, we rely on geographically located Weibo texts as data sources and incorporate data from multiple sources, such as street view, remote sensing, weather, and air quality, to study the relationship between public sentiment and green spaces. We employ a logistic regression model to quantify the association between green space and public sentiment while considering multiple covariates. We present three questions: (1) Are the green space indicators GVI and NDVI related to public sentiment? (2) Do different types of socioeconomic locations exhibit variations in public sentiment? (3) Do green spaces surrounding different socioeconomic locations have different impacts on the sentiments of young people?

2. Materials and Methods

2.1. Study Area

Hangzhou is located in the Yangtze River Delta region (29°11′ N to 30°33′ N, 118°21′ E to 120°30′ E) (Figure 1). It is an internationally renowned tourist city with developed financial services, e-commerce, and information technology. In 2023, the total population of Hangzhou exceeded 10 million, with a population density of nearly 2800 people per square kilometer. The study area has undergone rapid urbanization, leading to the significant conversion of natural landscapes for urban expansion and substantial changes in the built environment [31]. As a result, the lifestyles and psychological well-being of many urban residents have undergone dramatic transformations.

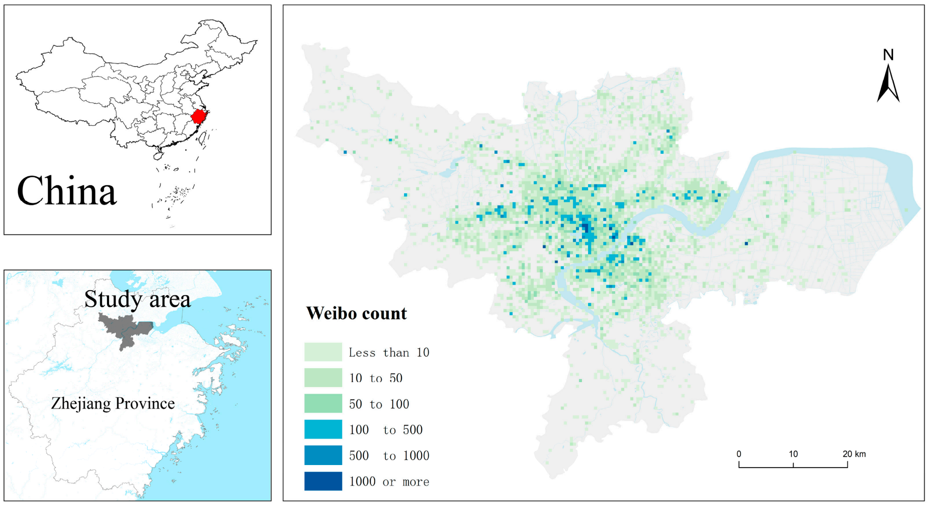

Figure 1. Location of the study area and spatial distribution of Weibo accounts in the sample.

2.2. Study Samples

In this study, web crawlers were employed to collect the required social media data. Web crawling is a technique that mimics browser access to online resources. It automatically gathers necessary data from one or more pages using specific strategies. The raw check-in data of Weibo in the selected research area are encoded in JSON (JavaScript Object Notation) format. To facilitate statistical analysis, we used Python scripts to extract key fields, including user ID, Post ID, text content, creation time, longitude and latitude, Weibo link, location name, and location type. Then, we stored the data in comma-separated value (CSV) format. After removing data outside the geographical scope of the research area and conducting text cleaning, we deleted duplicate Weibo posts, non-Chinese Weibo posts, empty expressions, and text with imprecise geographic locations [29,32]. Next, we excluded Weibo posts sent by robots, such as advertisements and weather reports [12]. Ultimately, 128,639 geotagged Weibo posts from 16,257 check-in locations were collected (Figure 1). Finally, to investigate the correlation between the sentiment of the public and the surrounding environments, we further removed check-in locations that are not in the Baidu Street View data distribution range. The data analysis was conducted on 105,214 geotagged Weibo posts sent from 14,651 geographical check-in locations in Hangzhou, Zhejiang Province, China, during the period from 1 August 2022 to 31 August 2023.

2.3. Data Acquisition

Sentiment classification. To extract the sentiment category of each Weibo image based on its content, we utilized the text sentiment analysis provided by the Baidu Natural Language Processing (NLP) platform (https://ai.baidu.com/tech/nlp, accessed on 8 October 2023) (Figure 2), which is one of the first four national new generation artificial intelligence open innovation platforms approved by the Ministry of Science and Technology of China in 2017. In the sentiment analysis for Weibo, Chinese characters are first extracted to construct Chinese word segments, and the sentiment scores of these word segments are obtained from Baidu words (https://cloud.baidu.com/doc/API/index.html, accessed on 8 October 2023) that contain sentiment scores for Chinese words. Using this technique, the sentiment polarity category (negative/neutral/positive) of the text can be automatically determined [33]. Like the English natural language processing toolkit TextBlob, the Baidu Natural Language Processing (NLP) platform is a powerful Chinese text processing library.

NDVI measurements (Figure 3a). NDVI is a satellite-based vegetation index used to quantify urban greenness. We selected cloud-free images covering the survey area and then identified a satellite image with a resolution of 30 meters taken by the Landsat 8 Operational Land Imager (OLI) on 12 June 2023. The obtained images underwent radiometric calibration, geometric correction, and atmospheric correction (Figure 2). The NDVI value is calculated using reflectance data from two electromagnetic spectrum bands, Landsat band 4 (near infrared) and Landsat band 3 (red), with values ranging from −1 to 1, where positive values indicate more vegetation. In our study, negative values representing water and bare soil were adjusted to 0 so that NDVI values would not cancel out positive normalized vegetation index values when averages are calculated [34]. Here, *RED* and *NIR* represent the spectral reflectance measurements obtained in the red and near-infrared regions, respectively. *NDVI* is calculated as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

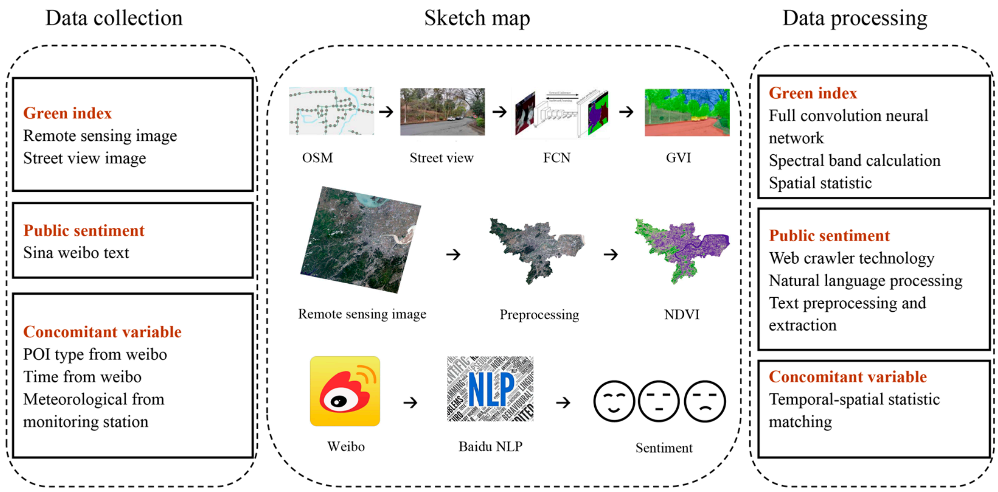

Figure 2. Data acquisition process.

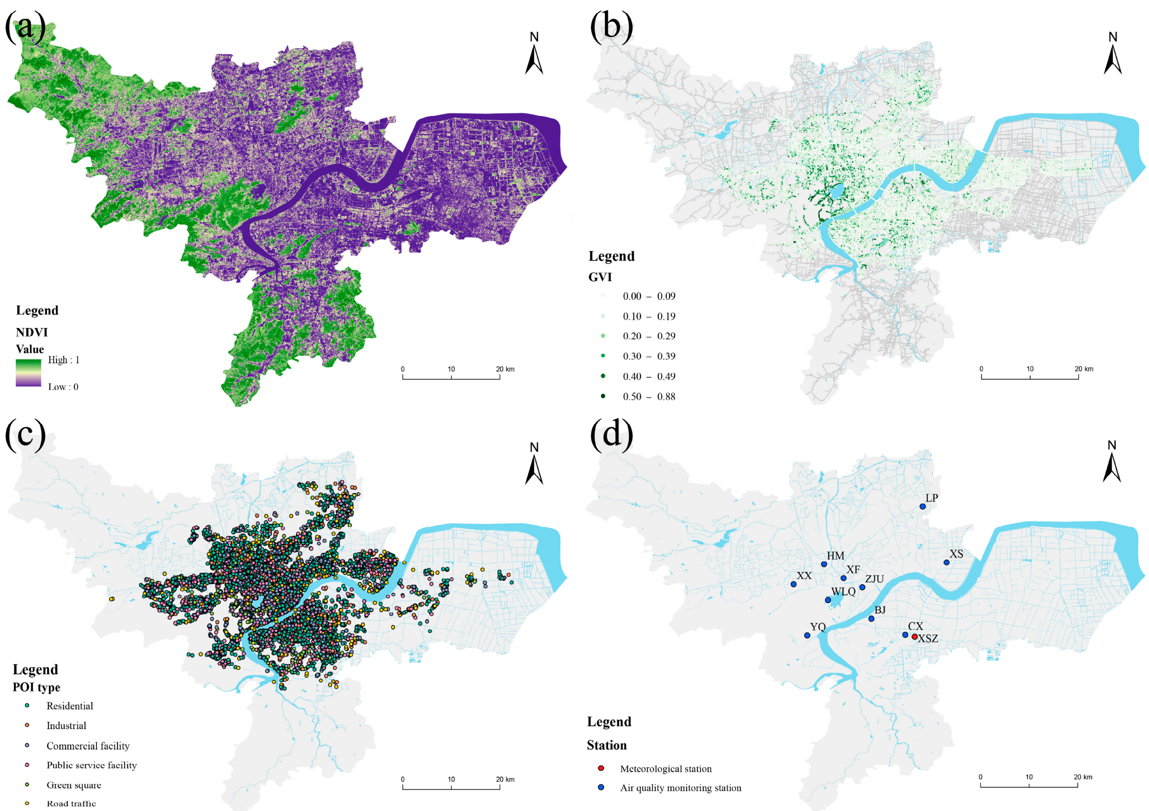

Figure 3. (**a**) Spatial distribution of NDVI, (**b**) Spatial distribution of GVI, (**c**) Spatial distribution of Weibo check-in points' POI types, (**d**) Weather monitoring site distribution.

GVI measurements (Figure 3b). GVI refers to the quantity of greenery that can be visually perceived from a specific location. It is identified by extracting green vegetation pixels from street view images using Baidu Online Maps. Road network data are obtained from OpenStreetMap (OSM) (https://www.openstreetmap.org, accessed on 1 September 2023), and the road network data are intersected with the buffer zone expanded from the check-in point position using ArcGIS 10.8 (Esri, Redlands, CA, USA) to obtain the surrounding road network. Sampling points are generated at an equal interval of 100 m along the road, and the coordinates of the generated points are input into a Python script obtained using an application programming interface (API). One point collects four static images of street view at horizontal angles of 0°, 90°, 180°, and 270° [29]. The above data were collected in October 2023, Baidu Maps provided street view data for June 2022, and the OSM platform provided road network data for 2021. Since some sampling points may return null values, these sampling points were deleted. A total of 193,868 street view images from 48,467 point locations were ultimately retained. Image semantic segmentation is a cornerstone technology for image understanding and an important task in the computer vision field. Many high-quality open-source frameworks are available for use. Fully convolutional networks (FCNs) are commonly used for the semantic segmentation of street view images. The existing FCN models can recognize up to 150 street view elements [35]. In this study, we use street view images to identify plant features through a well-trained FCN model, which exhibits an average estimation accuracy of over 90% [35]. According to research needs, we take the proportion of vegetation category pixels as GVI (Figure 2).

In addition to the main predictive factors of interest, we also include several covariates, which may help us adjust the relationship between public sentiment and green spaces. These data are divided into three groups: location type, weather conditions, and time. These variables have been found to be closely related to sentiment based on social media text data in previous studies [12,33,36], so we include them as covariates. For location type, we use point of information (POI) data, including cognitive and conceptual POIs [37]. These data can explain the socioeconomic attributes of human activities [38], comprehensively reflecting the socioeconomic activity background behind them by using Weibo POI data for urban functional zoning [39]. Therefore, by using the geolocation and POI types of Weibo, we can objectively reveal the activity background of public sentiment expression at each check-in place to a certain extent. For the convenience of this research, we reclassified the POI data of Weibo into six categories based on the national land classification standard (Figure 3c) and the national economic industry classification [40], with each category containing several subcategories. For weather conditions, we used four covariates: temperature, dew point, rain, and $PM_{2.5}$. $PM_{2.5}$ data were obtained from the national monitoring point of the air quality monitoring and analysis platform (https://www.aqistudy.cn, accessed on 9 September 2023). Other meteorological data were obtained from the National Oceanic and Atmospheric Administration (NOAA) integrated surface database. We spatiotemporally matched each located check-in on Weibo with the nearest weather station or air quality monitoring station (Figure 3d). In addition, two covariates related to time were created based on the time tags associated with each Weibo post: weekend and weekdays and day and night. The spatial data processing related to the above processes was conducted in ArcGIS 10.8.

2.4. Data Processing and Analytical Methods

We considered three circular buffer zone scales of 200 m, 500 m, and 1000 m. Social media data may have potential location ambiguity, and buffer zones are believed to overcome this issue [28] However, no consensus has been reached regarding the measurement of a green space's buffer distance, and spatial–temporal uncertainty may vary by region [41]. Based on previous studies on the association between sentiment and green spaces [34,42–46], green spaces within 500 m and 1000 m buffer zones are often found to have a good correlation with public sentiment. However, considering that some studies suggest that social media data are instantaneously expressed [12], we also used a smaller 200 m buffer zone scale to determine the relationships within it.

Previous studies on the impact of social media data and green space on public emotion mostly used *t* tests and variance significance tests. These statistical methods have certain limitations, such as the failure to consider the internal correlation between data points collected near the same place when making hypotheses [47]. And the influence of important confounding factors, such as weather conditions and time background, were also not considered. Statistical models, such as logistic regression, are gradually used to overcome such difficulties [12].

To analyze the data, we employed the Spearman correlation and constructed a linear model. Subsequently, we employed a random intercept mixed-effect ordered logistic regression model with check-in location as the random effect (Appendix A.1). Given that our sentiment data are ordinal in nature (negative/neutral/positive), an ordered discrete choice model can effectively explain the ordered characteristics of the response results. Most geotagged location samples consist of multiple texts and texts sent from the same location may not be independent due to environmental background influences, incorporating check-in locations as random effects allows us to account for unobserved heterogeneity between locations. To compare fixed-effect models and mixed-effect models (Table A1), we utilized the likelihood ratio test (LRT) and Akaike's information criterion (AIC) [48].

The model takes public sentiment as the dependent variable, and the GVI, NDVI, POI type, time factor, and meteorological factor as the fixed effect. We maintained the continuity of the main green space data. Since both NDVI and GVI data were between 0 and 1, we processed them as percentages so that each unit in our data analysis model was in the form 0.01 instead of 1. We classified other types of covariates according to previous research [12]. An overview of the data is provided in Tables A2 and A3. To explore the benefits of green spaces for public sentiment in different geographical locations, we constructed interaction terms GVI× POI type and NDVI ×POI type based on the previous random-effect ordered logistic regression model and plotted forest plots using the corresponding coefficient results. The above data analysis process was conducted using Stata 17.0 (StataCorp, College Station, TX, USA).

3. Results

3.1. Correlation Analysis of the Greening Index and Sentiment

We selected the check-in microblog points with more than 10 messages sent and calculated the proportion of positive texts for each location as the probability of positive sentiment at that specific place. Since both the green space data and the probability of positive sentiment data deviated from a normal distribution, we employed Spearman's rank correlation to investigate the relationship between each green space indicator and the probability of positive sentiment (Figure 4a). The correlation between GVI and the probability of positive sentiment was found to be stronger than that between NDVI and the probability of positive sentiment, with GVI 1000 m exhibiting the highest correlation with the probability of positive sentiment among all GVI indicators (Figure 4b), while NDVI 200 m showed the strongest correlation with the probability of positive sentiment among all NDVI indicators (Figure 4c). Street view green space indicators demonstrated a closer association with the probability of positive sentiment when compared to remote sensing levels. Moreover, a greater degree of correlation was observed among the different GVI indicators than among the NDVI indicators. Additionally, the variation in the relationship between the GVI and probability of positive sentiment across spatial scales was smaller than that observed for the NDVI. Notably, Spearman's rank correlation indicated that the highest correlation between the NDVI and GVI occurred when both were measured within a radius of 200 m (Spearman r = 0.382).

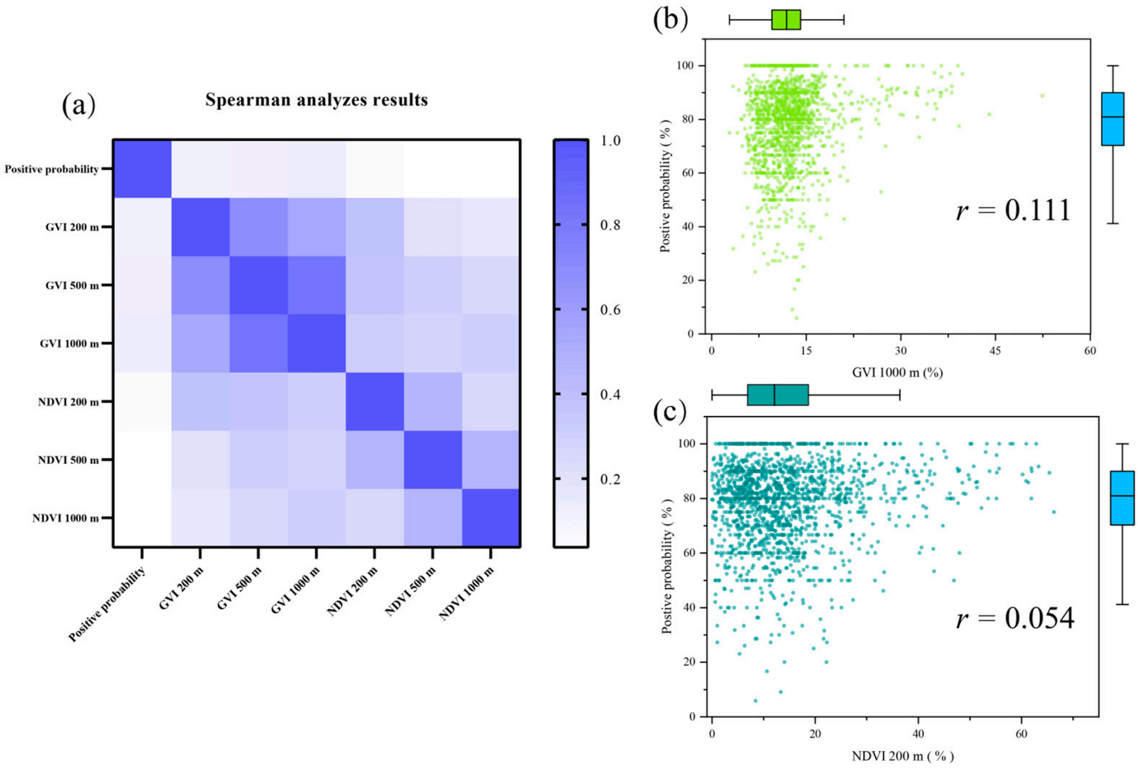

Figure 4. (**a**) Spearman correlation analysis results, (**b**) Scatter plot of GVI 1000 m and positive probability, (**c**) Scatter plot of NDVI 200 m and positive probability.

We also attempted to establish a linear relationship between the green space index and the probability of positive sentiment. GVI 1000 m exhibited a significant positive correlation with the probability of positive sentiment (B = 0.413). NDVI 200 m also demonstrated a significant positive correlation with the probability of positive sentiment (B = 0.112). However, importantly, the R2 values are relatively low, indicating limited explanatory power of green space in influencing public sentiment from an overall statistical effectiveness perspective. This highlights the need to further explore other potential influencing factors.

3.2. Effects of Greening and Related Potential Factors on Sentiment

The coefficients of GVI and public sentiment exhibit greater magnitudes than those of NDVI and public sentiment, suggesting that GVI aligns more consistently with the public's perception of green space. Table 1 shows a significant positive correlation between the coefficients of GVI and NDVI and public sentiment at a scale of 200 m, with values of 0.0052 and 0.0044, respectively. In terms of location type, the coefficients for other socioeconomic categories are significantly greater than those for residential areas, with parks displaying the highest coefficient, followed by commercial facilities. The coefficients for public sentiment on weekdays are lower than those on weekends, but this difference lacks statistical significance; similarly, the coefficients for public sentiment on rainy days are greater than those on non-rainy days, and this difference lacks statistical significance. Moreover, the coefficients for public sentiment during the daytime are significantly greater than those observed at night. Although not statistically significant, an increase in dew point temperature is associated with a decrease in the coefficient for public sentiment; furthermore, when pollution levels exceed reference values ($\leq$35 $\mu g/m^3$), the coefficients for $PM_{2.5}$-related sentiments generally decline, except within the range of 75–115 $\mu g/m^3$, where significance is observed. Last, when compared to temperatures below freezing (<0 °C), all temperature segments display greater coefficients for public sentiment without reaching statistical significance; notably, the segment ranging from 12–18 °C exhibits the highest coefficient.

Table 1. Estimation results for the random-effect models.

Characteristics		Coefficient (95% CI)		
		200 m	**500 m**	**1000 m**
Greening index	GVI 200 m (per 0.01 change)	0.0052 (0.0018, 0.0086) [a]	0.0116 (0.0069, 0.0163) [a]	0.0178 (0.0122, 0.0234) [a]
	NDVI 200 m (per 0.01 change)	0.0044 (0.0021, 0.0067) [a]	0.0015 (−0.0006, 0.0036)	−0.0006 (−0.0026, 0.0013)
POI type	Residential (base)			
	Industrial	0.3046 (0.1646, 0.4446) [a]	0.2977 (0.1579, 0.4376) [a]	0.294 (0.1544, 0.4337) [a]
	Commercial Facility	0.5187 (0.4594, 0.578) [a]	0.5037 (0.4442, 0.5632) [a]	0.499 (0.4395, 0.5585) [a]
	Public Service Facility	0.3812 (0.3145, 0.4479) [a]	0.3738 (0.3071, 0.4406) [a]	0.3711 (0.3044, 0.4378) [a]
	Green Square	0.7244 (0.5903, 0.8585) [a]	0.7242 (0.5902, 0.8582) [a]	0.7187 (0.5849, 0.8524) [a]
	Road Traffic	0.2353 (0.1304, 0.3402) [a]	0.2318 (0.127, 0.3366) [a]	0.2283 (0.1235, 0.333) [a]
Dew point (°C)	≤2 (base)			
	2–<16	−0.0799 (−0.1663, 0.0065) [b]	−0.0801 (−0.1664, 0.0063) [b]	−0.0797 (−0.1661, 0.0067) [b]
	16+	−0.0953 (−0.203, 0.0124) [b]	−0.0961 (−0.2038, 0.0116) [b]	−0.0954 (−0.2032, 0.0123) [b]
$PM_{2.5}$ (μg/m^3)	≤35 (base)			
	35–<75	0.0134 (−0.03, 0.0568)	0.014 (−0.0294, 0.0574)	0.0139 (−0.0295, 0.0573)
	75–<115	−0.1342 (−0.2596, −0.0088) [a]	−0.1332 (−0.2586, −0.0078) [a]	−0.1331 (−0.2584, −0.0077) [a]
	115–<150	−0.3167 (−0.634, 0.0007) [b]	−0.313 (−0.6304, 0.0044) [b]	−0.315 (−0.6322, 0.0023) [b]
	150+	−0.2698 (−0.9959, 0.4564)	−0.2715 (−0.9977, 0.4548)	−0.2667 (−0.9929, 0.4595)
Temperature (°C)	<0 (base)			
	0–<7	0.0629 (−0.1583, 0.2842)	0.0647 (−0.1565, 0.2859)	0.0645 (−0.1567, 0.2857)
	7–<12	0.1661 (−0.0629, 0.3952)	0.1673 (−0.0617, 0.3963)	0.1671 (−0.0618, 0.3961)
	12–<18	0.1907 (−0.0405, 0.4219)	0.1921 (−0.0391, 0.4232)	0.1921 (−0.039, 0.4233)
	18–<26	0.1705 (−0.0648, 0.4058)	0.1724 (−0.0628, 0.4077)	0.172 (−0.0632, 0.4072)
	26+	0.1446 (−0.094, 0.3832)	0.1462 (−0.0924, 0.3847)	0.1454 (−0.0931, 0.384)
Rain	No (base)			
	Yes	0.0221 (−0.0401, 0.0843)	0.0225 (−0.0398, 0.0847)	0.0225 (−0.0397, 0.0847)
Day	No (base)			
	Yes	0.0375 (0.0042, 0.0708) [a]	0.037 (0.0038, 0.0703) [a]	0.0371 (0.0039, 0.0704) [a]
Day of week	Weekend (base)			
	Weekday	−0.0226 (−0.0573, 0.0121)	−0.0221 (−0.0569, 0.0126)	−0.022 (−0.0567, 0.0127)

Note: [a] significant at p of 0.05; [b] significant at p of 0.1.

The variation in the performance of variables across different spatial scale models is also evident from the data presented in Table 1. The coefficients of GVI and public sentiment exhibit greater magnitudes than those of NDVI in each spatial scale model. The highest coefficient for GVI is observed in the 1000 m model, while the lowest is found in the 200 m model. Conversely, the highest coefficient for NDVI is identified in the 200 m model. At this particular scale (200 m), GVI and NDVI demonstrate similar coefficients with respect to public sentiment, albeit with slightly greater values for GVI. Notably, GVI and public sentiment exhibit significant positive correlations across all three models at scales of 200 m, 500 m, and 1000 m, yielding coefficients of 0.0053, 0.0116, and 0.0178 for public sentiment factors, respectively. Furthermore, as the spatial coverage range of GVI around check-in locations expands, the correlation coefficient gradually increases. However, only the 200 m scale exhibited a significant correlation with NDVI, with coefficients of 0.0044, 0.0015, and −0.0006 for public sentiment factors in the 200 m, 500 m, and 1000 m models, respectively. The NDVI and public sentiment coefficient gradually decrease with increasing spatial scale around the location. The characteristics of the other covariates in the 500 m and 1000 m models resemble those observed in the 200 m model.

3.3. Interaction between Greening Index and POI Type

Figure 5 and Table A4 show the interaction results between the green land index and POI types. The research results confirm that GVI can generally better characterize the sentiment benefits of spatial green spaces for the public than can NDVI in various socioeconomic places. For every 0.01 increase in NDVI, the public sentiment coefficient shows a significant positive correlation only at the 200 m scale for public service areas; this correlation is not significant at other types and scales. Excluding industrial areas, in other types of locations, the public sentiment coefficient for GVI exhibits an upwards trend with the increase in scale. For instance, with each unit increase in GVI in residential areas, the corresponding coefficients at distances of 200 m, 500 m, and 1000 m are 0.0077, 0.0094, and 0.0143, respectively.

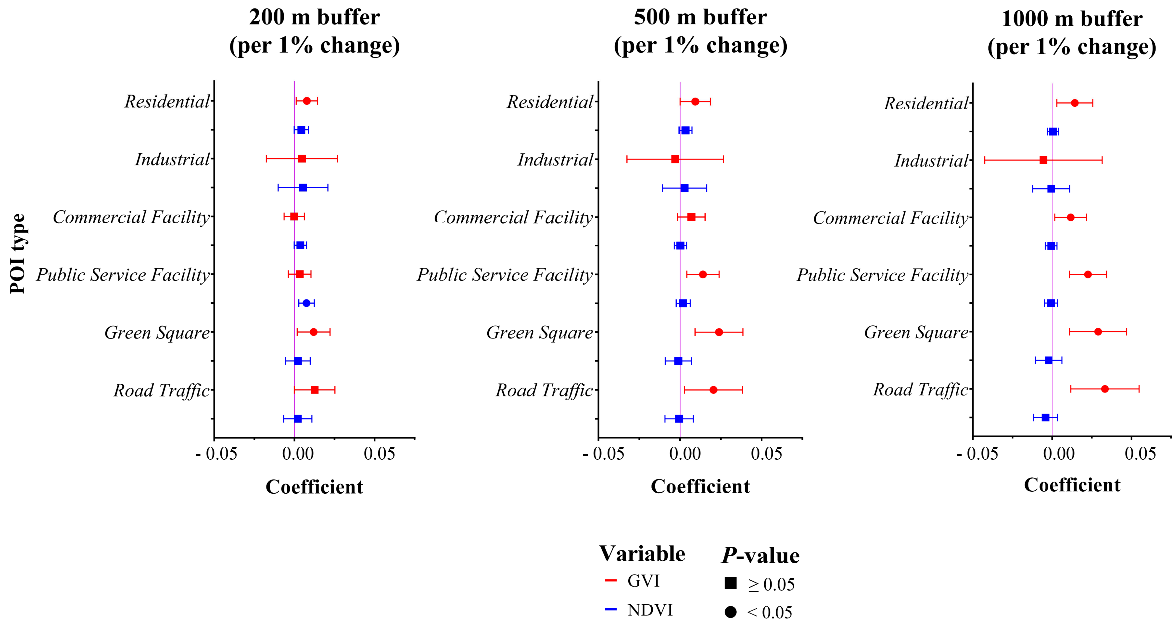

Figure 5. Forest plot of the interaction between POI type and greening index.

At the spatial scale of 200 m, the coefficients of the GVI and public sentiment are statistically significant only in residential and green park areas, with values of 0.0077 and 0.0126, respectively. At the larger 500 m scale, excluding residential and green spaces, the coefficients for GVI and public sentiment also show significance in relation to traffic and public service types, with values of 0.0205 and 0.0141, respectively. When considering a broader scale of 1000 m, a 1% increase in GVI has the greatest impact on public sentiment regarding road traffic, as indicated by a coefficient value of 0.0333. Furthermore, at this scale (1000 m), GVI can effectively reflect the association between green space availability and public sentiment across various socioeconomic categories; particularly notable improvements are exhibited for traffic-related places, while business-related places exhibit relatively minor enhancements.

4. Discussion

4.1. The Influence of GVI and NDVI on Sentiment

Our research indicates that GVI is more suitable than NDVI as a greenness indicator for studying public sentiment represented by Weibo (Table 1; Figure 4). Based on quantitative comparisons of the correlations between GVI and public sentiment and NDVI and public sentiment, GVI is clearly a more suitable indicator for studying the relationship between human perception of greenness and public sentiment [49]. The deviation between NDVI and GVI becomes larger as the scale expands, but at smaller scales, the two may exhibit some degree of substitution. The occurrence of this phenomenon can be attributed to the frequent interaction between GVI and public activities, while NDVI exhibits significant disparities with areas of public activity. Another contributing factor is that GVI, as a three-dimensional indicator of green spaces, aligns more closely with human visual perception than does the NDVI, which represents green spaces two-dimensionally. Previous health studies based on GPS activities, scales, and physiological levels have also shown that GVI is superior to two-dimensional green space indicators. Our study further confirms this point from the perspective of social media data. From the perspective of the public's activity range and perspective, GVI has a relatively independent and irreplaceable influence on public sentiment, and it cannot be inferred simply from NDVI. The concept of "planning GVI" should be expeditiously disseminated, and GVI databases based on plant morphology, specifications, and age should be established for early prediction of future GVI in green space planning and construction [8].

Overall, a positive correlation exists between public sentiment and green spaces, which is consistent with the findings of previous research indicating that high-quality green spaces can enhance public sentiment [12,24,27–29,50]. As urban populations continue to grow, these findings highlight the potential importance of green spaces in promoting positive public sentiment. The effect sizes of our findings are relatively small, but these small effects could still have a positive impact. For urban populations, the small differences we found among the check-in locations could translate into larger differences across cities [12]. For example, when the population of Hangzhou exceeds the 10 million mark, for every 1% increase in the probability of positive sentiment of the urban population, the improvement of green space will improve the sentiment of approximately 100,000 people in the city. This is of great significance to the planning and management of urban green space.

4.2. Differences in Public Sentiment among Different Socioeconomic Location Types

We confirmed the feasibility of capturing variations in public sentiment among different socioeconomic groups based on POI type (Table 1). Notably, comparative results across socioeconomic categories reveal lower levels of public sentiment in residential areas, potentially due to a relative lack of social support for residents who have been confined to their homes for extended periods. These residents are more susceptible to mental health issues, such as depression and loneliness [51], particularly among individuals with preexisting medical conditions [52]. Similarly, transportation categories also exhibit relatively low levels of public sentiment due to increased exposure to environmental factors such as air pollution [33,53], traffic noise [54], and traffic safety concerns [45]. Conversely, green parks demonstrate higher levels of public sentiment than other locations, followed by commercial areas. These types of places tend to facilitate leisure and entertainment activities, which generally contribute to elevated sentiments.

4.3. The impact of Green Space on Public Sentiment in Different Location Types

The impact of green spaces on public sentiment varies across different socioeconomic settings. In this study, we primarily focus on comparing and discussing the influence of GVI changes (Figure 5). In contrast to Wei et al.'s [29] study, in which no correlation was found between public sentiment and residential green spaces based on microblog data, our findings indicate a positive correlation between the quality of surrounding green spaces and residential types at various buffer scales. These results align more closely with previous traditional research [34,42]. Residential areas characterized by abundant greenery are generally acknowledged to possess enhanced restorative qualities, heightened mindfulness, and greater stress resilience [34]. Moreover, the presence of natural spaces within communities may help alleviate social isolation [55] by fostering increased social support networks, thereby enhancing public sentiment in residential areas. Notably, the positive impact of green spaces on public sentiment at transportation sites is most pronounced when considering a scale of 1000 m due to the heightened exposure to green environments during public travel. Furthermore, higher levels and broader coverage of green spaces can mitigate adverse environmental exposures faced by the general population by reducing noise and particulate matter (PM) [43,56], consequently improving the overall sentiment. Due to differences in functionality, green park areas have varying effects [27]. Green parks of different sizes provide space for various activities for the majority of the public, and higher levels and wider coverage of green spaces promote sentiment for such activities more significantly. This finding is consistent with previous findings [32], which showed that happiness among visitors to 34 green parks in three northeastern provinces of China was significantly positively correlated with the green area and NDVI based on social media facial photo data. Lin et al. [12] also reported that the probability of negative expressions in large natural parks in Seattle was lower than that in other parks and nonpark areas.

Spatial and temporal variations in the relationship between sentiment and green spaces are indicated by different buffer zone correlations. Lin et al. [12] found a positive correlation between individuals' sentiment and tree canopy coverage in industrial zones at a grid scale of 90 m, whereas our findings did not indicate such a relationship in work-related areas where people spend most of their time indoors at a single location. Our minimum range of 200 m differs significantly from the activity range of Lin et al., suggesting that green spaces may still have the potential to improve public sentiment in work areas. Lin et al. [12] also discovered that at a grid scale of 90 m, there is a tendency for individuals in commercial/mixed areas to exhibit negative sentiment given a higher degree of tree canopy. In contrast, our study reveals a positive correlation between public sentiment and green spaces in both commercial and public service areas at larger scales. The enhancement of urban green spaces can indeed enhance public sentiment; however, public sentiment is also influenced by the activity forms and spatiotemporal contexts of public groups. The variations observed across different spatial scales may reflect distinct modes of interaction between public group activities and green space. For instance, the large-scale environmental regulation and visual improvement of green spaces are more prominent, while vegetation contact at smaller scales can have adverse effects, such as by being common allergen sources [57] or exacerbating air pollution due to unreasonable vegetation layouts [58].

4.4. Green Space Optimization Based on the Psychological Benefits to Younger Populations

By using the socioeconomic status of different check-in locations to examine the relationship between green spaces and public sentiment, this research is highly important for the sustainable development of cities, as mentioned in the introduction. Previous studies on green spaces and health have proposed improvement strategies for residential and park green spaces for vulnerable groups, such as elderly people and young children [20,21,59]. However, those in Chinese youth groups have limited sentiment benefits from residential and park green spaces due to their high work-life pressures [22]. Socioeconomic level differences are generally considered key to green space equity in terms of design availability [26]. However, due to the mismatch between the green space needs of youth groups and those of traditionally considered vulnerable groups, such as elderly people and young children, the ecosystem services that green spaces can provide remain unequal [40].

In particular, the separation of work and housing causes fixed daily commuting problems for Hangzhou's youth groups. Transportation stations, such as subways and buses, are important commuter access points, and the green spaces around these stations can provide daily green space [60]. The extensive high green spaces around transportation stations can complement their natural sentiment needs, restore attention [15], alleviate work-life pressures [14], and improve the sentiment of youth groups in their daily lives. In addition, youth groups have high visitation rates to commercial locations, such as shopping malls and food service venues. Improving the green spaces around these locations can facilitate the daily green space exposure of youth groups. Therefore, when using green spaces as health intervention measures to regulate public sentiment, the government can consider matching the needs of most youth groups for green spaces based on differences in public activity at different locations, such as promoting mixed land use to better utilize urban green space and breaking down as much as possible the boundaries between urban areas and parks and various types of green spaces. These techniques are conducive to urban equity and sustainable development strategies.

4.5. Limitations and Prospects

Although our research confirms the differential impact of surrounding green spaces on public sentiment in different socioeconomic locations, there are limitations. First, the text sentiment expressed by Weibo users at geographic check-in points may not represent the expressions of the entire population at that location but only a portion of Weibo users [29]. Second, Weibo text is not a direct report of public sentiment. Sentiment expressed publicly on social media platforms may not truly reflect people's real sentiment states. Only a few Weibo posts are direct sentiment expressions, and achieving high accuracy with language interpretation tools is difficult [12]. Third, the activities and spatiotemporal contexts of public sentiment expression at check-in points have significant uncertainty. Assessing to what extent the public has experienced green space before expressing sentiment at a location and in what form the activities were experienced is difficult. As a result, it is difficult for us to directly match green spaces with public sentiment expressions. Although the setting of surrounding buffer zones and data cleansing alleviate these impacts to some extent, the purely cross-sectional study design makes it difficult to make direct causal inferences and explore potential mechanisms. In the future, further research should combine traditional methods such as human sensors and questionnaire consultations to further clarify the differential perception of green surroundings by the public in different socioeconomic locations.

5. Conclusions

The benefits of promoting public sentiment through green spaces have always been highly valued, and new forms of social media data provide prospects for investigating the relationship between public sentiment and green spaces. This study reveals the impact of green environments around different socioeconomic locations on public sentiment. The research shows that (1) NDVI and GVI are positively correlated with public sentiment at 200 m scales, but only GVI enhancement can promote public sentiment at larger scales; (2) compared with other types, the public sentiment in residential areas is the lowest, while that in parks is the highest; (3) for young people, green space improvement at a 1000 m scale around traffic-related sites has the best effect. Therefore, based on our research, it is recommended that urban green space planning strengthen the improvement of green spaces around transportation-related locations. In addition, the relationship between urban green spaces and public sentiment is complex and subtle, and the way people engage in activities and their spatial and temporal contexts are also particularly important. Urban green space planning should also comprehensively consider various influencing factors.

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Appendix A

Appendix A.1 Random Intercept Logistic Regression Model

To demonstrate the relationship between the estimated coefficient and probabilities, we use a logistic regression model as a simple example. We know that for any logistic regression model, the formula is:

$$logit(p) = log(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \quad \text{(A1)}$$

Note: β_1 is the coefficient of variable x_1, β_k is the coefficient of variable x_k, and β_0 is the intercept.

For hierarchical data, high-level data corresponds to different data subsets. Only intercept is regarded as a random effect, and the variation of intercept is split. The random intercept model is as follows:

$$Y_{ij} = \beta_{0j} + \beta_1 x_{ij} + e_{0ij} = \beta_0 + u_{0j} + \beta_1 x_{ij} + e_{0ij} \quad \text{(A2)}$$

Note that Y_{ij} is the measurement for the i subject at the j level. x_{ij} covariates for the j level i subject. Where (β_0 + $\beta_1 x_{\mathrm{ij}}$) is the fixed part, ($u_{0\mathrm{j}}$ + $e_{0\mathrm{ij}}$) is the random intercept part.

Then, the random intercept ordered logistic regression model is as follows:

$$logit(p) = \beta_{0j} + \beta_1 x_1 + \ldots + \beta_k x_k + e_{0ij} \quad \text{(A3)}$$

Table A1. Mixed model and fixed model compares performance summary.

Performance Statistic	200 m		500 m		1000 m	
	Mixed Model	Fixed Model	Mixed Model	Fixed Model	Mixed Model	Fixed Model
AIC	118,581.1	123,120.6	118,580.9	123,129.2	118,574.8	123,003.2
	0.033		0.033		0.032	

Table A2. Categorical variable summary.

Categorical Variable		Frequency	Percentage
Sentiment	Negative	19,466	18.5
	Neutral	2657	2.53
	Positive	83,091	78.97
POI type	Residential (base)	25,843	24.56
	Industrial	2405	2.29
	Commercial Facility	32,874	31.24
	Public Service Facility	31,424	29.87
	Green Square	8541	8.12
	Road Traffic	4127	3.92
Dew point (°C)	≤2 (base)	8020	7.62
	2–<16	34,307	32.61
	16+	62,887	59.77
$PM_{2.5}$ (μg/m^3)	≤35 (base)	83,818	79.66
	35–<75	19,421	18.46
	75–<115	1706	1.62
	115–<150	222	0.21
	150+	47	0.04
Temperature (°C)	<0 (base)	583	0.55
	0–<7	6855	6.52
	7–<12	11,550	10.98
	12–<18	16,493	15.68
	18–<26	29,519	28.06
	26+	40,214	38.22
Rain	No (base)	97,696	92.85
	Yes	7518	7.15
Day	No (base)	57,906	55.04
	Yes	47,308	44.96
Day of week	Weekend (base)	32,798	31.17
	Weekday	72,416	68.83

Table A3. Continuous variable summary.

Continuous Variable	Median (P25, P75)	IQR
Buffer of average GVI (%)		
GVI 200 m	11.22 (7.43, 15.54)	8.11
GVI 500 m	11.44 (9.38, 15.39)	6.01
GVI 1000 m	12.35 (10.35, 14.53)	4.18
Buffer of average NDVI (%)		
NDVI 200 m	12.18 (6.27, 20.04)	13.77
NDVI 500 m	13.99 (8.72, 22.36)	13.64
NDVI 1000 m	14.55 (9.30, 22.36)	13.06

Table A4. Estimation results for the interaction between greening index and POI type.

Buffer Size	POI Type	Coefficient (95% CI)	
		GVI	**NDVI**
200 m	Residential	0.0077 (0.0011,0.0143) [a]	0.0043 (−0.0002,0.0087) [b]
	Industrial	0.0047 (−0.0175,0.0269)	0.0054 (−0.0102,0.0209)
	Commercial Facility	−0.0001 (−0.0065,0.0062)	0.0037 (−0.0002,0.0076) [b]
	Public Service Facility	0.0032 (−0.0038,0.0103)	0.0075 (0.0027,0.0124) [a]
	Green Square	0.0119 (0.0017,0.0222) [a]	0.0022 (−0.0055,0.0099)
	Road Traffic	0.0126 (−0.0001,0.0252) [b]	0.002 (−0.0068,0.0109)
500 m			
	Residential	0.0094 (0,0.0187) [a]	0.0034 (−0.0006,0.0073) [b]
	Industrial	−0.0029 (−0.0325,0.0267)	0.0028 (−0.0108,0.0164)
	Commercial Facility	0.007 (−0.0015,0.0154)	0.0003 (−0.0035,0.0041)
	Public Service Facility	0.0141 (0.0042,0.0239) [a]	0.0019 (−0.0023,0.0062)
	Green Square	0.0239 (0.0093,0.0386) [a]	−0.0011 (−0.0091,0.0069)
	Road Traffic	0.0205 (0.0027,0.0384) [a]	−0.0006 (−0.0093,0.0081)
1000 m			
	Residential	0.0143 (0.0029,0.0256) [a]	0.0005 (−0.0029,0.0039)
	Industrial	0.0055 (−0.0425,0.0315)	−0.0006 (−0.0123,0.011)
	Commercial Facility	0.0117 (0.0016,0.0217) [a]	−0.0007 (−0.0044,0.003)
	Public Service Facility	0.0226 (0.0108,0.0343) [a]	−0.0008 (−0.0048,0.0033)
	Green Square	0.029 (0.011,0.0469) [a]	−0.0022 (−0.0105,0.0061)
	Road Traffic	0.0333 (0.0117,0.0548) [a]	−0.0042 (−0.0118,0.0034)

Note: [a] significant at p of 0.05; [b] significant at p of 0.1.

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