Applied Geography 148 (2022) 102803

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Visible green space predicts emotion: Evidence from social media and street view data

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ARTICLE INFO

Keywords:
Greenness
Mood
Big data
Machine learning
Health disparities

ABSTRACT

Social media data are increasingly used to examine associations between environmental exposures and mental wellbeing. In particular, studies highlight that exposure to natural outdoor environments (NOEs) is associated with fewer negative emotions. Also, people in socioeconomically disadvantaged neighbourhoods tend to benefit more from NOEs than their counterparts in more privileged neighbourhoods ("equigenic" effects). However, exposure to NOEs is principally studied with remotely sensed data that fail to measure peoples' lived experience and the visible environment at eye-level. The current study explored relationships between two forms of NOEs (green and blue spaces) using Tencent Map street view imagery and negative emotions from social media Weibo microblogs in 1540 neighborhoods of Guangzhou, China. Negative emotions and exposure to visible green and blue space were assessed at the neighborhood-level (averaged by neighborhood). Higher levels of visible green space were associated with lower levels of negative emotions (3rd quartile: coefficient [coef.] = −0.006, 95% confidence interval [CI] = −0.012 to −0.000; 4th quartile: coef. = −0.007, CI = −0.013 to −0.001), and these associations were stronger during non-work times. No associations were observed for visible blue space except in interactions with socioeconomic status (SES); blue space provided an equigenic effect whereby people in lower-SES neighborhoods expressed fewer negative emotions than other lower-SES neighbourhoods without blue space. Because negative emotions are strongly linked to depression and anxiety, the importance of green and blue space visible at eye-level should be considered when promoting equitable public health.

1. Introduction

Social media data are increasingly used to study the relationship between geospatially-reference environmental exposures and mental wellbeing. Researchers can use machine learning algorithms like the semantic analysis tool to identify the emotions of social media users through their geotagged posts (Yang et al., 2015; Zheng et al., 2019). Compared with questionnaire data, social media posts provide easier access to data from specific and broad geographic areas as well as in limited and wide time horizons (Coppersmith et al., 2014). Previous applications of social media data in mental wellbeing research include assessing depressive symptoms (Yang & Mu, 2015), postpartum symptoms (Choudhury et al., 2013), feelings of tranquility (Wartmann et al., 2019) and happiness across geographic space (Dodds et a., 2011; Nguyen et al., 2016; Mitchell et al., 2013; Frank et al., 2013; Schwartz et al., 2019). Other notable applications include testing for spatial associations between climate and depressed moods (Yang et al., 2015) and between air pollution and happiness (Zheng et al., 2019). A limitation of

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https://doi.org/10.1016/j.apgeog.2022.102803
Received 15 February 2021; Received in revised form 25 September 2022; Accepted 3 October 2022

these studies has been the insufficient attention paid to when social media posts are made and how this might influence the relationship between mental wellbeing and environmental exposures. Emotional sentiments in social media posts vary across times of day and days of the week or year (Mitchell et al., 2013). Further, the ways in which people interact with environments varies by time of day (Li et al., 2021; Liu, Wang, et al., 2020) and season (Brooks et al., 2017). In summary, combining geographic information systems (GIS) methods with social media data has accelerated researchers' ability to understand the relationship between environments and mental wellbeing (Yang et al., 2015), but further investigation of the relationship between timing of exposure and social media posts is warranted.

Natural outdoor environments (NOEs) are among the most recognized environmental exposure affecting mental wellbeing (Dzhambov et al., 2018; Helbich et al., 2019). NOEs generally are recognized as green spaces (parks, trees, grass, vegetative cover, etc.) and blue spaces (rivers, lakes, oceans, etc.) that act on mental wellbeing through three mechanisms (Dzhambov et al., 2020; Liu et al., 2019; Markevych et al., 2017; Liu et al., 2019; Liu, Xiao, & Wu, 2022; White, Elliott, Gascon, Roberts, & Fleming, 2020), although other NOEs such as deserts, caves, and polar and alpine regions might provide psychological benefits as well (Li et al., 2022). Health promoting mechanisms of NOEs include reducing harmful exposures to air pollution, noise, and heat (Gunawardena et al., 2017; Wang, Feng, Pearce, Liu, & Dong, 2021); restoring attentional capacities and reducing stress (Kaplan, 1995; Ulrich, 1983); and building capacities for healthy behavior, including sleep, physical activity, and social interaction, among others. (Wang, Feng, Pearce, Liu, & Dong, 2021). Increasingly of interest is NOE's possible "equigenic" role; this describes the environment's ability to overcome health disparities between vulnerable populations and more privileged populations (Pearce et al., 2018).

Most studies on the relationship between NOEs and mental wellbeing have used remotely sensed data that estimate NOE cover overhead (Labib, Lindley, & Huck, 2020; Nordbø et al., 2018). Such estimates may not accurately measure what people experience in their daily lives. Tree canopies and other elevated forms of green space can be too high for people to see as they travel along a streetscape or look out a window (Labib, Huck, & Lindley, 2020). Similarly, green walls, waterfalls and fountains, and other vertical forms of NOEs may be poorly captured with overhead estimates (Labib, Huck, & Lindley, 2020). These restorative elements can have impacts on people's lived experiences and mental wellbeing (van den Berg et al., 2016; Grafetstätter et al., 2016). Correspondingly, street view images have become a validated data source for eye-level estimates of NOEs (Helbich et al., 2019; Labib, Huck, & Lindley, 2020; Lu, 2019). Existing studies have found that street view-based green space is not necessarily associated with land use-based or remote sensing-based metrics (Li et al., 2015), which indicates street view-based measures may reflect different perspectives of NOE exposure.

The current study aims to fill several gaps in the bodies of literature discussed above. First, unlike existing data, street view data can reflect accurate visible NOE exposure, which is important for people's wellbeing. Meanwhile, social media data can be used to detect changes in people's emotion over long periods of time across large geographic scales. We are unaware of other studies that have combined the strengths of social media data with the accuracy of visible NOE exposure estimates from street view data. Neither are we aware of studies using street view data to examine the possible equigenic effects of NOEs. Therefore, we explored relationships between two forms of NOEs from street view images (visible green space and visible blue space) and one form of mental wellbeing from social media posts (negative emotions) using an ecological study design. Second, we conducted the study across a six-month time period that allowed us to evaluate differences in these relationships by time of day and days of the week/year. More specifically, we examined how NOEs impact mental wellbeing outside of workdays and weekdays when people are more likely to be working and not mentally attentive to the environments around them (Jiang et al., 2018). Third, equigenesis theory suggests that socioeconomically disadvantaged groups tend to benefit more from NOEs, which can be regarded as public amenities (Mitchell et al., 2015). Therefore, we tested whether visible measures of NOEs could have equigenic effects on mental wellbeing.

2. Methods

2.1. Study region

We conducted our study in Guangzhou, the capital and most populous city of Guangdong province in southern China (Fig. 1). Guangzhou spans 7434 km^2 and encompasses a diversity of environments. Mountains extend up to 1210 m in elevation, the 4th-largest river in China (the Pearl River) and associated riparian areas traverse through the city north-to-south, and the Pacific Ocean forms the southern terminus.

2.2. Data acquisition and processing

2.2.1. Social media posts

Our social media data came from "microblogs" on the Sina Weibo website (Weibo.com). Microblogging involves posting short sentences, images, or video links to an online social media platform (Aichner & Jacob, 2015). Weibo is the leading microblogging website in China with more than 600 million registered users. Other examples of popular microblogging websites are Twitter.com and Tumblr.com. Data were available through Application Programming Interfaces (APIs, https://op

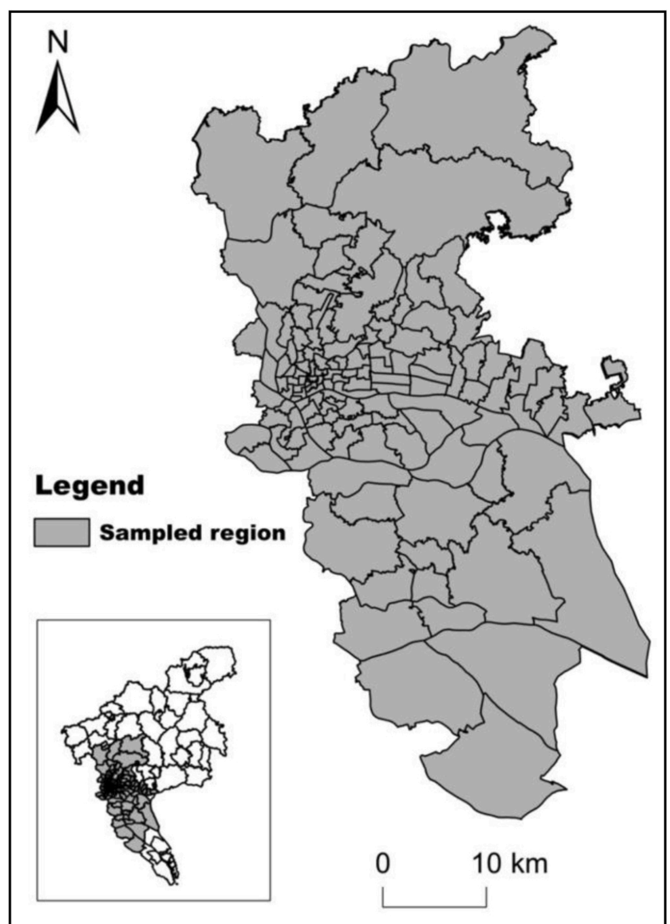


Fig. 1. The study area: Sampled region in Guangzhou city, Guangdong province, China.

en.weibo.com/wiki/2/place/pois/users). APIs allow third parties to retrieve data from user profiles, latitude and longitude of posts, and text of posts. We retrieved data over multiple months (May–October 2014) to consider how days of the week and holidays impact relationships between mental wellbeing and environmental exposures. A total of 158, 108 posts were available across our study region during this time period (60,753 for weekdays, 54,373 for weekend, and 42,982 for holidays). We excluded posts sent between 9:00 a.m. and 5:00 p.m. on weekdays, since most people would have been at the workplace (Zhang et al., 2017). In the Chinese context, most people work in high-rise buildings, which may limit their exposure to NOEs during work (Yu et al., 2016). Hence, we mainly focused on the association between NOEs and emotions in neighbourhoods. Posts were assigned at the neighborhood-level and covered 1540 of the 1677 neighborhoods (*juweihui*) in the city (mean population = 5751 persons; mean area = 6 km^2). Processing these posts occurred in three stages: preprocessing data, extracting features, and categorizing features.

We preprocessed the Weibo data with word segmentation, part-of-speech tagging, and stop word list construction (Hung & Lin, 2013; Zheng et al., 2013). The first two stages involved the complex process of recognizing individual Chinese words; for this, we applied the Institute of Computing Technology, Chinese Lexical Analysis System (ICTCLAS) with a hierarchical hidden Markov model (Zhang et al., 2003). The ICTCLAS segmented the words very accurately; testing accuracy was as high as 97.58%. Unlike English, there is no widely accepted Chinese stop words that indicate the end of a sentence. Thus, we constructed a list of common Chinese stop words based on the word frequencies in our data.

We then applied Latent Dirichlet Allocation (LDA) to extract emotional features from the Weibo posts (Blei et al., 2003). In its simplest form, LDA connects text with its latent topics (here, these topics were emotions). LDA regards a post as a collection of words with no sequence and acknowledges that a post and the words it contains can cover multiple topics (Liu, He, et al., 2017). The programming of LDA involves a three-layer Bayesian generation model of the "Document-Text-Word" approach that is subjected to the Dirichlet distribution by introducing a hyper-parameter to the probability distribution of "Document-Topic" (Blei et al., 2003). We queried subject terms and corresponding probabilities in LDA and used these probabilities to represent the documents as extracted emotions.

To categorize the emotions in the Weibo posts, we constructed training and testing datasets by manually labeling 3500 randomly selected posts (80/20 split). These posts were classified into one of three categories: negative emotions, positive emotions, or neutral emotions. In the current study, we focused on a single single category due to data processing limitations and feasibility. The chosen category was negative emotions because of their strong association with depressive and anxiety symptoms (Watson et al., 1988), which are mental wellbeing outcomes strongly linked in past research to NOEs (Roberts et al., 2019; Zhang et al., 2020). The 'Tencent' natural language processing (NLP) platform was not appropriate for the current study, since these training data were primarily from Mandarin posts (Zheng et al., 2019). Guangzhou has a large population of residents who post in Cantonese, not solely Mandarin.

Last, we applied support vector machine (SVM) to compute the probabilities of negative emotions in the Weibo data (Cortes & Vapnik, 1995). SVM is a supervised machine learning model that is commonly used for pattern recognition, classification, and regression analysis (Mountrakis et al., 2011; Peng, 2011). We chose SVM because the dimension of latent semantic features was usually too high to be classified; other machine learning algorithms such as neural networks would have increased the computational complexity and reduced model classifications. SVM applies kernel functioning to be very efficient when dealing with a classification problem with highly dimensional features (Lilleberg et al., 2015). SVM was applied by calling the LIBSVM algorithm package (Chang & Lin, 2011) and trained by fitting the testing dataset with the features extracted from the LDA. In this way, features extracted from LDA were automatically weighted based on the 3500 posts. Finally, we trained the SVM model to calculate the probability of negative emotions for each post: the higher the value, the more negative the emotion. The accuracy of the training and testing data were all above 0.85. To calculate negative emotion values for the entire neighborhood, we averaged the probability of negative emotions of all posts in each neighborhood.

2.2.2. Street view images

Street view images were collected from Tencent Map (https://map.qq.com/) to estimate visible NOE exposure. Tencent Map is the most comprehensive online mapping website in China and similar in function and coverage to Google Maps elsewhere.

We constructed sampling points every 100 m along the entire public road network in each neighborhood. Road network data were retrieved from Open Street Map (OSM, Haklay and Weber, 2008). Street view images in each of the four cardinal headings (0, 90, 180, and 270°) were retrieved at each sampling point (Helbich et al., 2019; Lu, 2019; Wang et al., 2021). In total, 202,543 images were obtained.

Following previous studies (Helbich et al., 2019; Wang, Feng, Pearce, Liu, & Dong, 2021), we used a machine learning approach to extract NOE features along streetscapes. We implemented a fully convolutional neural network for semantic segmentation (FCN-8s) (Long et al., 2015), which segments the images into the different objects that are visible along the streetscape (e.g., trees, grasses and water bodies). We trained our FCN-8s model with the ADE20K scene parsing and segmentation databases (Zhou et al., 2019). After obtaining the image segmentations by inserting the street view images into the trained model, the ratio of green-to-total pixels and blue-to-total pixels (for visible green and blue space, respectively) was calculated for each image at each sampling point in all four cardinal directions (Helbich et al., 2019; Wang, Feng, Pearce, Liu, & Dong, 2021). To calculate visible blue and green space across neighborhoods, we averaged these ratios across all sampling points in each neighborhood. Values ranged from 0.00 to 1.00 where 0.00 described images with no green (or blue) pixels and 1.00 described images covered entirely by green (or blue) pixels. Skewness Kurtosis tests (Mardia, 1970) indicated that there was no evidence that visible green and blue space were normally distributed. Hence, due to the potential for non-linear relationships between green/blue space and mental health, including emotions (Helbich et al., 2019), we calculated quartiles of visible green and blue space and used these in subsequent models. We also used remote sensing data at a 30 m × 30 m spatial resolution to calculate the normalized difference vegetation index (NDVI) (Tucker, 1979), which was obtained for the year 2016 from the USGS EarthExplorer (https://earthexplorer.usgs.gov/). We used cloud-free data in the greenest season (August). NDVI for each neighbourhood was calculated by averaging NDVI value of all pixels within the neighbourhood. The spatial distribution of social media and street view data are shown in Fig. S1.

2.2.3. Socio-demographic characteristics

We identified potential confounders in the association between green/blue space and mental wellbeing based on previous research (Houlden et al., 2019; Li et al., 2015; Li et al., 2016; Wang, Feng, Pearce, Liu, & Dong, 2021; Wang, Feng, Pearce, Liu, & Dong, 2021; Xie, 2019). In total, 11 variables at the neighborhood-level were obtained from the 2010 census. These variables included population density (people [ppl]/km^2), age (% ppl <18 yrs; % ppl >60 yrs), relationship status (divorce rate), socio-economic status (SES) (% ppl with low educational attainment; % ppl in low status occupation; % owner-occupied housing units; % migrants), and housing (ppl/household; house size in km^2/ppl; % buildings built before 1978). In the Chinese context, buildings built before 1978 were constructed by the government, and they usually do not have sufficient housing facilities (He et al., 2010; Xiao, Lu, Guo, & Yuan, 2017a). Skewness Kurtosis tests (Mardia, 1970) indicated that there was no evidence that population density was normally distributed, so it was transformed into a logarithm form for analysis.

2.3. Analysis

We first examined spatial clustering of the dependent variable (negative emotions). Local Moran's I values were calculated across the sample of neighborhoods and mapped using Local Indicators of Spatial Association (LISA). Clusters of high values (high-high, "HH") represented areas of unusually high levels of negative emotions. Clusters of low values (low-low, "LL") represented the opposite: areas with unusually low levels of negative emotions. Other spatial clustering results identified neighborhoods with high values surrounded primarily by low values (high-low, "HL") and neighborhoods with low values surrounded primarily by high values (low-high, "LH"). Correlation analysis in Table S1 suggested there was no evidence that visible green space was associated with visible blue space.

We then tested for associations between visible green and blue space and negative emotions using linear regression models. First, we regressed negative emotions on visible green space and visible blue space for the entire sample of neighborhoods. Both a crude model (**Model 1**) and adjusted model (**Model 2**) were examined. Second, we ran a sensitivity analysis with a subsample of social media data restricted to posts where the probability of negative emotions was at least 50%. For this, we calculated the proportion of negative posts for each neighborhood and used that as a new dependent variable to test the sensitivity of our dependent variable (**Model S2**). Hence, visible green space was replaced by NDVI to compare our metric with an overhead general green space exposure metric (**Model S3**). Third, we reran the regression model with the social media data posts outside of workday hours (**Model 3**) and outside of holidays (**Model 4**) to further check the robustness of our results. Fourth, we regressed negative emotions on visible green space and visible blue space using posts from weekdays, weekends, or holidays (**Models 5, 6,** and **7**, respectively) to test the temporal differences in visible NOE-emotion associations. Last, previous studies indicated that NOE might reduce socio-economic disparities in wellbeing (Mitchell et al., 2015), so we estimated the moderating effect of visible green space and visible blue space in the association between SES and negative emotions (**Models 8** and **9**, respectively). As for the moderation analysis, we focused on two SES indicators (low education and occupation status) and their interaction terms. If the interaction terms were significant and the direction was opposite to low SES status, than the findings supported the possibility of visible green space or blue space mitigating SES disparities in negative emotions and equigenesis theory. Variance inflation factor values < 3.0 demonstrated that there was not multicollinearity in the models. We defined statistical significance as $P < .05$ for main effects and interactions. Analyses were performed in Stata 15.1 (StataCorp., College Station, TX, USA) using the 'reg' commands.

3. Results

3.1. Sample characteristics

The neighborhoods in our sample ($N = 1540$) are described in Table 1. The average % ppl <18 yrs was 16% and the mean % ppl>60 yrs was 10%. The average household size was 2.7 persons. Approximately 17% of residents had low levels of educational attainment, and 31% had a low status occupation (i.e catering and service). The mean negative emotions value was 0.305. Regarding NOEs, visible green space levels were higher than visible blue space values ($M = 0.201$ vs. 0.026, respectively).

Fig. 2a shows the spatial clustering of negative emotions across neighborhoods. High values were concentrated in the inner city (central distracts) and outer city, whereas low values were concentrated in the outer city. Fig. 2b displays the local Moran's I values for negative emotion values. Areas with unusually high levels of negative emotions (HH) and areas with unusually low levels of negative emotions (LL) were distributed across the central districts and suburbs. Neighborhoods with high or low levels of negative emotions (HL and LH) that were surrounded by the opposite were mainly in the suburbs.

Table 1
Summary statistics of variables at the neighborhood-level included in regression analyses ($N = 1540$).

Variable	Mean (SD)
Dependent variable	
Negative emotions	0.305 (0.0375)
Independent variables Median (25th - 75th percentiles)	
Visible green space	
Q1	0.096 (0.061–0.115)
Q2	0.169 (0.151–0.184)
Q3	0.225 (0.211–0.240)
Q4	0.311 (0.278–0.348)
Visible blue space	
Q1	0.000 (0.000–0.001)
Q2	0.003 (0.001–0.005)
Q3	0.014 (0.010–0.018)
Q4	0.048 (0.033–0.100)
Socio-demographic characteristics	
Population density (ppl/km^2) Median (25th - 75th percentiles)	18116.764 (3564.446–47319.837)
% ppl <18 yrs	16.2 (4.9)
% ppl >60 yrs	10.8 (5.5)
% ppl with low educational attainment	17.3 (7.5)
% ppl working in low status occupation	31.2 (26.5)
% migrants	34.1 (22.9)
Divorce rate	1.6 (1.3)
Household size (ppl/household)	2.686 (0.444)
House size (km^2/ppl)	24.259 (9.677)
% owner-occupied residential units	54.9 (27.2)
% buildings built <1978	11.4 (16.6)

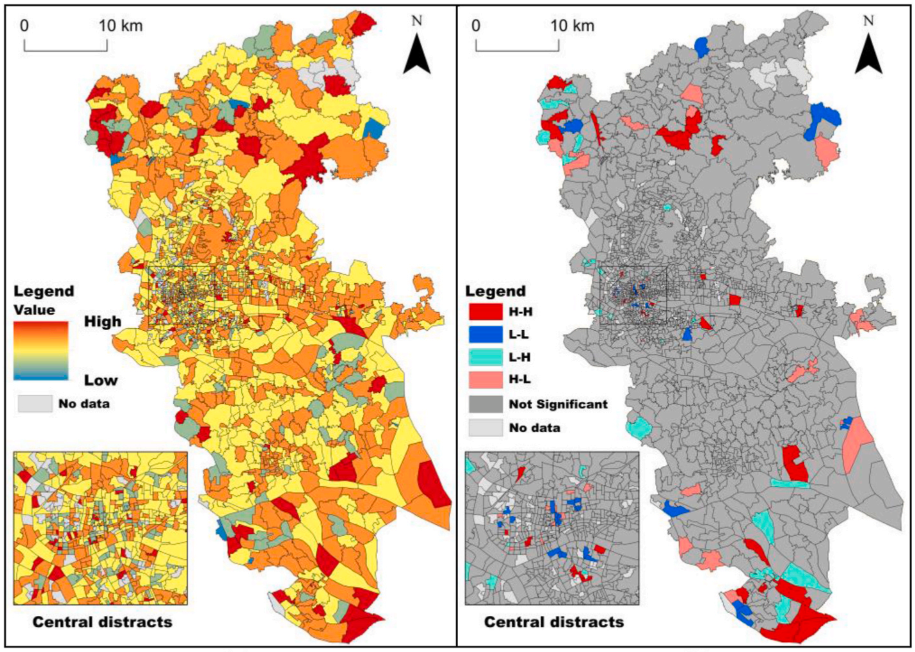
Dependent variable is the average probability of negative emotions of all posts in each neighborhood, with higher values indicating more negative emotions.

3.2. Associations between negative emotions and natural outdoor environments

Table 2 presents multivariate associations between negative emotions, NOEs, and socio-demographic characteristics in the full sample of social media posts (**Model 1** and **Model 2**). Quartiles three and four (Q3, Q4) of visible green space were associated with lower levels of negative emotions, relative to Q1. No associations between visible blue space and negative emotions were observed.

Table S1 shows the results of adjusted model with covariates presented. Three socio-demographic characteristics also predicted the dependent variable. Higher levels of population density were associated with lower levels of negative emotions, and lower levels of SES were associated with higher levels of negative emotions. The sensitivity analysis in a subsample of social media posts with more than a 50% probability of showing negative emotions produced similar results. Protective associations between visible green space and negative emotions were observed in Q3 and Q4 (**Model S2**, data shown in Supplementary). Again, no associations between visible blue space and negative emotions were found in this sensitivity analysis. Another sensitivity analysis (**Model S3**) suggested that there was no evidence that NDVI was associated with negative emotions.

Table 3 presents the results of models with social media posts when certain times and days wer excluded. Posts limited to non-work times (outside of 8 a.m. to 6 p.m.) showed that Q3 and Q4 of visible green space were associated with lower levels of negative emotions, relative to Q1. Associations with Q2 of visible green space approached statistical significance, $p < .10$. In contrast, posts limited to non-holiday days showed only Q4 of visible green space being associated with lower levels of negative emotions. Associations with Q3 only approached statistical significance, $p < .10$. In both of these models, visible blue space was not



(a) (b)

Fig. 2. (a) Distribution of negative emotions in Guangzhou neighborhoods (N = 1540); **(b)** Local Indicators of Spatial Association (LISA) map from Local Moran's I values showing clustering of negative emotions. High-high (H–H) = areas with unusually high levels of negative emotions; low-low (L–L) = areas with unusually low levels of negative emotions; high-low (H–L) = high values surrounded primarily by low values; low-high (L–H) = low values surrounded primarily by high values.

Table 2
Regressing negative emotions on natural outdoor environments in Guangzhou neighborhoods (N = 1504) (Model 1).

	Model 1 (crude main model)	Model 2 (adjusted main model)
	Coef. (95% CI)	Coef. (95% CI)
Visible green space [reference = Q1]		
Q2	−0.004 (-0.010, 0.002)	−0.005 (-0.011, 0.001)
Q3	**−0.005(-0.011, -0.000)***	**−0.006(-0.012, -0.000) ***
Q4	**−0.006(-0.012, -0.000)***	**−0.007(-0.013, -0.001) ***
Visible blue space [ref. = Q1]		
Q2	−0.000 (-0.006, 0.006)	−0.002 (-0.008, 0.004)
Q3	−0.002 (-0.008, 0.004)	−0.004 (-0.012, 0.002)
Q4	−0.004 (-0.010, 0.002)	−0.004 (-0.010, 0.002)

Models adjusted for population density, % ppl <18 yrs and >60 yrs, % ppl with low educational attainment and low status occupation, % migrants, divorce rate, household size, house size, % owner-occupied residential units, % buildings built <1978, Coeff. = coefficient; CI = confidence interval; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, coefficients approaching statistical significance ($p < .05$) shown in bold.

related to negative emotions.

Table 4 presents the results of models with social media posts restricted to certain days. Weekday posts showed no significant relationships between NOEs and negative emotions; however, associations with Q4 of visible green space approached significance and Q3 and Q4 of visible blue space approached significance, $p < .10$. In these cases, both types of NOEs trended toward lower levels of negative emotions. In contrast, weekend posts and holiday posts showed consistent associations between visible green space and negative emotions. Q3 and Q4 of visible green space in weekend posts were associated with lower levels of negative emotions, relative to Q1. Also, Q2, Q3, and Q4 of visible green space in holiday posts were associated with lower levels of negative emotions, relative to Q1. These effect estimates were similar across quartiles indicating a sharper plateau effect of visible green space on negative emotions for holiday posts. Visible blue space showed no associations with negative emotions in these models.

Table 3
Regressing negative emotions on natural outdoor environments during non-work times (8 a.m.–6 p.m. excluded, Model 3) and outside of holidays (Model 4) in Guangzhou neighborhoods (N = 1504).

	Model 3 (non-work times)	**Model 4** (outside of holidays)	**Model 2** (adjusted main model, for reference)
	Coef. (95% CI)	Coef. (95% CI)	Coef. (95% CI)
Visible green space [reference = Q1]			
Q2	−0.005 (-0.012, 0.001) $^{+}$	−0.003 (-0.007, 0.001)	−0.005 (-0.011, 0.001)
Q3	**−0.005 (-0.012, -0.000) ***	−0.005 (-0.012, 0.001) $^{+}$	**−0.006(-0.012, -0.000) ***
Q4	**−0.007 (-0.013, -0.001) ***	**−0.006(-0.010, -0.002) ***	**−0.007(-0.013, -0.001) ***
Visible blue space [ref. = Q1]			
Q2	−0.001 (-0.007, 0.005)	−0.005 (-0.012, 0.001)	−0.002 (-0.008, 0.004)
Q3	−0.003 (-0.009, 0.003)	−0.005 (-0.013, 0.003)	−0.004 (-0.012, 0.002)
Q4	−0.000 (-0.008, 0.008)	−0.004 (-0.012, 0.004)	−0.004 (-0.010, 0.002)

Models adjusted for population density, % ppl <18 yrs and >60 yrs, % ppl with low educational attainment and low status occupation, % migrants, divorce rate, household size, house size, % owner-occupied residential units, % buildings built <1978, Coeff. = coefficient; CI = confidence interval; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, coefficients approaching statistical significance ($p < .05$) shown in bold.

3.3. Role of natural outdoor environments in relationship between socioeconomic status and negative emotions

Table 5 presents the results of the models regressing negative emotions on NOEs, two measures of SES, and corresponding interaction terms, while adjusting for other socio-demographic characteristics. Multiplicative interaction terms between visible green space and SES were non-significant, $p > .10$. In contrast, interaction terms between Q4 of visible blue space and both SES variables were significant, $p < .05$, and in the negative direction. These findings suggested that visible blue

Table 4
Regressing negative emotions on natural outdoor environments (NOEs) during weekdays (Model 5), weekends (Model 6), and holidays (Model 7) in Guangzhou neighborhoods (N = 1504).

	Model 5	Model 6	Model 7	Model 2
	(weekdays)	(weekends)	(holidays)	(adjusted main model, for reference)
	Coef. (95% CI)	Coef. (95% CI)	Coef. (95% CI)	Coef. (95% CI)
Visible green space [reference = Q1]				
Q2	−0.001 (-0.007, 0.005)	−0.005 (-0.015, 0.005)	**−0.012 (-0.022, -0.002) ****	−0.005 (-0.011, 0.001)
Q3	−0.002 (-0.008, 0.004)	**−0.010 (-0.020, -0.000) ***	**−0.011 (-0.021, -0.001) ***	**−0.006(-0.012, -0.000) ***
Q4	**−0.005 (-0.011, -0.000) ***	**−0.010 (-0.020, -0.000) ***	**−0.012 (-0.022, -0.002) ***	**−0.007(-0.013, -0.001) ***
Visible blue space [ref. = Q1]				
Q2	−0.006 (-0.014, 0.002)	−0.005 (-0.015, 0.005)	0.004 (-0.006, 0.014)	−0.002 (-0.008, 0.004)
Q3	−0.008 (-0.018, 0.002) +	−0.003 (-0.013, 0.007)	0.002 (-0.008, 0.012)	−0.004 (-0.012, 0.002)
Q4	−0.009 (-0.019, 0.001) +	−0.005 (-0.017, 0.007)	−0.001 (-0.013, 0.011)	−0.004 (-0.010, 0.002)

Models adjusted for population density, % ppl <18 yrs and >60 yrs, % ppl with low educational attainment and low status occupation, % migrants, divorce rate, household size, house size, % owner-occupied residential units, % buildings built <1978, Coeff. = coefficient; CI = confidence interval; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, coefficients approaching statistical significance ($p < .05$) shown in bold.

space weakened the effect of neighborhood deprivation indicators (lower levels of educational attainment and status occupation) on negative emotions. We further performed a stratified analysis (Table S4), and the results indicated that associations of visible green space with negative emotions were stronger for higher levels of educational attainment and status occupation groups, while associations of visible blue space with negative emotions were stronger for lower levels of educational attainment and status occupation groups.

4. Discussion

4.1. Contributions of the study and interpretation of results

This study was the first to explore how visible natural outdoor environments (NOEs) related to mental wellbeing using a large dataset of social media posts. We found that higher levels of visible green space (but not blue space) were associated with lower levels of negative emotions. This central finding supports the growing body of research showing that visible green space is positively associated people's mental wellbeing (Liu, Wang, et al., 2020; Wang, Feng, Pearce, Liu, & Dong, 2021; Wang, Helbich, et al., 2019; Wu et al., 2020). For example, Helbich et al. (2019) found that visible greenspace was negatively associated people's depressive symptoms in Beijing, and Liu, Wang, et al. (2020) reported that visible green space was positively associated people's mental health in Guangzhou. Also, our sensitivity analysis indicated that there was no evidence that overhead greenness, as measured by NDVI, was associated with negative emotions. A possible explanation is that visual exposure to green space is best related to its restorative effects (Hedblom et al., 2019), while overhead measures may not be able to precisely reflect visual exposure and restoration potential (Wang, Feng, Pearce, Liu, & Dong, 2021). We also found that higher levels of visible blue space were not related to lower levels of negative emotions.

Table 5
Regressing negative emotions on natural outdoor environments (NOEs), lower levels of socioeconomic status (SES), and interactions between NOEs and SES with poorer educational achievement (Model 8) and occupational status (Model 9) in Guangzhou neighborhoods (N = 1504).

	Model 8	Model 9
	(education)	(occupation)
	Coef. (95% CI)	Coef. (95% CI)
% ppl with low levels of educational attainment ("low education levels")	**0.046(0.003, 0.089)***	**0.040(0.003, 0.077) ***
% ppl working in low status jobs ("low status occupations")	**0.022(0.004, 0.040)***	**0.020(0.002, 0.038) ***
Interactions with visible green space [ref. = Q1]		
Q2 x low education levels	0.004 (-0.004, 0.012)	
Q3 x low education levels	0.003 (-0.005, 0.012)	
Q4 x low education levels	0.003 (-0.005, 0.012)	
Q2 x low status occupations		0.003 (-0.019, 0.025)
Q3 x low status occupations		0.005 (-0.017, 0.027)
Q4 x low status occupations		0.011 (-0.011, 0.033)
Interactions with visible blue space [ref. = Q1]		
Q2 x low education levels	−0.007 (-0.019, 0.005)	
Q3 x low education levels	−0.009 (-0.019, 0.001)+	
Q4 x low education levels	**−0.012(-0.022, -0.002)***	
Q2 x low status occupations		−0.009 (-0.021, 0.003)
Q3 x low status occupations		−0.006 (-0.016, 0.004)
Q4 x low status occupations		**−0.011(-0.021, -0.001)****

Models adjusted for population density, % ppl <18 yrs and >60 yrs, % migrants, divorce rate, household size, house size, % owner-occupied residential units, % buildings built <1978, Coeff. = coefficient; CI = confidence interval; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, coefficients approaching statistical significance ($p < .05$) shown in bold.

A growing number of studies have found exposure to blue space are indeed associated with better mental wellbeing; however, these studies are dominated by remotely sensed (overhead) measures of exposure (Gascon et al., 2017; Labib, Lindley, & Huck, 2020). The studies that do use visible blue space measures have found protective effects of exposure (i.e., Liu, Wang, et al., 2020). One explanation for the differences we found regards water quality; this has been increasing in recent years in China but remained poor in our study region during the year when the social media posts were retrieved (Zhao et al., 2020). Poor water quality can reduce the restorative potential and use of blue space (Angermeier et al., 2021). Another explanation for these disparate findings regarding blue space is that water sports were not very popular in our study area, which further restricted people's use of blue space relative to countries where many of the other studies on blue space exposure and mental wellbeing have been conducted (Gascon et al., 2017; Huan et al., 2009).

This study also extended the literature on relationships between NOEs and mental wellbeing by investigating timing of exposing and social media posts. We found that the protective effects of visible green space were stronger during non-work times and days. People tend to be distracted from their environment while on electronic devices, so if their work entails screen time, visible NOEs may not have measurable impacts on their mental wellbeing (Jiang et al., 2018). Further, non-work hours are when people have leisure time to visit and attend to NOEs, thereby increasing their impacts on mental wellbeing (Pasanen et al., 2019; Pietilä et al., 2015). The strength of the protective effects of visible green space on negative emotions was stronger on holidays than other non-work times; this may because people are more relaxed on holidays and more focused on NOEs, which also may increase their mental wellbeing benefits (Lin et al., 2019; Packer, 2021).

Last, the study contributed to the growing interest in NOEs' potential to overcome health disparities by having equigenic effects. We found that visible blue space buffered the negative effects of low socioeconomic status (SES) on negative emotions. This finding supports the "equigenesis hypothesis" regarding vulnerable populations benefiting more from health-promoting neighborhood services, facilities, and environments than other populations, since vulnerable populations have less resources to maintain/improve health status and rely more on public health resources (Mitchell et al., 2015). Although there was no significant evidence that visible green space also had equigenic effects in lower-SES neighborhoods, we observed a pattern that the potential moderation effect of visible green space on low status occupation neighborhoods became stronger with increasing levels of visible green space. Low status occupation neighborhoods often have limited resource of recreational amenities, so residents in such neighbourhoods may tend to rely more on NOEs such as green space to relieve stress (Wang et al., 2022). Visible green space in our study region was unequally distributed so people posting in lower-SES would have had less physical access to green spaces than posts elsewhere, thereby limiting the potential use, visitation, and benefits to mental wellbeing of green spaces in these more vulnerable populations (Wang, Feng, Pearce, Liu, & Dong, 2021). We recommend future research and health promotion strategies not rule out the possibility of the equigenic effects of green space.

4.2. Limitations

This study's sources of data presented both strengths and limitations. First, the large sample size of social media users increased the reliability of the results and generalizability to populations within and beyond the study region. Simultaneously, the use of social media data in general has drawbacks. Posts can overrepresent feelings of adolescents and young adults, since these populations are more likely to use these platforms than older populations (González-Bailón, 2013; Goodchild, 2013; Gorman, 2013). This study was also limited by its cross-sectional, ecological design. The cross-sectional data did not allow us to determine that exposure to NOEs caused changes in emotional states. The ecological design with data aggregated within neighborhoods meant our results may not translate to how individual residents' emotional states correspond to NOEs (González-Bailón, 2013; Goodchild, 2013; Gorman, 2013). Furthermore, sentiment analysis could only measure emotion tendency from the text posts, so future studies may use hospitalization and prescription data to validate the results and composite better health indicators. Since our data were mainly collected in summer, we were not able to identify seasonal variations in the negative emotions. In addition, as there was not much vertical blue space, it may have been hard to detect exposures using street view data (Helbich et al., 2019). Future studies could also use LiDAR and other sources of spatial data to better measure people's actual exposure to blue space (Prošek et al., 2020). Finally, social media can only reflect people's emotions for a short period. Negative emotions may not appear or disappear within seconds of entering NOEs. This occurance further limited our ability to infer causality between NOE exposure and emotions.

5. Conclusion

Exposure to natural outdoor environments (NOEs) is linked to mental wellbeing, including negative emotion levels. NOE exposure is primarily measured with remotely sensed data that estimates the amount of green and blue space overhead. However, people usually experience NOEs at eye-level. Measures from the ground (what is "visible") are more accurate depictions of a person's lived experience. In this study, we examined associations between two eye-level measures of NOEs (visible green and blue space) and negative emotions using street view and social media data in a large city of China.

We found that higher levels of visible green space were associated with lower levels of negative emotions. These associations were stronger during non-work times (i.e., outside of 8 a.m. to 6 p.m. on weekdays, on weekends, and over holidays). No associations were observed between visible blue space and negative emotions; however, visible blue space buffered against the harmful effects of low socio-economic status on negative emotion levels. Given these findings, visible green space may be important for promoting public health related to mental wellbeing while visible blue space may be important for overcoming health disparities related to mental wellbeing.

Funding

This work was supported by the National Natural Science Foundation of China (grant numbers 41871140, 41971194, 52278085 and 41801306), the Program for Guangdong Introducing Innovative and Enterpreneurial Teams (grant number 2017ZT07X355), National Office for Philosophy and Social Sciences (20ZDA037) .

Declaration of competing interest

The authors declare that they have no competing interest.

Acknowledgements

We would like to thank the anonymous reviewers for their helpful and positive comments. These have improved the quality of the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2022.102803.

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