The Relationship Between Natural Environments and Subjective Well-being as Measured by Sentiment Expressed on Twitter

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Abstract

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There is growing evidence that time spent in nature can affect well-being. Nonetheless, assessing this relationship can be difficult. We used social media data—1,971,045 geolocated tweets sent by 81,140 users from locations throughout Seattle, Washington, USA—to advance our understanding of the relationship between subjective well-being and natural environments. Specifically, we quantified the relationships between sentiment (negative/neutral/positive) expressed in individual geolocated tweets and their surrounding environments focusing on land-cover type, tree-canopy density, and urban parks. Controlling for multiple covariates such as location types and weather conditions, we estimated three random-intercept partial proportional odds models corresponding to the three environmental indicators. Our results suggest that for a given type of land-use, tweets sent from some natural land-cover types were less likely to be negative compared to tweets sent from the urban-built land-cover type. We also found that for tweets sent in industrial zones, the association between tree-canopy coverage and sentiment polarity was positive: an increase in tree-canopy coverage was associated with a lower

probability of having negative sentiments and with a higher probability of having positive sentiments; but for tweets sent in commercial/mixed zones, the association between tree-canopy coverage and sentiment polarity was negative. For parks, tweets sent from urban parks in commercial/mixed zones and residential zones were less likely to be negative compared to tweets sent from outside parks. In industrial zones, only tweets sent from large natural parks (with area >= 40,000 sf^2 and impervious surface < 30%) were less likely to be negative. Surprisingly, we also found that tweets sent from large natural parks in residential zones were less likely to be positive compared to tweets sent from outside parks. Geolocated social media data allows nuanced analyses that reveal the complexity of the relationship between subjective well-being and natural environments.

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1. Introduction

According to the United Nations, by 2050, about 68% of the world's total population is expected to live in cities, and the urban population is projected to increase by 2.5 billion (United Nations, 2019). Although urban living may provide more job opportunities, higher income, and more convenience, an urban lifestyle that leads to more time spent indoors and less contact with nature may have negative impacts on mental health and well-being (Soga & Gaston, 2016; White et al., 2013; Cox et al., 2018; Hartig et al., 2011). In response, an increasing number of studies have explored the link between mental well-being and people's surrounding environments, especially natural environments in urban areas (Frumkin et al., 2017; Hartig et al., 2014).

1.1 Natural environments and psychological well-being

There are several possible mechanisms through which natural environments can provide psychological benefits to urban populations. Some of the most direct mechanisms proposed and examined are the Biophilia Hypothesis (Kellert & Wilson, 1995; Wilson, 1984), Stress Reduction Theory (SRT) (Ulrich et al., 1991), and Attention Restoration Theory (ART) (R. Kaplan & Kaplan, 1989; S. Kaplan, 1995). The Biophilia Hypothesis suggests that human beings have an inborn emotional need to affiliate with nature. SRT posits that humans feel less stressed when viewing unthreatening natural environments that were favorable to survival during human evolution. ART suggests that nature can restore people's directed attention from fatigue because they facilitate the experience of being away, soft fascination, extent, and compatibility, which are the four key restorative qualities. According to these theories, exposure to natural environments in urban areas may benefit people psychologically by satisfying their innate emotional needs, reducing their stress levels, and helping them recover from attention fatigue. In addition, it has been proposed that natural environments may benefit urban populations psychologically through mediators such as physical activity (Richardson et al., 2013), social interactions (Maas et al., 2009), and the mitigation of environmental hazards (Dadvand et al., 2012).

In line with these theories, a growing body of evidence suggests that various types of exposure to, and contact with, the natural environment are associated with a wide range of mental health benefits, including higher levels of psychological well-being (McMahan & Estes, 2015) and lower risks of certain types of mental illness (Bratman et al., 2019). Laboratory experiments have demonstrated that exposure to images, videos, and sounds of the natural environment can reduce stress levels and help people recover from attention fatigue (Berto, 2005; Wang et al., 2016). Field experiments that assigned participants actual exposure to the natural environments have demonstrated that walking in natural versus urban environments can improve positive affect, memory span, mood, and directed-attention abilities (Berman et al., 2008, 2012; Bratman et al., 2015), and reduce anger, stress, negative affect, and rumination (Bratman et al., 2015; Hartig et al., 2003; Marselle et al., 2013). Observational studies using traditional survey data also provide a range of evidence for the positive association between nature exposure and mental well-being. For example, it has been shown that people living with a large amount of green space around their homes are less affected by stressful life events (van den Berg et al., 2010). Higher greenness (as measured by normalized difference vegetation index--NDVI--values) in residential areas has been negatively associated with the risk of depression for people with diabetes (Gariepy et al., 2015). The probability of reporting positive well-being significantly increases for people who spend at least two hours a week in nature (White et al., 2019).

1.2 Approaches to investigating relationships between nature and psychological well-being

Previous studies have used a number of approaches to advance our understanding of the psychological benefits that exposure to nature may have. However, all approaches have some weaknesses and present tradeoffs. Laboratory experiments have the greatest potential to make causal inference and test underlying mechanisms but have the lowest ecological validity as they can only examine the exposure to simulated or virtual natural environments rather than real nature experiences. Field experiments have more ecological validity, but have less control over potential confounders such as weather conditions (Browning et al., 2020). Also, it becomes less feasible to examine the impacts of several different environment types on a large number of subjects because field experiments require a relatively large amount of time and effort from both researchers and participants, as well as research funding. Observational studies that focus on the proximity of homes to natural environments and the local amount of greenness tell us more about potential exposure to nature, but they can only approximate real exposure (Frumkin et al., 2017). Some observational studies try to address this shortcoming by collecting data on actual nature exposure through retrospective interviews and surveys, but these are subject to recall bias and the lack of objective data on the participants' actual location and of data on potential confounders such as weather conditions. In addition, it can be expensive and time-consuming to collect survey data if the studies have large sample sizes, broad geographic extents, or aim to collect longitudinal data.

A few studies have tried to overcome some of these challenges by crowdsourcing data from people who volunteer information through smartphone applications or social media platforms. There are two main types of volunteered data that are distinguished by how they engage data producers—active crowd-sourced data and passive crowd-sourced data (Bubalo et al., 2019). In active crowdsourcing projects, participants generally contribute data with full knowledge of the study goals. Some examples of active crowdsourcing projects that investigated people's emotional responses to surrounding environments are the Mappiness (MacKerron & Mourato, 2013) and the EmoMap projects (Klettner et al., 2013). By contrast, studies harnessing data from social media platforms such as Twitter and Instagram rely on passively generated data. Social media data have been increasingly used in various fields such as social sciences, environmental studies, and public health over the last decade. It has been shown that the large volume of social media data coming with precise geolocation and real-time information can inform the understanding of people's diurnal and seasonal mood patterns across different cultures (Golder & Macy, 2011), predict stock market trends (Bollen et al., 2011), estimate park visitation (Hamstead et al., 2018; Wood et al., 2020), and track and predict influenza (Lampos & Cristianini, 2010). Also, some Twitter-based studies provide evidence supporting the benefits of visiting urban green space (Lim et al., 2018; Plunz et al., 2019; Roberts et al., 2019; Schwartz et al., 2019). However, most of the Twitter-based studies have focused on urban parks only and have different limitations such as the inability to take the dependence between data points collected from the same user into account when doing hypothesis testing, and failing to adjust for potentially important confounders such as weather conditions when estimating effects of green spaces. Additionally, these studies have taken numerous different approaches to measuring subjective sentiment from the language contained within tweets, and some of them have not been well compared and contrasted.

1.3 Study focus

Here, we address some of the challenges faced by research using more traditional ways of data collection as well as the limitations of previous passively crowdsourced projects. We examined the relationship between subjective momentary sentiment using geolocated tweets and people's surrounding environments with a focus on land cover, tree canopy, and urban parks. We quantified the relationships using statistical models that allowed us to adjust for potential confounders and account for heterogeneity between data contributors. Specifically, we asked the following three questions.

a) How does subjective momentary sentiment expressed in tweets vary across urban built and more natural land-cover types?
b) Within a given land-cover type, how does the amount of tree canopy associate with the sentiment expressed in tweets?
c) Are people more likely to express more positive sentiment in urban parks than they are elsewhere?

2. Methods

We investigated the association between subjective momentary sentiment and the surrounding environments using 1,971,045 geolocated tweets sent between September 2010 and February 2020 by 81,140 users from locations throughout Seattle, WA. Using geolocated tweets, we were able to objectively locate users and thus to infer their real-time momentary sentiment at that location. Assuming that most users were honest when they composed their tweets, the tweets potentially reflect their sentiment at that moment.

2.1 Sample

From Twitter's streaming application programming interface (API), we obtained 2.6 M random English geolocated tweets (Fig. 1) sent between November 2012 and January 2019 in Seattle. Each tweet retrieved from the API is a JavaScript Object Notation (JSON) object that includes the text content of the tweet, the geolocation, the timestamp, the source type, and other attributes. Only tweets containing a "coordinate" value, which includes latitude and longitude coordinates of the tweets' exact locations, instead of just a generic "place" value, were considered as geolocated tweets. It should also be noted that retweets do not have a "coordinate" value according to Twitter's API documentation. Retweets may also be problematic because they potentially better reflect the mood of their original authors than the mood of people who retweeted.

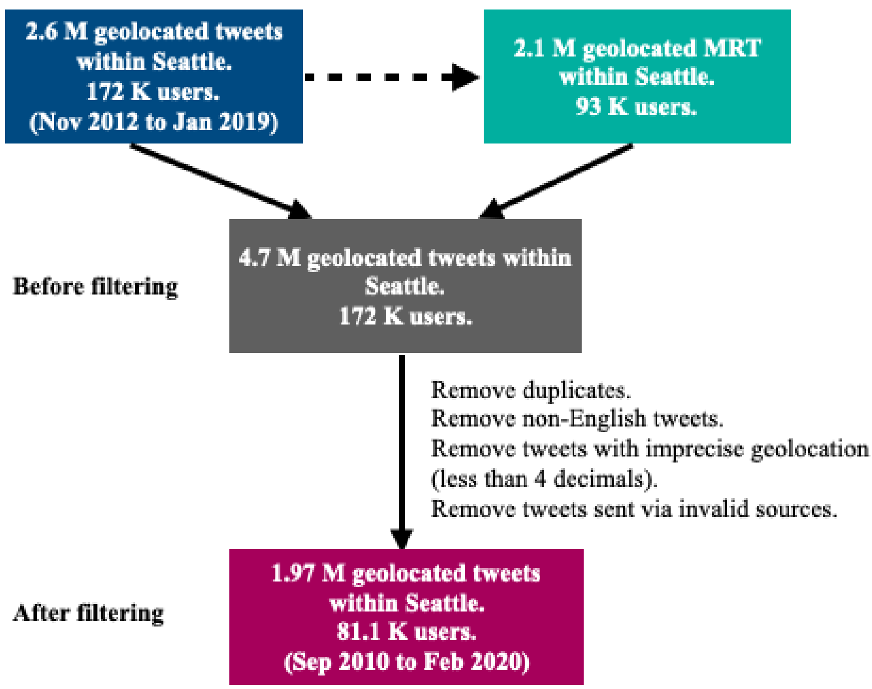

Fig. 1. Sampling Process.

The 2.6 M geolocated tweets were sent by 172 K Twitter user-accounts. In February 2020 we retrieved from the Twitter API up to 3,200 of the most recent tweets posted by each user to their timeline for the accounts that still existed and were public. The API returned 2.1 M tweets that were sent within Seattle from 93 K out of the 172 K user-accounts. Therefore, in total, we had 4.7 M geolocated tweets from 172 K user-accounts before any further filtering (Fig. 1).

In the filtering process, we first removed duplicate tweets, non-English tweets, and tweets with imprecise geolocations whose latitude or longitude coordinates had less than four decimal places. We then excluded tweets sent via bots, such as advertisements and weather condition reports because they do not reflect the feelings or moods of Twitter users. We identified bots by checking the "tweet source labels" attached to each tweet and removed all tweets sent from suspicious sources (such as "TweetMyJOBS") that are not listed in Box 1. In addition, tweets cross-posted from other social media platforms such as Instagram were excluded because the geo-coordinates associated with cross-posted tweets may not be the exact location of the tweets. Cross-posted tweets were also identified through the "tweet source labels". Box 1 shows the acceptable sources adopted by this study. After filtering, there were 1.97 M tweets sent between September 2010 and February 2020 by 81 K user-accounts throughout Seattle. The spatial distribution of tweets is shown in Fig. 2.

Box 1. Acceptable tweets sources

Twitter for iPhone, Twitter for Android, Twitter for Windows Phone, Tweetbot for iOS, Twitter for iPad, iOS, Tweetbot for Mac, Tweetbot for iOS, Plume for Android, Twitter for Android, Tablets, TweetCaster for Android, Mobile Web (M5), Twitterrific, OS X, TweetCaster for iOS, Fenix for Android, Camera on iOS, Photos on iOS, Twitter for iPhone, Twitter for Android, Twitter for BlackBerry®, Twitter for BlackBerry, Twittelator, TweetDeck, Talon (Plus), Safari on iOS, Twitter for Windows, Tweetings for Android, Flamingo for Android, Falcon Pro, Talon Android, Tweetings for Android, Talon (Classic), Twitterrific for iOS, Falcon for Android.

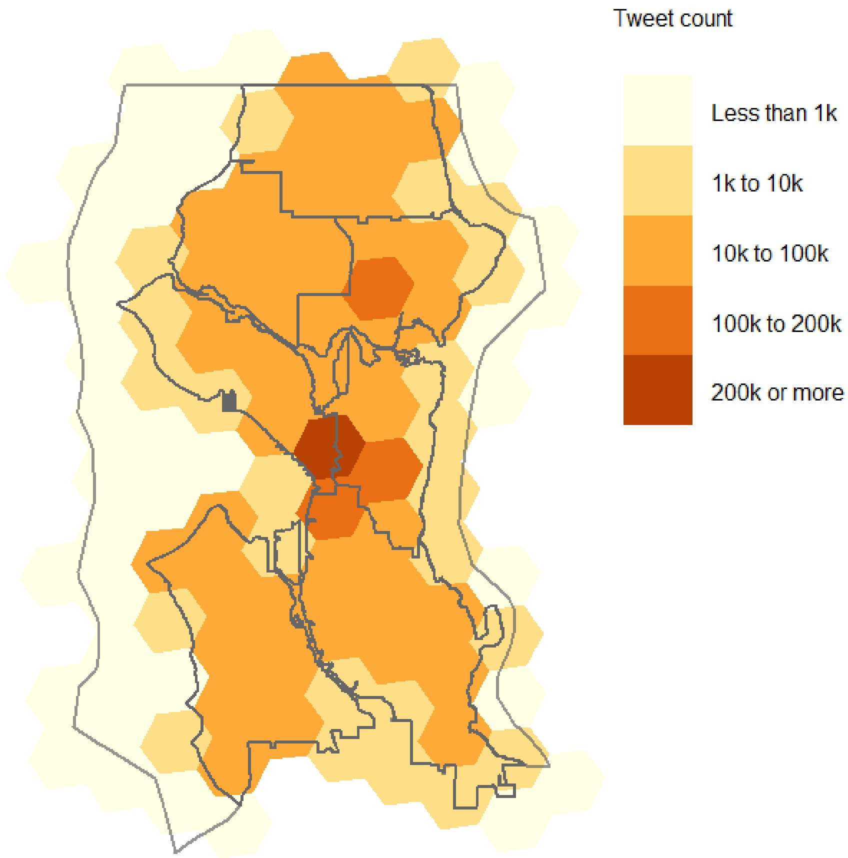

Fig. 2. The spatial distribution of tweets in the sample.

2.2 Measures

2.2.1 Momentary sentiment

To extract the real-time subjective momentary sentiment of each tweet based on its content, we employed the widely used sentiment analysis tool—Valence Aware Dictionary for Sentiment Reasoning (Vader; Hutto & Gilbert, 2014). Vader is a lexicon and rule-based sentiment analysis approach emerging from the field of natural language processing. Combining the carefully chosen lexical features with certain grammatical and syntactical rules, Vader was tailored to extract sentiments expressed in social media texts, but it also works well for texts in other domains. It has been shown that Vader's performance (with classification thresholds set at

-0.05 and 0.05) to detect 3-class sentiment polarity (positive vs neutral vs negative) is among the best for social media posts such as tweets (Hutto & Gilbert, 2014; Ribeiro et al., 2016). In addition, it is fully open-sourced, self-contained, and computationally efficient. Studies in various disciplines such as environmental management, computer engineering, and computational Linguistics have employed Vader (Althoff et al., 2016; Becken et al., 2017; Kim et al., 2016; Tamersoy et al., 2015).

We assessed and calibrated classification thresholds for Vader and then evaluated its performance using a random sample of 1,000 tweets from our full dataset (before filtering). We (three human raters) manually labeled the polarity of every tweet. Of the 1,000 tweets, 171 were detected as spam and removed by the human raters. Within the remaining 829 tweets, 98.2% were labeled with the same polarity by at least two raters, and 67% with the same polarity by all three raters. The value of Fleiss's Kappa, a widely used inter-annotator agreement metric, was 0.62 for these 829 tweets. According to Landis and Koch (Landis & Koch, 1977), a Kappa score between 0.61 and 0.80 suggests substantial agreement among raters. We aggregated the annotation of the three human raters by assigning each tweet the sentiment polarity with the majority of the votes. The 15 tweets that received totally different annotations were considered neutral. As a result of the aggregation, 52% of the 829 tweets were classified as neutral; 35% were positive, and 13% were classified as negative. Some examples of tweets are shown in Box 2 with sentiment labels. Based on the aggregated human annotation, we found that Vader performed best with classification thresholds set at -0.15 and 0.35 for our dataset. At these thresholds, the overall accuracy = 69%, weighted macro F1-score = 0.69, macro F1-score = 0.64, and average recall = 0.65. The precision, recall, and F1-score for each of the three classes can be found in Table A1. We have also compared Vader's performance with that of other commonly used sentiment analysis tools such as SentiStrength (Thelwall et al., 2012), Google's Natural Language API, Sentiment140 (Go et al., 2009), and TextBlob using the aggregated human annotation. Vader performed best among all sentiment analysis tools tried.

Box 2. Examples of tweets with sentiment labels

"I love Carrie and her cookies 💗 " (Positive)
"Stronger nonprofits! (at in Seattle WA)" (Positive)
"ice cream is condensed happiness" best weekend with my best for 18 years 😘🍦…" (Positive)
"What do charter schools feed children? Curious #uppers." (Neutral)
"Be good or be good at it." (Neutral)
"I'm going to get a bottle tomorrow." (Neutral)
"Its back to work today but all I want to do is be at home with these crazies. #crazycats…" (Negative)
"I do 😔 " (Negative)
"I'm sooooo tired! Trying to rally :(" (Negative)

2.2.2 Predictors of main interest: Land-cover type, Tree-canopy cover, Park

We used three spatial data layers representing the environments from which tweets were sent including data on land-cover type, tree-canopy cover, and urban park boundaries. Land-cover and tree-canopy data were from the 2016 National Land Cover Database (NLCD) (Dewitz, 2019) downloaded from the Multi-Resolution Land Characteristics (MRLC) Consortium. NLCD provides nationwide data on land-cover classes and tree-canopy cover at a 30 m resolution. The land-cover data has 15 subclasses based on a modified Anderson Level II classification system. The definition of each of the subclasses can be found in Table A2. For tree-canopy cover, the value assigned to every 30 m by 30 m grid cell in NLCD represents the percentage of tree-canopy coverage in that grid cell. Polygons representing urban parks within Seattle (Fig. 3) were downloaded from Seattle GeoData portal (Seattle Parks, 2020). For each tweet, we assigned values to

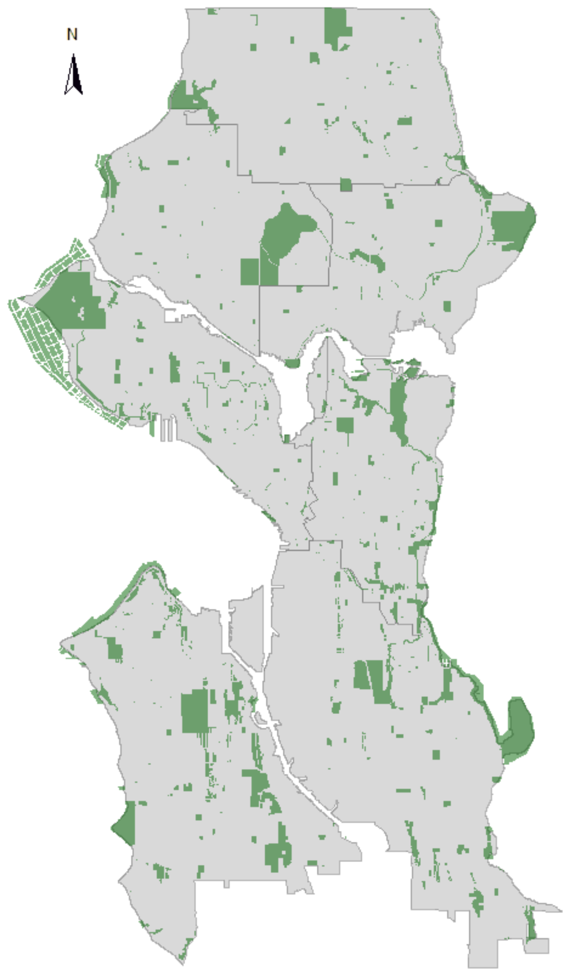

Fig. 3. Parks in Seattle.

the three predictors—*Land-cover type*, *Tree-canopy cover*, *Park*—according to the extracted values from each of the three spatial layers based on the tweet's coordinates. For land-cover type, we grouped the 15 subclasses in NLCD into seven broad land-cover categories (Table A2; Fig. 4), resulting in a predictor *Land-cover type* with seven categories. To force the continuous predictor *Tree-canopy cover* to have a similar scale as that of other explanatory variables, we divided the raw tree-canopy cover percentage by 10. We created a categorical variable *Park* with three categories—within a large natural park (parks that are larger than or equal to 40,000 ft^2 and with less than 30% impervious surface), within one of the other parks, and not in any park.

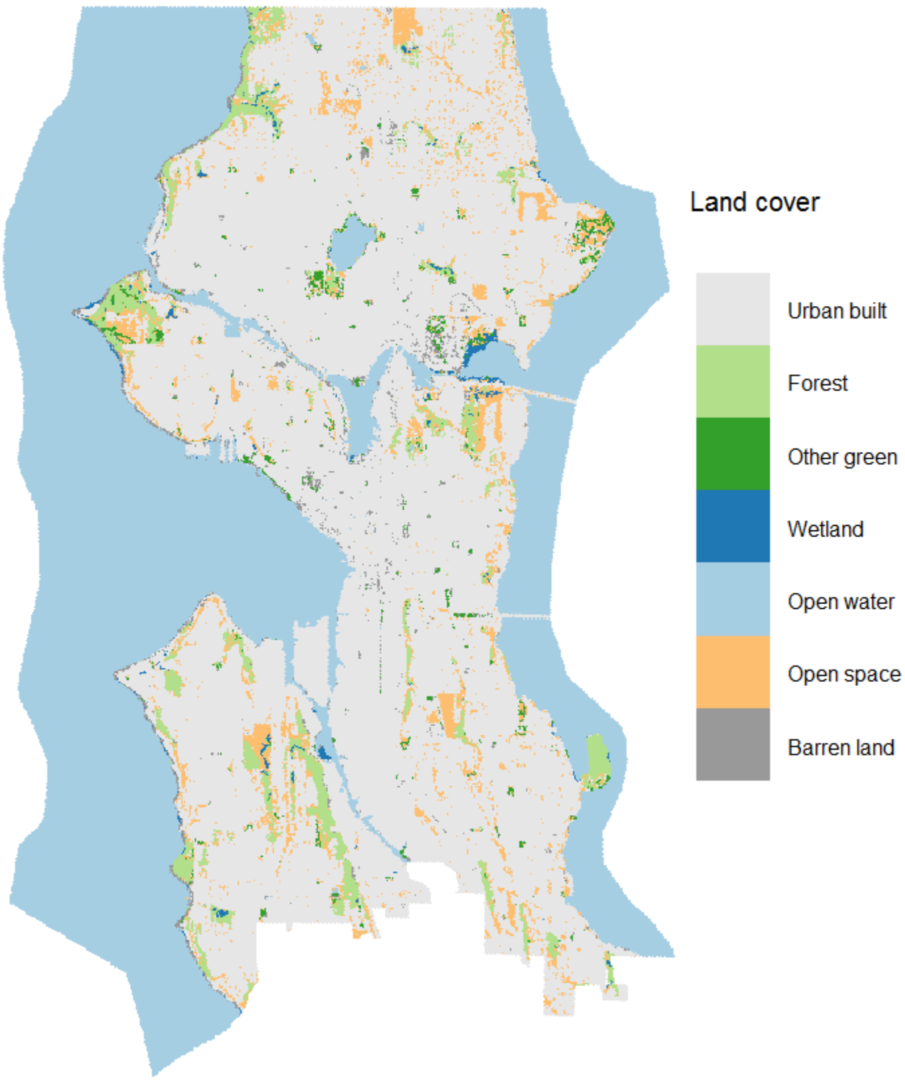

Fig. 4. Land cover in Seattle.

2.2.3. Adjusting covariates

In addition to the predictors of main interest, we included a number of time-varying covariates that may obscure the relationship between momentary sentiment expressed in tweets and the predictors of main interest. These were divided into four groups according to what they measure: location type, weather conditions, time, and tweet type. All of these variables covary with momentary sentiment, and many of them may also be correlated with the predictors of main interest, thus potentially confounding their effects. For instance, people may tend to be happier and also more likely to visit parks on weekends. Therefore, we adjusted for these covariates in the regression analyses presented in Section 2.3.

For location-type covariates, we used *Zoning type* and *Outdoor*. *Zoning type* indicates the type of land development that is allowed (e.g., residential, industrial, commercial, etc.) and is likely indicative of the types of activities people are performing in a given location. *Outdoor* is a binary variable that indicates whether a tweet was sent from an outdoor (*Outdoor* = 1) or indoor (*Outdoor* = 0) location. The data on the zoning (*Current Land Use Zoning Detail*, 2020) and building outlines (*Building Outlines 2015*, 2019) were downloaded from the Seattle GeoData portal. For weather conditions, we included five categorical covariates—*Temperature*, *Dew point*, *Visibility*, *Rain*, and *Sky cover*. Weather data were obtained from the NOAA Integrated Surface Dataset (ISD) (*Integrated Global Surface Hourly Data*, 2001) that consists of global hourly observations collected from over 14,000 active stations. For Seattle, ISD contains comprehensive hourly data observed at two stations—one located at the Boeing Field International Airport (within Seattle) and the other at the Seattle-Tacoma International Airport (near Seattle). We associated each geolocated tweet with the weather conditions from the station closest to the tweet both spatially and temporally. Furthermore, based on the timestamp associated with each tweet, three time-related covariates were created: *Time*, *Day of week*, and *Day*. *Time* was continuous. For each user, Time was set to 0 for his/her earliest tweet included in the sample. *Time* has month as its unit to make its scale similar to other explanatory variables included in the model, but is measured in seconds (five decimal places). *Day of week* is a categorical covariate with five levels: Monday to Wednesday, Thursday, Friday, Saturday, and Sunday. *Day* is a binary covariate that indicates whether a tweet was sent at day or night: *Day* was set to 1 when a tweet was sent between 6 a.m. and 5 p.m. and *Day* to 0 otherwise. Lastly, according to the tweet-type indicators associated with each tweet, we created one binary tweet-type covariate—*Tweet type*. *Tweet type* was set to 1 when a tweet was a reply or a quote tweet and to 0 when a tweet was an original tweet.

2.3 Statistical analysis

To investigate the association between sentiment polarity expressed in tweets and the surrounding environments, we used random-intercept partial proportional odds models with *User* as the random effect. Ordinal logistic regression was chosen because the outcome variable—sentiment polarity—has ordinal categories (1 = negative, 2 = neutral, and 3 = positive). We allowed users to have random intercepts because about 70% of the 81 K users have more than one tweet included in the sample and tweets sent by the same user may not be independent. Using mixed models allowed us to take the unobserved heterogeneity between users into account when estimating the fixed effects coefficients (Rabe-Hesketh & Skrondal, 2012). We also explored random-slope models that allow users to have subject-specific trends over time. Because the random-slope models failed to converge, we chose to use the more parsimonious random-intercept models. Finally, we chose partial proportional odds models instead of proportional odds models because for most covariates, except for *Outdoor*, *Time*, *Tweet type*, and *Tree-canopy cover*, the proportional odds assumption is not valid based on likelihood ratio tests and AIC.

We fitted three main models corresponding to each of our three research questions. The first main model used *Land-cover type* as the predictor of main interest to investigate the relationship between different land-cover types and the sentiment polarity of tweets while controlling for other covariates. We also tested the interaction between *Land-cover type* and *Zoning type* and the interaction between *Land-cover type* and *Outdoor*. We kept only the interaction between *Land-cover type* and *Zoning type* in the final model because the interaction between *Land-cover type* and *Outdoor* was not significant based on the likelihood ratio test and AIC. Model 1 was specified as:

Model 1: *Sentiment* ~ (*Land-cover type* * *Zoning type* + <u>*Outdoor)*</u>

+ (<u>*Time*</u> + *Day of week* + *Day)*

+ (*Temperature* + *Dew point* + *Visibility* + *Sky cover* + *Rain)*

+ (<u>*Tweet type*</u>)

+ (1| *User*).

Sentiment has three categories (1 = Negative, 2 = Neutral, 3 = Positive) and is treated as an ordinal categorical variable. On the right-hand side of the model, we included the predictor of main interest *Land-cover type*, its interaction with *Zoning type,* and other covariates including *Zoning type* as fixed effects. All predictors except *Time* were included as categorical variables, and their categories are shown in Table 1. Covariates that are underlined in the model are those for which the proportional odds assumption holds. The last term on the right-hand side of the model is the random effect *User* indicating who sent the tweet.

The second main model examined the association between tree-canopy coverage and sentiment polarity while adjusting for land-cover type and all other covariates included in Model 1. We adjusted for land-cover type because it was a potential confounder, and we wanted to isolate the tree-canopy effects from the land-cover effects. In Model 2, we allowed the interaction between *Tree-canopy cover* and *Zoning type*. Other potential interactions—interactions between *Tree-canopy cover* and *Land-cover type*, between *Tree-canopy cover* and *Outdoor*, and between *Land-cover type* and *Zoning type*—were tried, but were not significant based on likelihood ratio tests and AIC. Therefore, we specified Model 2 as:

Model 2: *Sentiment* ~ (*Tree-canopy cover* * *Zoning type* + *Land-cover type* + *Outdoor)*

+ (*Time* + *Day of week* + *Day)*

+ (*Temperature* + *Dew point* + *Visibility* + *Sky cover* + *Rain)*

+ (*Tweet type*)

+ (1| *User*).

The third main model with *Park* as the predictor of main interest investigated the differences in sentiment polarity of tweets between being sent within large natural parks, being sent within other parks in Seattle, and being sent outside parks while controlling for other covariates. We included the interaction between *Park* and *Zoning type*. We explored the interaction between *Park* and *Outdoor*, but found it not significant based on the likelihood ratio test and AIC. Therefore, the final Model 3 was specified as:

Model 3: *Sentiment* ~ (*Park* * *Zoning type* + *Outdoor)*

+ (*Time* + *Day of week* + *Day)*

+ (*Temperature* + *Dew point* + *Visibility* + *Sky cover* + *Rain)*

+ (*Tweet type*)

+ (1| *User*).

All model fitting was conducted using the ‘mixor’ package in R, and model parameters were estimated via the maximum likelihood method (Archer et al., n.d.). To make interpretation more straightforward, we present model results as odds ratios (OR = exp(coefficient)) and 95% confidence intervals of odds ratios in Section 3. In addition, we adjusted p-values for multiple testing for all two-way interactions following the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). All explanatory variables, except *User*, included in the models are time-varying variables (level-1 variables), and their effects are subject-specific (Rabe-Hesketh & Skrondal, 2012). As mentioned above, to allow the fixed effects to vary according to which cumulative logits—logit(Pr(Y>1)) or logit(Pr(Y>2)—of the model we are considering, we relaxed the proportional odds assumption for some fixed-effect variables—*Land-cover type, Parks, Zoning type, Day of week, Day, Temperature, Dew point, Visibility, Sky cover, Rain*—based on likelihood ratio tests and AIC, which resulted in partial proportional odds models. As a result, we produced two sets of estimated odds ratios for these variables when they were included in a model, one set for each of the two odds contrasts—the odds of being neutral or positive (Y=2 or 3) as opposed to being negative (Y=1) and the odds of being positive (Y=3) as opposed to being negative or neutral (Y = 1 or 2). In other words, for each model, there were two estimated odds ratios for each of these explanatory variables, one for each of the two odds contrasts, given that it was included in the model. To be concise, we refer to the first odds contrast as the "non-negative odds contrast" and the other as the "positive odds contrast."

3. Results

3.1 Descriptive statistics

After removing observations with missing land-cover data, the dataset had 1.97 M observations from 81 K users. The median number of observations per user was three (first quartile = 1, third quartile = 11). Most of the tweets (96.48%) were sent between 2012 and 2015.

Table 1. Descriptive statistics for categorical explanatory variables

Variable	Frequency	Percentage
Predictors of main interest		
Land cover types		
Urban built	1843919	93.55
Open space	23088	1.17
Barren land	61256	3.11
Other green	11527	0.58
Forest	5754	0.29
Wetlands	1164	0.06
Open water	24337	1.23
Park		
In large natural parks	17616	0.89
In other parks	16185	0.82
Outside parks	1937244	98.29
Covariates		
Zoning types		
Residential	891022	45.20
Industrial	126125	6.40
Commercial/Mixed	953898	48.40
Outdoor		
Yes	1288261	65.36
No	682784	34.64
Day of week		
Mon to Wed	834107	42.31
Thu	281850	14.30
Fri	280856	14.25
Sat	276475	14.03
Sun	297757	15.11
Day		
Yes	923977	46.88
No	1047068	53.12

Variable	Frequency	Percentage
Temperature (°C)		
< 0	27691	1.40
0 - < 7	247474	12.56
7 - < 12	600068	30.44
12 - <18	535914	27.19
18 - <26	464177	23.55
26+	95721	4.86
Dew point (°C)		
<=2	303903	15.42
2 – 16	1656151	84.02
>16	10991	0.56
Visibility (Statute miles)		
Clear (<0.63)	1900631	96.43
Haze (0.63 – <1.2)	47509	2.41
Mist (1.2 – <3.1)	9090	0.46
Fog (>=3.1)	13815	0.70
Sky cover		
Clear/scattered	1412049	71.64
Broken	80211	4.07
Obscured	46632	2.37
Overcast	401201	20.35
Unknown	30952	1.57
Rain		
No	1766469	89.62
Yes	204208	10.36
Tweet type		
Original	1358660	68.93
Reply/quote	612385	31.07

“Twitter for iPhone” (70.29% of all tweets) and “Twitter for Android” (20.88%) were the two major sources from which tweets were sent. Regarding the sentiment of the tweets, 35.18% were positive, 45.15% were neutral, and 19.67% were negative.

All explanatory variables except *Time* and *Tree-canopy cover* in our analysis were categorical (Table 1). All percentages in Table 1 were calculated by dividing frequencies by the sample size (1.97 M). Although most of the tweets were sent within urban built environments, our dataset still contained large numbers of observations for each of other land-cover type. Ninety percent of all tweets were sent in a grid cell (30 m by 30 m) with no tree cover. The distribution of tree-canopy coverage for the remaining 10% of tweets sent from grid cells with trees is shown in Fig. 5.

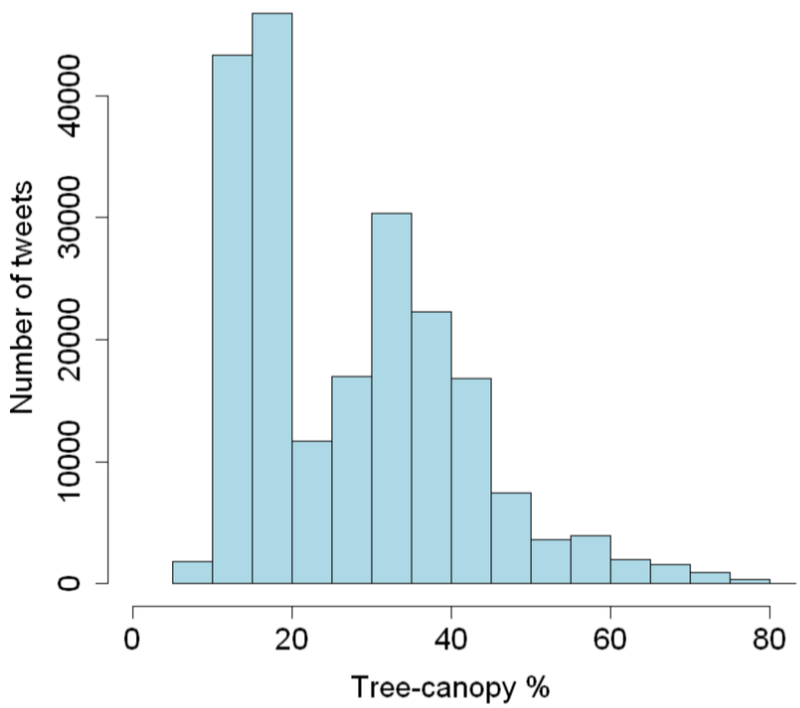

Fig. 5. Histogram of non-zero tree-canopy percentage.

3.2 Random-intercepts partial proportional odds models

3.2.1 Land-cover types

We found no evidence that tweets sent from places with more natural land cover were more likely to be positive than tweets sent from urban built environments (Fig. 6; Table A3). However, we did find that tweets sent from some natural land-cover types were less likely to be negative than those sent from urban built environments. More specifically, given any

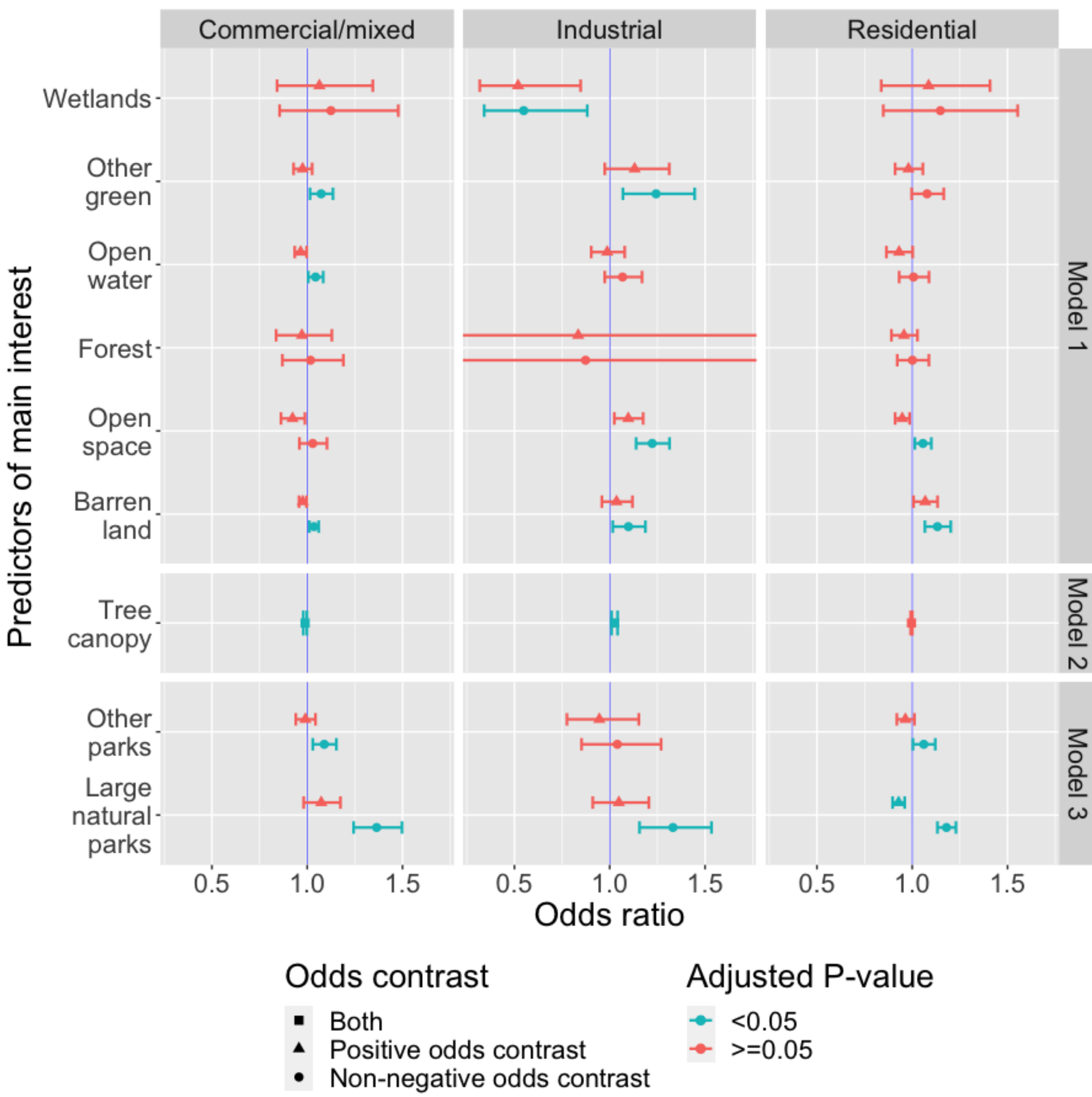

Fig. 6. Estimated odds ratios and 95% CI for predictors of main interest in Model 1, 2, and 3.

zoning type, there were no significant natural land-cover effects in terms of the "positive odds contrast" after Benjamini-Hochberg correction. However, there were some natural land-cover types that were positively significant in terms of the "non-negative odds contrast."

Looking closer at the effects of *Land-cover type* (Table A3), we see that for tweets sent from "Other green" in commercial/mixed zones, the odds of being non-negative rather than negative was 7.32% (95% CI = [1.46%, 13.52%]) higher than that of tweets sent from urban built environments by the same user (or users with the same value of the random intercept). For tweets sent from "Barren land" and "Open water", the same odds were 3.55% ([1.13%, 6.02%]) and 4.40% ([0.55%, 8.40%]) higher, respectively, than tweets sent from urban built environments. Conversely, the estimated odds ratios for the "non-negative odds contrast" can be interpreted as the odds of being negative as opposed to the odds of being non-negative (neutral or positive). For example, for tweets sent from "Other green" in commercial/mixed zones, the odds of being negative was 6.82% (95% CI = [1.44%, 11.91%]) lower than that of tweets sent from urban built environments. To be consistent with the odds ratios shown in Tables A3–A5, we use the first type of interpretation for the "non-negative odds contrast" when referring to the exact values of estimated odds ratios in the rest of the paper.

For tweets sent in industrial zones, those sent from "Open space", "Barren land", and "Other green" land-cover types were associated with 22.29% ([13.84%, 31.38%]), 9.82% ([1.58%, 18.72%]), and 24.33% ([6.93%, 44.57%]) higher odds of being non-negative compared to tweets sent from urban built environments. Surprisingly, we also found a significant negative association between the "Wetlands" class and the non-negative odds. However, it is worth noting that only 53 tweets in the sample were sent from wetlands in industrial zones. Lastly, for residential zones, the odds of being non-negative for tweets sent from "Open space" and "Barren land" were 5.60% ([1.37%, 10.01%]) and 13.22% ([6.64%, 20.20%]) higher than those of tweets sent from urban built environments respectively.

We found associations between the sentiment of tweets and several of the covariates included in the model (Table A3). For instance, tweets sent on Thursday, Friday, and weekends were all less likely to be negative compared to tweets sent on Monday to Wednesday, with Saturday being the least negative day of the week. However, tweets sent on weekends were also less likely to be positive compared to tweets sent on Monday to Wednesday. Tweets sent at night were more likely to be negative and less likely to be positive compared to tweets sent during the day. The absence of rain was associated with higher odds of being positive. Higher temperatures (>=18 °C) were associated with lower odds of being negative relative to low temperatures (<0 °C). Tweets sent when temperatures were between 0 and 7°C were more likely to be positive than tweets sent while temperatures were under 0 °C in Seattle. Tweets sent under overcast skies were more likely to be negative and less likely to be positive relative to tweets sent under clear or scattered skies.

3.2.2 Tree canopy

Tweet sentiment was associated with tree canopy in commercial/mixed and industrial zones after Benjamini-Hochberg correction (Fig. 6; Table A4). In commercial/mixed zones, tweets were less likely to have a higher sentiment polarity when there was more tree canopy: in other words, tweets were more likely to be negative and less likely to be positive. By contrast, in industrial zones, tweets were more likely to have a higher sentiment polarity when there was more tree canopy. It should be noted that the proportional odds assumption was kept for *Tree-canopy cover* in Model 2 based on the likelihood ratio test and AIC. Therefore, the effect of tree-canopy coverage was the same for both odds contrasts. For instance, for tweets sent in commercial/mixed zones, each 10 percentage-point increase in tree canopy was associated with 1.10% ([0.16%, 2.03%]) lower odds of being non-negative (Y=2 or 3) and also 1.10% ([0.16%, 2.03%]) lower odds of being positive (Y=3). The effect detected in industrial areas was a bit larger—a 10 percentage-point increase in tree-canopy cover was associated with 2.53% ([0.97%, 4.12%]) higher odds of being non-negative (Y=2 or 3) and also of being positive (Y=3). The estimated effects for other covariates under Model 2 were similar to those estimated under Model 1 (Table A4).

3.2.3 Urban parks

We found that in commercial/mixed zones and residential zones, tweets sent from urban parks, no matter large natural parks or other parks, were less likely to be negative compared to tweets sent from outside parks; in industrial zones, only tweets sent within large natural parks were less likely to be negative compared to tweets from outside parks (Fig. 6; Table A5). Also, we found that tweets sent within large natural parks in residential zones were less likely to be positive compared to tweets sent from outside parks. More specifically, for tweets sent from large natural parks and other parks in commercial/mixed zones, the odds of being non-negative rather than being negative was 36.45% ([24.35%, 49.73%]) and 8.95% ([2.95%, 15.30%]) higher, respectively, compared to tweets sent from outside parks. For tweets sent from industrial zones, being within large natural parks was associated with 33.18% ([15.62%, 53.40%]) higher odds of being non-negative, but there was not enough evidence to show that tweets sent from other parks had a different probability of being negative compared to tweets sent from outside parks. It is worth noting that the number of tweets sent from other parks in industrial zones, 369, was relatively small in our study. For tweets sent from large natural parks and other parks in residential zones, the odds of being non-negative was 17.97% ([13.22%, 22.93%]) and 6.06%

([0.37%, 12.08%]) higher respectively compared to tweets sent from outside parks. However, being in large natural parks in residential zones was also associated with 7.18% ([3.95%, 10.30%]) lower odds of being positive compared to outside-park tweets. In other words, tweets sent from large natural parks in residential zones were less likely to be negative, but also less likely to be positive. The estimated effects for other covariates under Model 3 (Table A5) were similar to those estimated under Model 1 and Model 2.

3.2.4 Discrete changes in predicted probabilities

The large size of our sample provides us more power to detect small and complex effects. However, large samples also drive p-values to zero quickly (Sullivan & Feinn, 2012). Therefore, it is more appropriate to gauge the practical significance of statistically significant effects based on size effects instead of relying solely on p-values (Lin et al., 2013). Because it can still be difficult to assess the substantive effects of the predictors of main interest based on odds ratios, we explored the effect of the statistically significant ones on the predicted probabilities, holding all other variables at their sample means. To improve interpretability, we calculated these predicted probabilities as average marginal probabilities by averaging over predicted probabilities that corresponded to simulated values of random intercepts. As a result, the predicted probabilities have population-level interpretation (Steele, 2009).

Based on the results of Model 1, the predicted probabilities of being negative for tweets sent from land-cover types that were significantly different from urban built environments in the same zones regarding their association with sentiment, except for Wetlands in industrial zones, were 0.38 to 3.17 percentage-points lower than for tweets sent from urban built environments, while holding other explanatory variables at their average values (Fig. 7). We did not show the predicted probabilities of being positive in Fig. 7 because there were no natural land-cover types that were significantly different from urban built environments regarding their association with the probability of being positive.

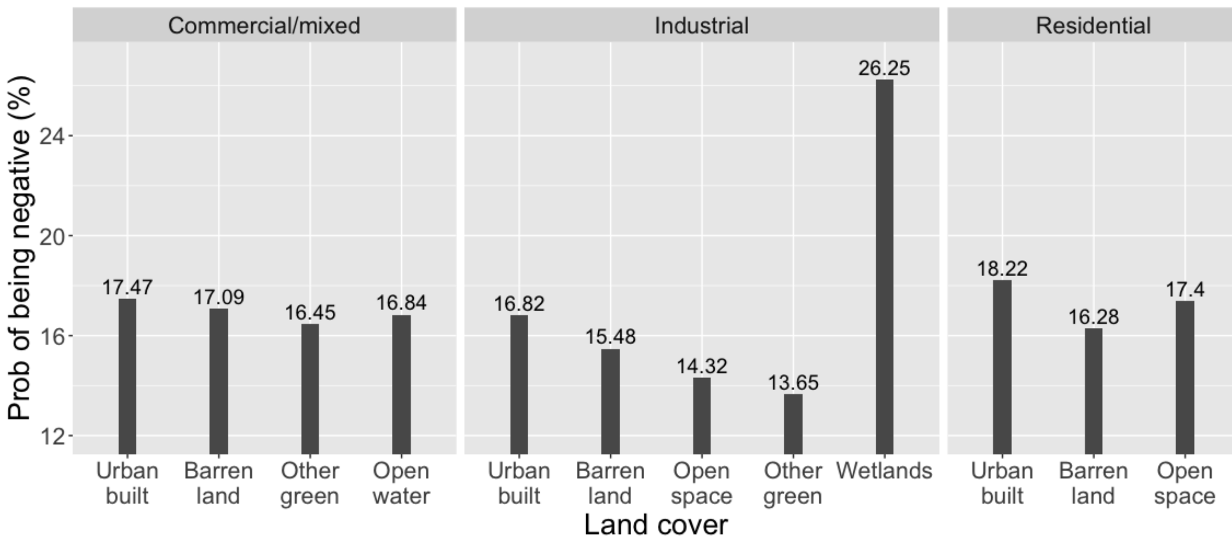

Fig. 7. Predicted probabilities for Model 1.

The discrete changes in predicted probabilities for Model 2 are shown in Fig. 8. For commercial/mixed zones, a 20 percentage-points increase in tree canopy (from 0% to 20% tree canopy for all land cover except "Forest"; from 20% to 40% tree canopy for "Forest") was associated with a 0.06 to 0.73 percentage-points increase in the probability of being negative (Fig. 8A) and 0.06 to 1.36 percentage-points decrease in the probability of being positive (Fig. 8B). For industrial zones, a 20 percentage-points increase in tree canopy was associated with a 0.15 to 1.01 percentage-point decrease in the probability of being negative (Fig. 8A) and 0.37 to 1.81 percentage-points increase in the probability of being positive (Fig. 8B).

The discrete changes in predicted probabilities for Model 3 are shown in Fig. 9. Being in parks, except for the "Other parks" in industrial zones, was associated with a 1.14 to 3.92 percentage-points decrease in the probability of being negative (Fig. 9A). Being in "Large

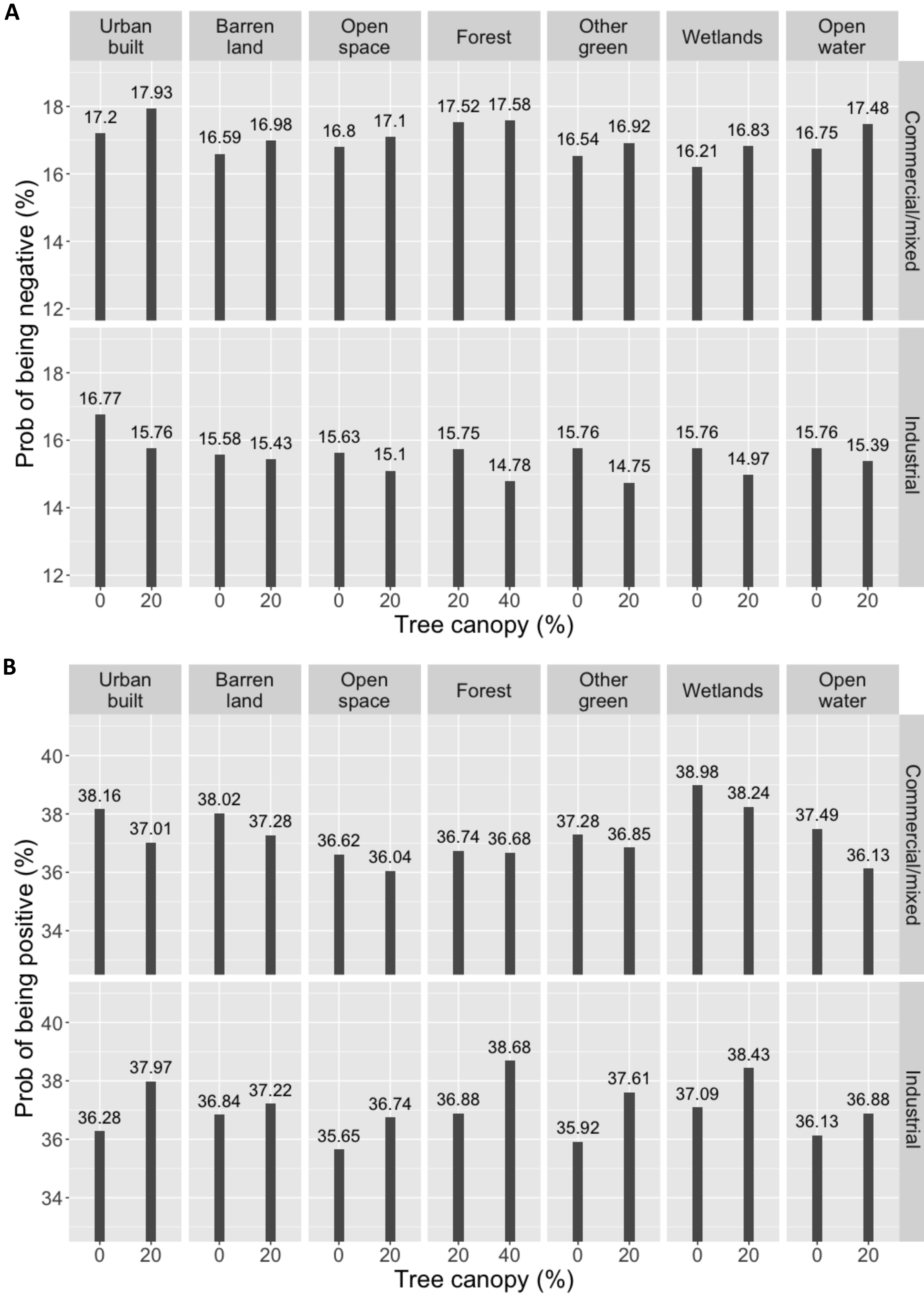

Fig. 8. Predicted probabilities for Model 2. (A) Predicted probabilities of being negative. (B) Predicted probabilities of being positive.

natural parks” in residential zones was associated with a 1.56 percentage-points decrease in the probability of being positive (Fig. 9B).

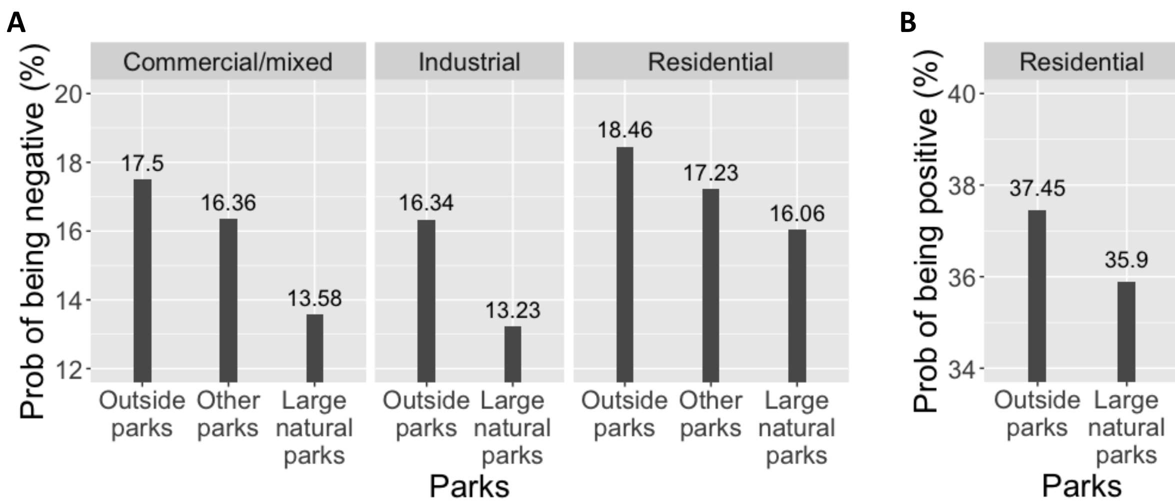

Fig. 9. Predicted probabilities for Model 3. (A) Predicted probabilities of being negative. (B) Predicted probabilities of being positive.

4.Discussion

4.1 Main results

We examined the relationship between subjective momentary sentiment expressed on Twitter and the surrounding environments using 1.97 M geolocated tweets sent throughout Seattle, WA. The results suggest that tweets sent from some natural land-cover types were less likely to be negative than tweets from urban built environments. Within a particular land-cover type, the relationship between tree-canopy cover and sentiment depended on the zoning type. Also, with the exception of other parks in industrial zones, urban parks were associated with a lower probability of being negative compared to areas outside parks. However, large natural parks in residential zones were also associated with a lower probability of being positive. These findings highlight the potential of social media data to inform our understanding of how the natural environments affect sentiment, the importance of taking into account the larger environment that a location is situated in and how people are using lands, and the complexity of the relationship between people's sentiment and their surrounding environments.

To make the results of this study clearer, we computed some marginal average predicted probabilities at the means with a population-level interpretation. The discrete changes in the predicted probability for the chosen discrete changes in the variables of main interest shown in Section 3.2.4 are around 0.06 to 9.43 percentage points, holding all other variables in the corresponding model at their sample means. For city planners, the small differences that we detected for individuals translate into important differences for a large population. For every 100,000 tweets, for instance, a one percentage-point increase in the probability of being negative results in 1,000 more negative tweets by people in the region.

4.2 Links to other studies

There have been a few similar passive-crowdsourcing studies examining the relationship between sentiment expressed in tweets and natural environments. Those studies primarily focused on urban parks and green spaces. The negative correlation between parks and the probability of being negative detected in our study is generally in line with previous studies suggesting a positive association between subjective sentiment expressed in tweets and visits to urban parks. For instance, in central Melbourne, Australia, Lim et al. (2018) found that tweets sent in green spaces expressed less negative emotions and more positive emotions compared to tweets sent outside green spaces. Also, tweets in urban areas with greater proximity to green spaces had a more positive sentiment. Plunz et al.(2019) found that in boroughs of New York City, with the exception of Manhattan, the daily average sentiment scores of in-park tweets were higher than that of tweets from outside parks. In San Francisco, CA, Schwartz et al. (2019)

compared sentiment of tweets sent before, during, and after visits to urban parks. The authors found that the sentiment of tweets sent during park visits was happier than that before park visits and that the park effects remained for several hours after the visit. The park effects were found to be larger for parks that were larger and greener. Another study (Roberts et al., 2019) conducted in Birmingham, United Kingdom, focusing only on tweets sent in parks without comparing them with tweets sent outside parks, suggested that for tweets sent within the 60 urban green spaces chosen by the authors, positive tweets were more common than negative ones. We did not detect significant differences in how positive tweets were sent in parks and outside parks in commercial/mixed zones and industrial zones; for residential zones, the results even suggest that tweets sent within large natural parks were less likely to be positive compared to tweets sent outside parks. Among the previous studies mentioned above, Plunz et al.(2019) is the only one that also found a negative association between sentiment expressed in tweets and being within parks: in Manhattan, NY the daily average of sentiment expressed in parks was less positive than those expressed outside parks.

Although we have attempted to compare our work to previous studies, it is often difficult to make direct comparisons among passive-crowdsourcing studies because there is high heterogeneity in methods across the small number of existing studies. The heterogeneity that may lead to different conclusions includes, but is not limited to, the following. First, all of these studies use different methods to measure and classify the sentiment of tweets. Plunz et al.(2019), for instance, adopted a NBLR+POSwemb model (Yu et al., 2017) to assign each tweet a sentiment score (1 = positive; 0 = neutral; -1 = negative). Lim et al. (2018) computed eight scores, each corresponding to one sentiment category introduced by Plutchik's theory of emotions, and also the positive score, negative score, and polarity for each tweet. Schwartz et al.

(2019) employed a bag-of-words approach to calculate sentiment for hourly bins of tweets, instead of for individual tweets. In Roberts et al. (2019), tweets were manually assigned to the three sentiment categories (positive/neutral/negative). Positive and negative tweets were further categorized into eight classes based on Ekman's six basic emotions and other previous research. As explained in Section 2.2.1, we classified tweets into the three sentiment categories (positive/neutral/negative) using the sentiment analysis tool Vader.

The second type of heterogeneity among methods involves how sentiment scores were analyzed. Descriptive statistics and t-tests, but no statistical models were used in previous studies. Our results suggest that previous studies making simple comparisons of sentiment inside vs outside of urban parks are likely missing important context and the role of covariates such as weather and day of week that are necessary to interpret the effect of park. Similarly, we find that the effect of parks on visitors' sentiment varies depending on whether they are in an commercial/mixed, industrial, or residential part of the city. Therefore, it may be inappropriate and ineffective to draw too many comparisons or to synthesize results of these studies before research follows our example. Until then, the differences and similarities between results could be achieved by mere chance when the number of studies is small.

A few of our results, such as the negative effects of tree canopy in commercial/mixed zones on the probability of having a more positive sentiment and the negative effects of large natural parks in residential zones on the probability of being positive, were not consistent with theory—SRT, ART, the Biophilia Hypothesis—and the growing body of research observing psychological benefits of natural environments. We are unsure about the exact reasons behind this discrepancy. However, it is important to note that these theories do not suggest that all natural environments or natural elements in urban areas will benefit people psychologically, nor equally. For example, wet ground covered by fallen leaves under trees may be unsightly; trees and grasses can cause allergies or asthma (Roman et al., 2021); criminal activity in parks may make visitors to the parks feel unsafe. Another possible reason for the seeming inconsistency between our results and these theories is the lack of information about people's purposes for visiting green spaces. For visitors who had been stressed and mentally fatigued, and then visited urban green spaces to "escape" or relax, the probability of being positive when surrounded by natural environments could still be lower than that when surrounded by developed urban environments when people are not stressed or mentally fatigued. This would be true even when natural environments helped people recover from their negative moods by raising them to a neutral state.

Our results on associations between sentiment and land-cover types are generally consistent with previous studies using active crowd-sourced data (e.g. MacKerron & Mourato, 2013) and survey data (Alcock et al., 2015). Nonetheless, contrary to expectations, we did detect a positive association between Wetlands and the probability of being negative for tweets sent in industrial zones (although it should be noted that only 53 tweets in the sample were sent from wetlands in industrial zones). Not finding higher probabilities of being positive in natural land-cover types is likely related to our use of categorical compound sentiment score. Instead of finding that tweets were likely to be higher on a continuous index of sentiment (e.g. MacKerron & Mourato, 2013), our analytical approach allowed us to disentangle instances in which tweets were less likely to be negative from those in which tweets were more likely to be positive.

The differences in sampling methods may also contribute to the seeming inconsistency between our results and existing research that has found broad psychological benefits across all types of natural environments. Our passive sampling was completely non-intrusive. By contrast, many studies have been based on survey data or active crowdsourcing data. Unlike in other studies, the data in our study were derived from subjects who did not choose to participate with knowledge of what the research was about. For instance, on the Mappiness project's (MacKerron & Mourato, 2013) public-facing website that provided potential participants information about the project, it was clearly stated that the researchers were "particularly interested in how people's happiness is affected by their local environment — air pollution, noise, green spaces" (*Mappiness, the Happiness Mapping App*, n.d.). It is possible that a large proportion of data contributors chose to participate because they enjoy spending time in nature. This selection bias may make it inappropriate to generalize the results of those studies to other populations in which the proportion of people who care about nature or landscape may be lower. It is also possible that knowing the purpose of the study primes the participants to respond in a particular way (Orne, 1962). Therefore, it is not surprising that this study (and other passive crowdsourcing studies) might reveal weaker positive relationships between sentiment and the natural environment.

4.3 Implications, limitations and future studies

This study demonstrates the potential of using passive-crowdsourcing data such as tweets to investigate the association between people's momentary subjective sentiment and various surrounding environments with wide temporal and spatial coverage. The development of technologies in GPS positioning, remote sensing, and natural language processing creates new more ways for researchers to explore the link between natural spaces and psychological well-being, and may help inform city planning and land management. Compared to traditional survey data, Twitter data sent from various environments are easier to obtain and more cost-effective. Large sample sizes provide more power to detect and quantify nuanced, complex, and small effects. The real-time sentiment expressed by geolocated tweets is not subject to recall biases.

With data on timestamp and geolocation, more accurate information on potential confounders such as weather conditions and more specific data on the physical environments such as land-cover types and tree-canopy coverage can be linked to each tweet. Compared to active-crowdsourced data that shares many of the strengths mentioned above, tweets are not subject to demand effects (Orne, 1962) and the selection bias due to subjects recruitment targeted at participants' interests in nature or landscape (Bubalo et al., 2019).

In spite of all these strengths, it is important to recognize the challenges associated with passively-crowdsourced data such as tweets. Twitter users who send geolocated tweets may not be representative of other people who are less likely to use Twitter, such as individuals older than 65 (Wojcik & Hughes, 2019). Thus, extra care should be taken when trying to generalize the results to wider populations. The lack of demographic information on the users further hinders the ability to understand the representativeness of the data and to account for potential tweet-level potential confounders. Although including the user random effect in regression models accounts for a combination of unobserved individual characteristics that are independent of other explanatory variables included in the model, unobserved tweet-level confounders are still not controlled for (Rabe-Hesketh & Skrondal, 2012). Therefore, the estimated effects may suffer from omitted variable bias if there exist significant tweet-level confounders. Some possible confounders could be users' income levels and health conditions.

Furthermore, tweets are neither anonymous nor direct reports on users' sentiment. Sentiment expressed publicly on social media platforms may not reflect people's true emotional states. Also, because the tweets are rarely a direct report of sentiment, interpretations of the raw data are needed. Regardless of whether the interpretations are done manually or by natural language processing techniques such as Vader, high accuracy can be hard to achieve due to the limited information provided by the short texts and lack of context (Hutto & Gilbert, 2014). A standard way to assess the performance of a sentiment analysis method such as Vader is to compare it with human raters, assuming that human raters' interpretation of the passively-crowdsourced data is correct. However, how well human raters interpret the passively-crowdsourced data such as tweets is still an unanswered question. One possible way to investigate this question is to compare human raters' interpretations with Twitter users' self-reported answers, which can be obtained by developing a mobile application that asks participants to report their sentiment/mood every time they send out a tweet.

Lastly, we assumed in this study that Twitter use wasn't impacted by people's sentiment and surrounding environments significantly. This assumption is a necessary condition for us to approximate the relationship between environments and people's sentiment using the estimated relationship between environments and sentiment expressed in tweets. Although to our knowledge there is no evidence suggesting that this assumption is wrong, it is still important to acknowledge that what we directly detected based on Twitter data was the relationship between natural environments and the probability of tweets being positive or negative, instead of the probability of people being positive or negative. To see the difference, we can imagine a scenario in which a person is actually equally likely to be positive when she is within parks vs. outside parks in residential zones. However, she is more likely to send tweets when she feels happy outside parks compared to when she feels happy within parks, and she is equally likely to send tweets when she does not feel happy outside parks vs. within parks. In this scenario, what we will detect from her tweets is that tweets sent outside parks are more likely to be positive compared to tweets sent within parks, even though the fact is that she is actually equally likely to be positive when she is within parks vs. outside parks. Although there is no evidence, to our knowledge, suggesting that people use Twitter or other social media as described above, it is still important for future studies to examine people's Twitter or social media usage patterns across different environments so that we can be more confident in what social media data is telling us.

4.4 Conclusions

This research contributes to the discussion of the relationship between nature and human's mental well-being and the exploration of the usage of social media data to inform our understanding of that relationship. Particularly, this work broadens and deepens the existing research that uses passive-crowdsourced data by quantifying how multiple natural elements are related to sentiment using statistical models that account for potential confounders and heterogeneity between data contributors. The results suggest that the relationship between natural environments and peoples' sentiment can be much more complicated than the general belief that exposure to nature is beneficial to humans' psychological well-being. How humans respond to their surrounding environments can depend on various factors including but not limited to the degree of naturalness or greenness. Additionally, the general type of naturalness, the amount of natural elements such as tree canopy, how well the green spaces are maintained, and the ways in which people use the space are also important. Therefore, it is not enough to know that in general including more naturalness in the city may benefit people. More studies that take multiple factors into account and conduct in-depth analyses are needed. Big observational studies based on large samples and objective geolocation such as this one are one cost-effective way to do so. Follow-up studies should explore whether the results suggested by these observational studies hold true with other types of data and study designs, and investigate the mechanisms behind the phenomena observed.

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Appendix

Performance of Vader

Table A1. Performance of Vader

	Precision	Recall	F1-scoure	Support
Negative	0.44	0.52	0.47	110
Neutral	0.74	0.71	0.73	432
Positive	0.72	0.72	0.72	287

Definition of land-cover types

Table A2. Land-cover types description

Land cover type	NLCD Classification Description*
Open water	**Open Water**- areas of open water, generally with less than 25% cover of vegetation or soil.
Open space	**Developed, Open Space**- areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
Urban built	**Developed, Low Intensity**- areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
	Developed, Medium Intensity -areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
	Developed High Intensity-highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.
Barren land	**Barren Land (Rock/Sand/Clay)** - areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Forest	**Deciduous Forest**- areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
	Evergreen Forest- areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
	Mixed Forest- areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.

Other green	**Shrub/Scrub**- areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
	Grassland/Herbaceous- areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
	Pasture/Hay-areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
	Cultivated Crops -areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.
Wetlands	**Woody Wetlands**- areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
	Emergent Herbaceous Wetlands- Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

* NLCD Classification Description can be assessed through https://www.mrlc.gov/data/legends/national-land-cover-database-2016-nlcd2016-legend.

Models' results

Table A3. Estimated odds ratios and 95% CIs for Model 1

	Non-negative odds contrast: (Positive or Neutral (Y=2 or 3) vs. Negative (Y=1))					**Positive odds contrast: (Positive (Y=3) vs. Neutral or Negative (Y= 2 or 1))**			
Predictors of interest	**OR**	**Lower**	**Upper**	**Adjusted P-value**		**OR**	**Lower**	**Upper**	**Adjusted P-value**
Land-cover type in commercial/mixed zones									
Urban built (base)									
Open water	1.0440	1.0055	1.0840	0.0497	*	0.9654	0.9345	0.9973	0.0863
Open space	1.0289	0.9591	1.1038	0.5486		0.9232	0.8624	0.9882	0.0812
Barren land	1.0355	1.0113	1.0602	0.0209	*	0.9767	0.9572	0.9967	0.0812
Forest	1.0172	0.8698	1.1896	0.9207		0.9721	0.8368	1.1293	0.8002
Other green	1.0732	1.0146	1.1352	0.0351	*	0.9759	0.9284	1.0259	0.5549
Wetlands	1.1244	0.8554	1.4779	0.5486		1.0639	0.8421	1.3442	0.7242
Land-cover type in industrial zones									
Urban built (base)									
Open water	1.0673	0.9739	1.1695	0.2671		0.9869	0.9030	1.0786	0.8161

Open space	1.2229	1.1384	1.3138	0.0000	*	1.0973	1.0243	1.1754	0.0523	
Barren land	1.0982	1.0158	1.1872	0.0417	*	1.0359	0.9589	1.1191	0.5567	
Forest	0.8732	0.1730	4.4062	0.9207		0.8345	0.1654	4.2100	0.8265	
Other green	1.2433	1.0693	1.4457	0.0209	*	1.1306	0.9740	1.3124	0.2132	
Wetlands	0.5487	0.3413	0.8822	0.0351	*	0.5192	0.3182	0.8473	0.0523	
Land-cover type in residential zones										
Urban built (base)										
Open water	1.0066	0.9314	1.0878	0.9207		0.9308	0.8644	1.0022	0.1287	
Open space	1.0560	1.0137	1.1001	0.0325	*	0.9474	0.9101	0.9863	0.0523	
Barren land	1.1322	1.0664	1.2020	0.0004	*	1.0680	1.0068	1.1328	0.0863	
Forest	1.0010	0.9214	1.0874	0.9820		0.9566	0.8907	1.0273	0.4010	
Other green	1.0779	0.9970	1.1654	0.1069		0.9802	0.9101	1.0557	0.7242	
Wetlands	1.1476	0.8480	1.5531	0.5486		1.0859	0.8373	1.4083	0.7242	
Covariates	**OR**	**Lower**	**Upper**	**P-value**		**OR**	**Lower**	**Upper**	**P-value**	
Outdoor										
Yes (base)										
No	1.0089	1.0024	1.0154	0.0073	*	-	-	-	-	
Time	0.9991	0.9987	0.9995	0.0000	*	-	-	-	-	
Day of week										
Mon to Wed (base)										
Thu	1.0320	1.0198	1.0443	0.0000	*	1.0100	0.9999	1.0203	0.0534	
Fri	1.0516	1.0390	1.0643	0.0000	*	1.0026	0.9927	1.0125	0.6127	
Sat	1.0788	1.0664	1.0914	0.0000	*	0.9812	0.9718	0.9907	0.0001	*
Sun	1.0323	1.0207	1.0441	0.0000	*	0.9856	0.9760	0.9952	0.0034	*
Day										
Day (base)										
Night	0.9651	0.9577	0.9725	0.0000	*	0.9689	0.9628	0.9751	0.0000	*
Temperature (℃)										
< 0 (base)										
0 - < 7	1.0090	0.9736	1.0458	0.6226		1.0380	1.0084	1.0686	0.0116	*
7 - < 12	1.0155	0.9793	1.0530	0.4072		1.0151	0.9857	1.0454	0.3163	

12 - <18	1.0250	0.9878	1.0635	0.1900		1.0241	0.9940	1.0552	0.1179	
18 - <26	1.0454	1.0073	1.0849	0.0192	*	0.9954	0.9658	1.0259	0.7657	
26+	1.0518	1.0099	1.0955	0.0149	*	0.9779	0.9461	1.0108	0.1859	
Dew Point (°C)										
<=2 (base)										
2 – 16	0.9780	0.9644	0.9918	0.0018	*	0.9942	0.9825	1.0060	0.3333	
>16	0.9240	0.8738	0.9772	0.0056	*	1.0027	0.9614	1.0457	0.9014	
Visibility (Statute miles)										
Clear (base)										
Haze	0.9746	0.9480	1.0020	0.0691		0.9946	0.9738	1.0158	0.6147	
Mist	0.9959	0.9345	1.0614	0.9000		0.9679	0.9177	1.0209	0.2304	
Fog	0.9644	0.9092	1.0229	0.2277		1.0522	1.0030	1.1039	0.0374	*
Sky Cover										
Clear or scattered (base)										
Broken	0.9805	0.9615	0.9999	0.0488	*	1.0022	0.9858	1.0188	0.7934	
Obscured	1.0072	0.9724	1.0432	0.6906		0.9819	0.9537	1.0109	0.2189	
Overcast	0.9713	0.9610	0.9817	0.0000	*	0.9828	0.9738	0.9919	0.0002	*
Rain										
No (base)										
Yes	0.9861	0.9723	1.0000	0.0505		0.9846	0.9732	0.9962	0.0096	*
Tweet type										
Original (base)										
Reply/quote	1.2666	1.2595	1.2736	0.0000	*	-	-	-	-	

* p < 0.05

Table A4. Estimated odds ratios and 95% CIs for Model 2

	Non-negative odds contrast: (Positive or Neutral (Y=2 or 3) vs. Negative (Y=1))				**Positive odds contrast: (Positive (Y=3) vs. Neutral or Negative (Y= 2 or 1))**			
Predictors of interest	**OR**	**Lower**	**Upper**	**Adjusted P-value**	**OR**	**Lower**	**Upper**	**Adjusted P-value**
Tree-canopy cover (per 10% change)								

In commercial/mixed zones	0.9890	0.9797	0.9984	0.0325	*	-	-	-	-	
In industrial zones	1.0253	1.0097	1.0412	0.0041	*	-	-	-	-	
In residential zones	0.9960	0.9918	1.0003	0.0712		-	-	-	-	
Covariates	**OR**	**Lower**	**Upper**	**P-value**		**OR**	**Lower**	**Upper**	**P-value**	
Land-cover type										
Urban built (base)										
Open water	1.0402	1.0042	1.0776	0.0284	*	0.9621	0.9344	0.9906	0.0095	*
Developed, open space	1.0671	1.0287	1.1070	0.0005	*	0.9581	0.9252	0.9921	0.0160	*
Barren land	1.0485	1.0254	1.0721	0.0000	*	0.9892	0.9706	1.0082	0.2627	
Forest	1.0212	0.9426	1.1063	0.6075		0.9759	0.9116	1.0447	0.4819	
Other green	1.0863	1.0343	1.1408	0.0009	*	0.9883	0.9474	1.0309	0.5834	
Wetlands	1.0852	0.8799	1.3385	0.4448		1.0445	0.8811	1.2382	0.6163	
Outdoor										
Yes (base)										
No	1.0083	1.0018	1.0148	0.0125	*	-	-	-	-	
Time	0.9991	0.9986	0.9995	0.0000	*	-	-	-	-	
Day of week										
Mon to Wed (base)										
Thu	1.0319	1.0198	1.0442	0.0000	*	1.0100	0.9998	1.0203	0.0538	
Fri	1.0516	1.0390	1.0643	0.0000	*	1.0025	0.9927	1.0125	0.6185	
Sat	1.0788	1.0664	1.0914	0.0000	*	0.9812	0.9718	0.9908	0.0001	*
Sun	1.0323	1.0207	1.0441	0.0000	*	0.9856	0.9761	0.9952	0.0035	*
Day										
Day (base)										
Night	0.9653	0.9579	0.9727	0.0000	*	0.9691	0.9629	0.9753	0.0000	*
Temperature (°C)										
< 0 (base)										
0 - < 7	1.0090	0.9735	1.0457	0.6248		1.0380	1.0083	1.0685	0.0117	*
7 - < 12	1.0155	0.9793	1.0530	0.4075		1.0151	0.9857	1.0454	0.3170	
12 - <18	1.0250	0.9878	1.0635	0.1902		1.0241	0.9940	1.0551	0.1183	
18 - <26	1.0454	1.0073	1.0849	0.0190	*	0.9955	0.9659	1.0259	0.7671	

26+	1.0519	1.0100	1.0956	0.0147	*	0.9780	0.9462	1.0109	0.1876	
Dew Point (°C)										
<=2 (base)										
2 – 16	0.9780	0.9644	0.9917	0.0018	*	0.9942	0.9825	1.0060	0.3316	
>16	0.9241	0.8739	0.9771	0.0055	*	1.0026	0.9614	1.0456	0.9021	
Visibility										
Clear (base)										
Haze	0.9745	0.9479	1.0020	0.0684		0.9946	0.9738	1.0158	0.6123	
Mist	0.9958	0.9344	1.0613	0.8979		0.9678	0.9176	1.0208	0.2295	
Fog	0.9644	0.9093	1.0229	0.2278		1.0522	1.0029	1.1039	0.0375	*
Sky Cover										
Clear or scattered (base)										
Broken	0.9805	0.9615	0.9999	0.0493	*	1.0022	0.9859	1.0189	0.7894	
Obscured	1.0072	0.9725	1.0432	0.6873		0.9819	0.9537	1.0109	0.2196	
Overcast	0.9712	0.9610	0.9816	0.0000	*	0.9828	0.9738	0.9919	0.0002	*
Rain										
No (base)										
Yes	0.9861	0.9724	1.0001	0.0509		0.9846	0.9732	0.9962	0.0096	*
Tweet type										
Original (base)										
Reply/quote	1.2666	1.2596	1.2736	0.0000	*	-	-	-	-	

* p < 0.05

Table A5. Estimated odds ratios and 95% CIs for Model 3

	Non-negative odds contrast: (Positive or Neutral (Y=2 or 3) vs. Negative (Y=1))					**Positive odds contrast: (Positive (Y=3) vs. Neutral or Negative (Y= 2 or 1))**			
Predictors of interest	**OR**	**Lower**	**Upper**	**Adjusted P-value**		**OR**	**Lower**	**Upper**	**Adjusted P-value**
Parks in commercial/mixed zones									
Outside parks (base)									
Large natural parks	1.3645	1.2435	1.4973	0.0000	*	1.0736	0.9815	1.1744	0.2703
Other parks	1.0895	1.0295	1.1530	0.0045	*	0.9904	0.9402	1.0434	0.7169

Parks in industrial zones										
Outside parks (base)										
Large natural parks	1.3318	1.1562	1.5340	0.0001	*	1.0479	0.9110	1.2053	0.6949	
Other parks	1.0401	0.8521	1.2694	0.6993		0.9455	0.7755	1.1527	0.6949	
Parks in residential zones										
Outside parks (base)										
Large natural parks	1.1797	1.1322	1.2293	0.0000	*	0.9282	0.8970	0.9605	0.0001	*
Other parks	1.0606	1.0037	1.1208	0.0439	*	0.9641	0.9191	1.0115	0.2703	
Covariates	**OR**	**Lower**	**Upper**	**P-value**		**OR**	**Lower**	**Upper**	**P-value**	
Outdoor										
Yes (base)										
No	1.0088	1.0024	1.0153	0.0074	*	-	-	-	-	
Time	0.9991	0.9986	0.9995	0.0000	*	-	-	-	-	
Day of week										
Mon to Wed (base)										
Thu	1.0315	1.0193	1.0438	0.0000	*	1.0101	0.9999	1.0204	0.0512	
Fri	1.0515	1.0389	1.0642	0.0000	*	1.0027	0.9929	1.0127	0.5886	
Sat	1.0780	1.0656	1.0905	0.0000	*	0.9815	0.9721	0.9911	0.0002	*
Sun	1.0316	1.0200	1.0434	0.0000	*	0.9857	0.9762	0.9954	0.0037	*
Day										
Day (base)										
Night	0.9653	0.9579	0.9727	0.0000	*	0.9691	0.9630	0.9753	0.0000	*
Temperature (°C)										
< 0 (base)										
0 - < 7	1.0082	0.9727	1.0449	0.6559		1.0382	1.0086	1.0686	0.0111	*
7 - < 12	1.0147	0.9785	1.0522	0.4316		1.0154	0.9861	1.0457	0.3057	
12 - <18	1.0239	0.9868	1.0624	0.2092		1.0247	0.9946	1.0557	0.1090	
18 - <26	1.0440	1.0059	1.0835	0.0230	*	0.9962	0.9667	1.0266	0.8048	
26+	1.0498	1.0079	1.0933	0.0192	*	0.9790	0.9472	1.0118	0.2066	
Dew Point (°C)										
<=2 (base)										

2 – 16	0.9782	0.9646	0.9920	0.0020	*	0.9940	0.9824	1.0058	0.3206	
>16	0.9239	0.8738	0.9769	0.0054	*	1.0027	0.9614	1.0458	0.9008	
Visibility										
Clear (base)										
Haze	0.9746	0.9480	1.0020	0.0694		0.9945	0.9737	1.0157	0.6058	
Mist	0.9955	0.9343	1.0608	0.8903		0.9682	0.9179	1.0212	0.2341	
Fog	0.9642	0.9091	1.0226	0.2243		1.0522	1.0030	1.1039	0.0371	*
Sky Cover										
Clear or scattered (base)										
Broken	0.9806	0.9616	1.0000	0.0495	*	1.0022	0.9859	1.0189	0.7898	
Obscured	1.0075	0.9728	1.0435	0.6764		0.9818	0.9537	1.0108	0.2166	
Overcast	0.9713	0.9611	0.9817	0.0000	*	0.9828	0.9738	0.9919	0.0002	*
Rain										
No (base)										
Yes	0.9861	0.9723	1.0000	0.0501		0.9846	0.9732	0.9962	0.0094	*
Tweet type										
Original (base)										
Reply/quote	1.2665	1.2595	1.2736	0.0000	*	-	-	-	-	

* $p < 0.05$