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Research Paper

Twitter sentiment in New York City parks as measure of well-being

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A B S T R A C T

While there is an extensive literature regarding the benefits of natural environments within urban settings, there is relatively little statistical research on the correlation of well-being with urban green space. This research uses social media to develop a methodology for understanding the varying levels of feelings in urban green space. Using a geolocated Twitter database, this research correlates quantified sentiment levels inside parks in New York City. It addresses the following: are people more positive when they are in parks as compared to when they are in other places? Specifically, among Twitter users in New York City do people who visit parks have more positive Twitter-sentiment expression compared to their sentiment in other places? Our results show that sentiment expressed in tweets varies between areas inside and outside of parks. We find that in Manhattan in-park tweets express less positive sentiment as compared to tweets outside of parks, but park visitors in the other boroughs of New York City generate more positive in-park tweets as compared to those outside of parks. We discuss the use of tweets as an indicator of the public expressed sentiment and derive suggestions for further research.

1. Introduction

1.1. Urban green space and well-being

For the purposes of this study, urban green space is defined as a component of urban green infrastructure, comprising urban public space, completely or partially covered with grass, trees or other vegetation, which is accessible and available for leisure, play or sport as well as for walking and cycling. Urban parks are publicly accessible and conventionally meet "vegetation" criteria. For this study, New York City parks have been considered synonymous with the category of urban green space.

Urban green space has been an important consideration in recent research into next generation indicators that correlate the well-being of urban residents with Environmental, Health and Livability (EHL) criteria (Van Kamp, Leidelmeijer, Marsman, & de Hollander, 2003; Taylor & Hochuli, 2016); to be added to a long history of concepts and applications. For city residents, well-being is deeply influenced by various components of urban green infrastructure that can play an essential role (Sandström, 2002; Tzoulas et al., 2007; Benedict & McMahon, 2012). Benedict and McMahon (2002) define green infrastructure as "an interconnected network of green space that conserves natural ecosystem values and functions and provides associated benefits to human populations." In the age of the Internet, urban green infrastructure still offers unique opportunities for community members to exchange "real, social interactions" in an open and green environment, and Internet use

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[1] Current research interest: Research into interface between Twitter usage data and urban spatial planning determinants and new decision-making tools.
[2] Current research interest: Analysis of social media discourse with machine learning methods as a determinant in understanding how cyberspace interacts with real space.
[3] Current research interest: Research on built environment impacts on the society and the natural environment; spatialization of data through the use of GIS tools.
[4] Current research interest: Research on big data with interests that include text summarization, question answering, natural language generation, multimedia explanation, digital libraries, and multilingual applications.
[5] Current research interest: Natural language processing, deep learning, and machine learning. Specifically, in sequence to SQL, question answering, knowledge graph, and text generation.
[6] Current research interest: Natural language processing, Bayesian statistics, machine learning.
[7] Current research interest: Equitable and innovative use of social media and big data. And their relationship relative to the functionality of human knowledge/biological and neural systems.

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within public spaces has the potential to be used to promote social engagement (Thompson, 2002; Hampton, Livio, & Sessions Goulet, 2010).

While various studies have acknowledged the psychological benefits of urban green infrastructure at the scale of local communities, there are relatively few studies that directly examine the sentiment that individual visitors may experience in urban parks.

As stated in Kaplan and Kaplan's (1989) foundational work, natural environments have played an indispensable role in human lives since ancient times, and urban green infrastructure today specifically offers residents an opportunity to connect to green space without having to leave the city, and with associated physical and psychological health benefits at a community level.

In modern urban history, exposure of urban residents to green space has been promoted as beneficial to well-being at least since the massive urbanization around industrial production in the nineteenth century fed by smokestack industry and inordinately high residential propinquity. At the same time modern medicine evolved, such that germ theory would lead to geospatial correlation between disease and environmental contexts. In this context New York City is of particular interest. By mid-nineteenth century data had emerged that correlated domestic living conditions and water supply with geo-spatial mapping of diseases such as cholera, yellow fever, tuberculosis and malaria (Griscom, 1845; Griscom, 1850; Rosenberg & Rosenberg, 1968; Citizen's Association of New York, 1865a, 1865b; Plunz, 2016).

The urban parks movement grew from air quality concerns and from the connection between tuberculosis and its "cure" which involved extra-urban residence in sanatoria. Within cities, increased green space through construction of public parks was considered a preventative strategy. In New York City by mid-nineteenth century, construction of Central Park was the first large such intervention as a metaphorical "urban lung" (Jones, 2018). Over the next century in New York City, the urban parks movement morphed into de-urbanist strategies around green space concepts; as well as urban "slum" clearance and replacement with parks or ultimately with "tower-in-the-park" urbanism that combined high-rise densities integrated with green open space (Plunz, 2016). However, the scientific correlation of benefits related to this urbanism and well-being was little corroborated and, at least for tuberculosis, an eventual decline had to do with other causes including widespread use of penicillin (Wilkinson, Sendstad, Parnell, & Schewenius, 2013).

A number of quantitative studies have explored the relationships between the residents' physical well-being and urban green infrastructure, especially parks (Kaplan, 1995; Grahn & Stigsdotter, 2003; Giles-Corti et al., 2005; Benedict & McMahon, 2012). de Vries, Verheij, Groenewegen, and Spreeuwenberg (2003) discover a causal relationship between green space and health mediated by socioeconomic factors in the Netherlands. Similar results are also found in qualitative studies that use focus groups and semi-structured interviews (Henderson et al., 2001; Krenichyn, 2006).

There is an abundance of studies that focus on the benefits of green space for psychological well-being, that includes but is not limited to stress levels, self-esteem, and sense of community. As Kaplan (1995) writes, being in "a nearby, highly accessible natural environment" like urban parks reduces fatigue and redirects people's attention to nature, which consequently helps to reduce stress level for park visitors (Ulrich, 1984; Grahn & Stigsdotter, 2003; Stigsdotter et al., 2010). Thompson et al. (2012) measure stress levels using biomarkers in salivary cortisol, finding that a higher percentage of green space in an environment is associated with lower stress levels, which is consistent across the biomarkers and self-reported survey results. Similarly, other scholars have argued that performing physical activity in urban green space in particular–as opposed to other urban areas – boosts self-esteem for participants (Gladwell, Brown, Wood, Sandercock, & Barton, 2013; Pretty, Peacock, Sellens, & Griffin, 2005).

Aside from offering individual personal mental health benefits, urban parks as public space also provide opportunities for social interaction among members of a community, which in turn improve a sense of belonging for individuals and enhance neighborhood ties inside communities: "one vital role that urban parks play is providing space for the expression of diversity, both personal and cultural" (Thompson, 2002, p. 59). Kuo, Sullivan, Coley, and Brunson (1998) specifically examine the relationship between local green space and neighborhood social ties, finding that individuals living in close proximity to green space perceive a stronger sense of belonging to their communities than those who do not. Peters, Elands, and Buijs (2010) similarly find that by stimulating social cohesion, urban parks help various ethnic groups to develop feelings of comfort and familiarity in their local neighborhoods.

Psychological studies related to local park users can produce conflicted results, and seldom offer a comparison of sentiment when users are in parks as opposed to other non-green urban spaces, a particularly meaningful distinction in discussion of the immediate positive effects that parks have on visitors' moods (Godbey & Blazey, 1983; Hull & Michael, 1995). For instance, Beheshti (2010) surveyed randomly chosen participants in public parks, with the majority of them feeling more relaxed during their stay in parks. By contrast, Hull and Michael (1995) compared the restorative effects of outdoor and indoor recreational activities, and did not find a difference in mood change experienced by participants. The lack of studies comparing sentiment in urban green spaces versus non-green spaces is not surprising, given that traditionally the majority of research on parks and psychological well-being relies on self-reported survey studies, a method that makes it inherently difficult to follow a large group of park users across time and to compare their feeling of happiness in and outside of parks (Tzoulas et al., 2007).

1.2. Public Urban Parks, Twitter and sentiment

The rise of social media with location sharing services since the late 2000s has made large-scale comparison of the expression of sentiment in-park and out-of-park for urban residents not only possible, but also meaningful in our age of social media's popularity, real-time nature, and accessibility as open and high-dimensional datasets. As major social networking sites such as Facebook and Twitter gain popularity across nations, cities, and demographic groups by the beginning of the 2000s, there have been numerous attempts in academia to define and describe the potential roles of social media in our society (Duggan & Smith, 2014; Lenhart, Purcell, Smith, & Zickuhr, 2010; Lenhart, Duggan, Perrin, Stepler, Rainie, & Parker, 2015).

Twitter is a platform by which users can broadcast text updates about their thoughts and activities in 280 characters, a limit recently enlarged from 140 characters (Java, Song, Finin, & Tseng, 2007; Rosen & Ihara, 2017). As of 2016, the Twitter social networking site boasts an average number of 330 million monthly active users in more than a hundred countries, which provides scholars with an unprecedentedly large and high-dimension dataset conveniently accessible with the use of Twitter APIs (Hawelka et al., 2014; Morstatter, Pfeffer, Liu, & Carley, 2013). Since Twitter does not require a reciprocal relationship between following and being followed, it allows for the circulation of real-time information that potentially reaches a huge audience, and consequently may serve as a public sphere for discussing various socio-economic, political and cultural issues (Kwak, Lee, Park, & Moon, 2010; Shirky, 2011; Zhao & Rosson, 2009).

Aside from the use of text analysis techniques, the real-time nature of Twitter also prompts researchers to adopt geospatial analysis tools for geolocated Twitter data voluntarily shared by users, since it reveals how people react to their immediate surroundings as well as their mobility patterns. By design, Twitter allows users to share their geographic coordinates in tweets as reflected by either GPS in their mobile device or the IP address of a computer, and as of 2015 over 80% of Twitter users were using Twitter on mobile devices (Hawelka et al., 2014; Brandt & Richter, 2015). While geolocated tweets account for only around 1% of total tweets, the enormous volume of tweets created daily still generates a sizeable dataset of geotagged tweets thanks to the wide adoption of smartphone devices and the popularity of Twitter around the world (Hawelka et al., 2014; Morstatter et al., 2013). Connected with a tweet's "temporal, semantic, and social content," geolocated tweets represent an open and "richly contextual" data source for a variety of research fields (Malik, Lamba, Nakos, & Pfeffer, 2015). Some researchers have focused on using geotagged datasets to study human mobility patterns, both on a global and local scale (Cheng, Caverlee, Lee, & Sui, 2011; Hawelka et al., 2014).

The representativeness of the overall Twitter population has always been a concern for scholars, since social media users are likely to be younger, more urban and more highly educated as compared to the general population in the United States (Lenhart et al., 2015; Mislove, Lehmann, Ahn, Onnela, & Rosenquist, 2011). Mislove et al. (2011)'s early exploration of the user-defined "location" profile on Twitter reveals that populous counties in the United States, especially those associated with major cities, are overrepresented on Twitter, and Hecht and Stephens (2014)'s findings also support the presence of urban bias in Twitter data in their work that compares geolocated tweets, corrected for spatial dependency, with United States census data. However, when studies are restricted to urban areas, geolocated Twitter data still yields generalizable results, which is particularly true for all densely populated metropolitan areas with a high percentage of smartphone users. To validate the use of Twitter in human mobility studies, Lenormand et al. (2014) compare spatial distribution and mobility patterns of urban residents in Barcelona and Madrid from three different datasets: Twitter, census, and cellphone data. Results show that these three data sources offer comparable information despite their differing natures.

Twitter data has seen increasing use in urban green space research (Roberts, 2017), suggesting that geolocated Twitter data in metropolitan cities can be used as an alternative source of information characterizing commercial, leisure, and residential areas for urban planners, especially given their affordability and real-time nature. In contrast to other large metropolitan areas, New York City enjoys a particularly active Twitter crowd. Frias-Martinez and Frias-Martinez (2014) identify an 84.13 tweet/km2 Twitter density in Manhattan. In their study they cluster 49 days of geolocated tweets in Manhattan, and discover that urban land uses reflected by tweets are in fact comparable to government data provided by the NYC Department of City Planning. As well, in New York City Bertrand et al. (2013) find a correlation between parks and high sentiment in contrast with low sentiment in transportation hubs.

Given the history of research into the psychological benefits of urban parks, it is of interest to examine how geolocated tweets in metropolitan cities may be used to analyze people's sentiment when they are in parks as compared to when they are in non-green urban spaces. In other words, observing the varying level of feelings for the same group of Twitter users as they travel in the city may provide valuable insights on the immediate psychological influence of urban green infrastructure and people's tendency to express positive thoughts versus negative ones. In this paper, we present a study that focuses on Twitter users in New York City who have tweeted at least once in urban parks over an extended period, and we attempt to measure and compare their expressed sentiment reflected by tweets in and out of parks. We use a sentiment identifier for overall sentiment. This tool is not specific to the topics the users are expressing sentiment about.

New York City has been chosen as test bed, given its particularly active Twitter presence, and public park visitors are identified by their unique combination of screen names and profile descriptions. In so doing, we address the following question:

RQ: Will people's sentiment towards a place be more positive when they are in New York City parks as compared to their sentiment when they are in other places?

Specifically, these hypotheses are examined:

H1: On average, tweets generated in New York City public parks will express a more positive sentiment on a daily basis than tweets in other places in New York City.
H2: Twitter sentiment in-park and out-of-park will be equal across New York City borough locations and across varied density of tweets.

2. Methods

2.1. Data collection

For 549 days between June 17th, 2016 and December 17th, 2017, tweets were collected by using the filter method of Twitter's streaming API. A python wrapper called tweepy was used to handle the connection. The only filter provided in query was location.

This method captures geolocated tweets from within a user-specific bounding box, which in this paper is defined by the latitude range [40:41] and longitude range [−74: −73] corresponding to New York City, with the exception of Staten Island, due to its negligible density of tweets. See Figs. 1 and 2.

Tweets come as JSON objects that contain tweet text and metadata, such as timestamp, user profile description, source, and volunteered geolocations. For geolocations, some tweets are geotagged with actual coordinates based on the GPS location of the device, while others are delivered with a "Place" object which includes a location associated with the tweet, but do not necessarily represent where the user is at that time. For the purpose of our study, after filtering, only tweets with exact geo-coordinates are included in the dataset. Though Twitter defines a maximum data rate per minute for APIs, the fact that this study only collects geolocated tweets within a relatively small bounding box renders the rate limiting errors insignificant for this dataset.

To avoid gaps in collection due to power failures or cyber-attacks, we duplicate our data recording on differing independent platforms. The data is recorded both on local computers on the East Coast and on an Amazon Linux Machine located on the West Coast. As a result, while we lost a day of recording on one machine during the massive cyber-attack on October 21st 2016 that resulted in numerous popular sites being inaccessible to East Coast users, we were able to obtain the data via the duplicate recording.

2.2. Data processing

Raw tweets collected from Twitter API are subsequently processed to focus on English tweet texts generated by Twitter users who tweeted at least once in New York City parks. Language was limited to English because of the reliability of text analysis tools and dictionaries, such as Wordnet, for English texts. This analysis aimed to compare sentiment reflected by tweets inside of parks versus outside of parks by the same group of Twitter users. New York City parks were defined based on the shapefiles given the Open Space (Parks) layer from the Department of Parks and Recreation. To capture the effect of parks, in-park tweets are defined as tweets geolocated either inside or within 50 feet (15.24 m) of the park boundary. The buffer averages for the secondary effect of vegetation, and accounts for the margin of error for tweet geo-location.

This research aimed to study how residents use parks as opposed to tourists who only experience the city in a short period of time, following the assumption that tourist visits tend to be less than two weeks. Analysis of the location field under the user attribute showed the use of unstandardized text with many variations in spelling, location type, and content. For our purposes only users who have at least a 15-day gap between their first and last geolocated tweet were selected. However imperfect, resulting statistics provide evidence that the measure does

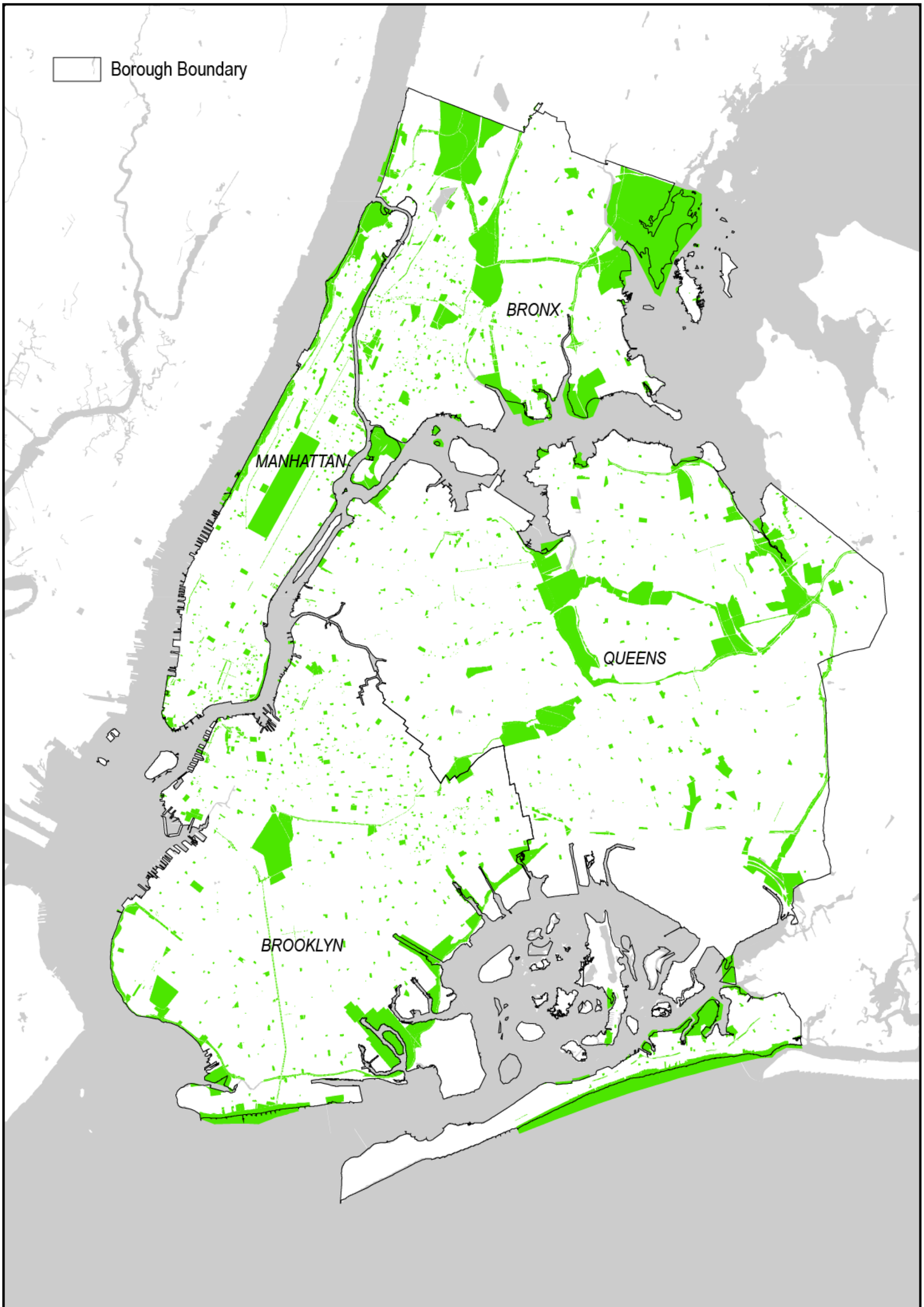

Fig. 1. New York City Borough Boundaries with Parks.

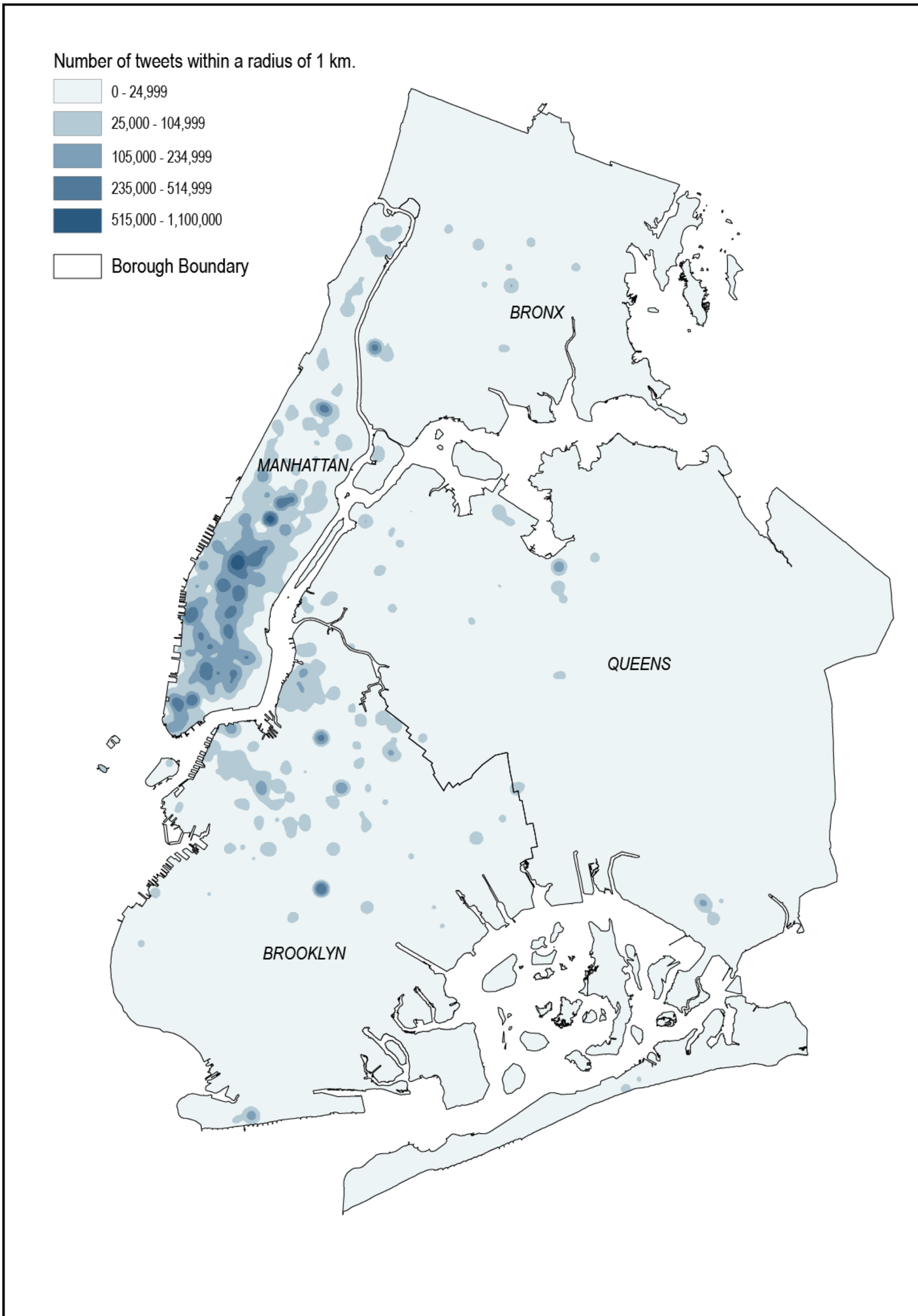

Fig. 2. New York City Twitter Density from June 17, 2016 to December 17, 2017.

reflect known patterns in New York City (Uguccioni, 2016). Bots like 511 New York, the web service for transportation conditions offered by New York State, are excluded from the dataset as they do not reflect emotion experienced by real humans. Spam tweets created by marketers are also filtered for the same reason. This filtering was implemented obtaining a list of sources with the highest tweet frequencies and manually reviewing the names of the sources to determine definite bots. Moreover, it was observed that a high percentage of Twitter users link their Twitter account with Instagram accounts, and allow Twitter to sync-post their Instagram updates automatically. Given that Instagram automatically associates a post that mentions “New York, NY” with New York City Hall, this phenomenon results in an over-representation of tweets at that location. Therefore, tweets geotagged at New York City Hall are removed from the dataset because they may not reflect users' real-time location. After filtering, the updated dataset contains 3,285,537 tweets generated by 85,284 unique users, among which 16.67% of total geolocated tweets are generated in New York City public parks.

2.3. Natural language processing

Tweet texts are subsequently cleaned to remove extra spacing and hyperlinks. For the training dataset, 10,000 tweets are randomly sampled, and labeled as positive, neutral, or negative by two trained researchers from among the authors of this paper, and one Amazon Mechanical Turk staff following a codebook generated by the research team. The Cohen's Kappa score between the two researchers is 0.59 (moderate-substantial agreement). The agreement between the two researchers and the Amazon Mechanical Turk is 0.37 (fair). Tweets are labeled positive when the author expresses positive sentiment about a topic. They are labeled negative when the expressed sentiment is negative. Finally, they are labeled neutral when the expressed sentiment is neither positive nor negative. Some examples of tweets that were labeled positive, negative and neutral are shown in Table 1.

In this paper, we adopt Naive Bayes Logistic Regression with embedding features (NBLR + POSwemb model) developed by Yu, Hidey, Rambow, and McKeown (2017), to classify tweets into three categories of sentiment: positive ($p = 1$), neutral ($p = 0$), or negative ($p = -1$). As an extension of Naive Bayes Support Vector Machine (Wang & Manning, 2012), the NBLR + POSwemb model uses sparse and dense feature combinations. First, it appends positive or negative sentiment indicator tokens at the end of each sentence corresponding to the words used in the tweets. These indicators are determined by the sentiment lexicons of MPQA (Wilson, Wiebe, & Hoffmann, 2005) and Liu (Hu & Liu, 2004). If the sentence includes negators and adversatives, it adds additional indicators to the end as well. After this step, the model tokenizes each sentence into ngrams up to length 3. A ngram is a single word, a pair of words or a triple of words, where pairs and triples occur consecutively in a twitter post (e.g., “New York City” is a ngram of length 3). For each ngram, the model counts the number of times that the ngrams appears in the possible training sentences. For each label l, it defines two count vectors p_l and q_l for ngrams with label l:

$$\begin{cases} p_1 = \alpha + \sum_{i:y^i=l} f(i) \\ q_1 = \alpha + \sum_{i:y^i \neq l} f(i) \end{cases}$$

where α is a smoothing parameter and $f(i)$ is a count vector for training case i with label

$y^i \in \{-1, 0, 1\}$. We set $\alpha = 1$. Then the log-count ratio for class l is computed:

$$r_l = \log\left(\frac{p_l/||\mathrm{p}_1||_1}{q_l/||\mathrm{q}_1||_1}\right)$$

where $||q_l||_1$is the L1 norm of vector q_l. Finally, the model generates a sparse feature vector $r(x)$ by concatenating the log-count ratios of each class:

$$r(x) = r_1 \circ r_0 \circ r_{-1}$$

where ∘ represents the concatenation operator.

To create the dense feature representation, the model first groups words in the sentence x into the set $W = \{NOUN, VERB, ADJECTIVE\}$based on their part-of-speech (POS) tags using NLTK part-of-speech tagger. For words in each group, the model averages their pre-trained word embedding vectors as a dense feature vector for this group. The concatenation of the three averaged word vectors is the final dense feature representation $v(x)$ for sentence x.

The final input feature $e(x)$ for sentence x is the combination of the sparse and dense feature vectors:

$$e(x) = r(x) \circ v(x)$$

e(x) is input to the logistic regression classifier, which classifies each tweet into positive, neutral or negative.

Our sentiment system achieves high accuracy on multiple datasets that are commonly used as benchmarks. For example, it achieves 90% accuracy on the Multiple Perspective Question Answering (MPQA) dataset that has been used for testing by many researchers in the field.

Table 1
Tweets Sample and Sentiment Labeling.

Original Tweet Message	Sentim. Label
01. Abigail Adams, writing to her eleven year old son, John Quincy Adams. #americanspirit.	Neu
02. #brunch #aye #foodie @ Catch NYC.	Pos
03. @grimmales #sundaybeer gorgeous layers of flavor #brooklynbeer #summerbeer @Clinton Hill.	Pos
04. I'm at @Flywheel Sports in New York, NY.	Neu
05. Just posted a photo @ Williamsburg Bridge	Neu
06. #StrykeEsquire strikes again! No pun intended! @ Trailer Park Restaurant.	Neu
07. MORNING TIME GOING TO THE CITY I MADE THIS AS I WAS DRIVING.	Neu
08. He’s smiling at me #foodporn #japanesefood #sushi #sushiden #sushiday #myphonehaseyes.	Pos
09. Beautiful Spring day in NYC #colorsofnewyork #newyor_instagram #ilove_newyo #outdoors.	Pos
10. Die In for Healthcare at Foley Square NYC organized by #nyc womensmarchnyc @ Foley Square.	Neu
11. My 1st trip to #NY wasn't that great. This trip was awesome! Until next time #ciao.	Neu
12. #wizardsandwitches @cieloclub Saturday Oct 29 Music.	Neu
13. Getting around one museum at a time. @ Museum of the American Gangster.	Neu
14. You gotta keep on selling produce even if there is a downpour. #newyork #nyc #Manhattan.	Pos
15. Our poor kitty, Cedric, is sick and needed some drugs. He is a sloppy mess of happiness.	Neu
16. on my way @ Chelsea, Manhattan.	Neu
17. A family affair #nyc @ld_amanda and vnetanus advocating for me.	Neu
18. I’m at Fort Greene Park – @nycparks in Brooklyn, NY.	Neu
19. Multipurpose morning miles. #AchillesNYC #MarathonGuideTraining @ Bronx Terminal	Neu
20. Nothing like surprises snow on the walk home. @Fort Tryon Park.	Neu

Table 2
Descriptive Statistics for Average Daily Tweet Count by Location.

	In-Parks		Outside-Parks		Total	
	M	SD	M	SD	M	SD
Manhattan	681	163	3006	617	3687	724
Bronx, Brooklyn and Queens	318	196	1990	372	2309	500
New York City	**999**	**309**	**4996**	**905**	**5996**	**1008**

The bold for NYC represents the cumulative total for all the boroughs.

For Twitter data, it achieves 70% accuracy on a standard benchmark, the highest of any system developed as of 2017.

3. Results

The goal of this analysis was to assess if tweets generated in parks may express a more positive sentiment than tweets generated in other places in New York City, as stated in the RQ. Two hypotheses were tested, and the results suggest that tweets in Manhattan exhibit a lower level of positivity in Twitter sentiment in parks than outside of parks, but park visitors in other boroughs have a more positive sentiment in parks as compared to what they reveal in tweets geolocated in other places (Figs. 4 and 5) Manhattan also generates the majority of geolocated tweets in New York City, which makes its tweet pattern a substantial influence in the results of New York City as a whole. Within Manhattan, however, tweet density varies considerably, with most located in the southern half of the island. See Fig. 2.

3.1. Outcome

Table 2 presents the descriptive statistics for daily tweet counts by boroughs as well as by location in or outside of parks. As the table shows, Manhattan ($M = 3687$, $SD = 724$) accounts for 61.49% of geolocated tweets in New York City ($M = 5996$, $SD = 1008$) on daily average, which is not unexpected considering the population density of Manhattan as compared to the other boroughs. Similarly, Manhattan ($M = 681$, $SD = 163$) generates 68.17% of in-park tweets in the city ($M = 999$, $SD = 309$). The other three boroughs combined have a lower daily average tweet count ($M = 2309$, $SD = 500$) as well as a lower percentage of in-park tweets (31.83%) relative to all of New York City. They also account for a lower borough percentage of in-park tweets (13.77%) as compared to Manhattan (18.47%). See Fig. 3. Therefore, the variation in tweet densities by borough led to testing Hypothesis 1 separately for three different geographic areas: New York City, Manhattan, and other three boroughs combined.

As discussed, three independent-samples t-tests were conducted to compare daily average expressed sentiment in parks and outside of parks in New York City. As shown in Table 3, there was a difference in the sentiment scores for parks ($M = 0.320$, $SD = 0.029$) and that outside of parks ($M = 0.327$, $SD = 0.021$); $t(1000) = -4.490$, $p < 0.01$. This result suggests that on average, for all of New York City the sentiment expressed in parks is less positive than outside of parks. This result reflects the inordinately negative sentiment expressed in Manhattan. For the other Boroughs, in-park sentiment is higher.

Sentiment scores in Manhattan report the same result, as in-park sentiment ($M = 0.319$, $SD = 0.032$) is also lower than out-of-park sentiment ($M = 0.340$, $SD = 0.023$); $t(1000) = -12.142$, $p < 0.01$. However, for the other three boroughs in New York City – Bronx, Brooklyn and Queens – tweets generated in parks ($M = 0.321$, $SD = 0.048$) record a more positive sentiment as compared to those outside of parks ($M = 0.306$, $SD = 0.026$); $t(1000) = 6.392$, $p < 0.01$, suggesting that Manhattan has some characteristics that are fundamentally different from the other four boroughs in terms of park use and context as reflected in geolocated tweets.

4. Discussion

This paper represents an attempt to use geolocated Twitter data for understanding whether New York City residents using Twitter are more disposed to say positive things when in a public park than when they are not. Similar research is emerging in other urban contexts, with significant differences in scope and definitions. Lim, Lee, Kendal, Rashidi, Naghizade, Winter, and Vasardani (2018) explore tweet sentiment in green spaces in the city of Melbourne. Our results for New York City appear to differ from the Melbourne study. Their definition of "green space," however, appears to differ from "urban public park" in New York City, pointing to the issues of comparative analysis discussed by Taylor and Hochuli (2016). Recent European Twitter research in Birmingham, UK points to the usefulness of Twitter sentiment analytics as a substantial data source for urban planning, with reservations about the efficacy of each of the three methods that are compared (Roberts et al., 2018). For Birmingham, specifics of identification of "green space" criteria would appear to benefit from more explicit definitions for acquiring the data sets. In the United States a more refined definition of urban parks types was employed in a recent San Francisco study (Schwartz, Dodds, O'Neil-Dunne, Danforth, & Ricketts, 2018), by tracking the same users in-park and out-of park with reduced Twitter negativity for in-park users. It should be noted that for these studies, including Bertrand et al. (2013) in New York City, both the collection period is shorter and the volume of tweets are smaller than the dataset used in this paper.

In this research, the geolocation differences in datasets are defining factors in the overall findings; they indicate that while Manhattan Twitter users express a less positive sentiment inside of parks on a daily basis than when they tweet in other places, Twitter users in the other boroughs combined suggest the opposite. For the other boroughs the daily average sentiment score expressed in parks is higher than outside of parks.

The results suggest that there is a fundamental difference in park usage patterns between Manhattan Twitter users and their counterparts in other boroughs of New York City. While it may be difficult to definitively identify the specific reasons behind this difference due to the lack of demographic information on Twitter users, the characteristics of

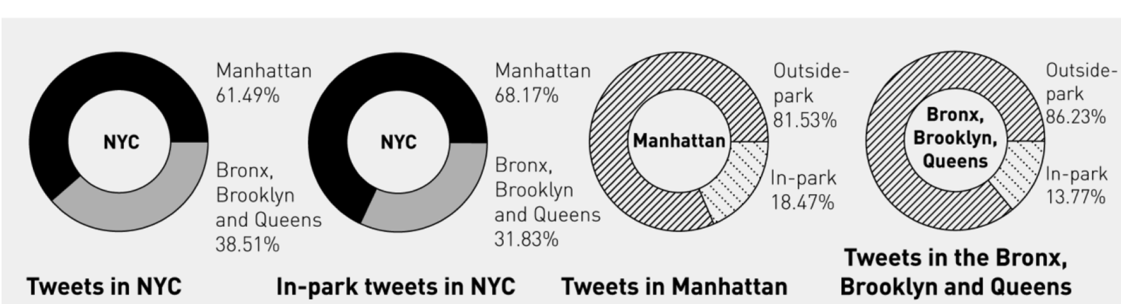

Fig. 3. Percentages for Average Daily Tweet Count by Location.

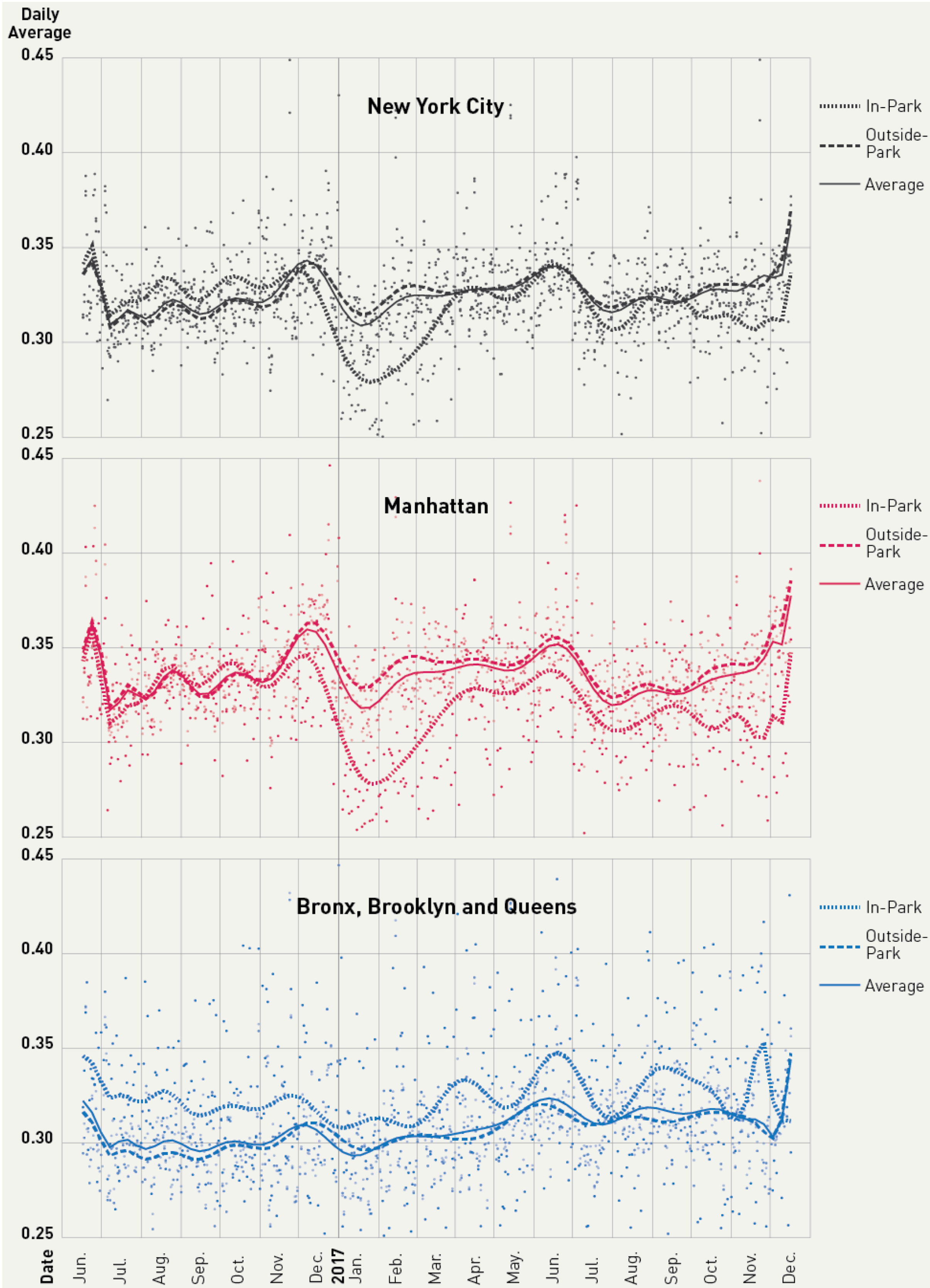

Fig. 4. Average Daily Sentiment Score Trends by Location.

Manhattan working population, substantially more numerous than the other boroughs, can be a major factor behind it. Manhattan differs from the other four boroughs for its big variation between daytime population and actual resident population.

The 2012–2016 American Community 5-Year Survey estimate reports a Manhattan total working population of 2,496,169, of which

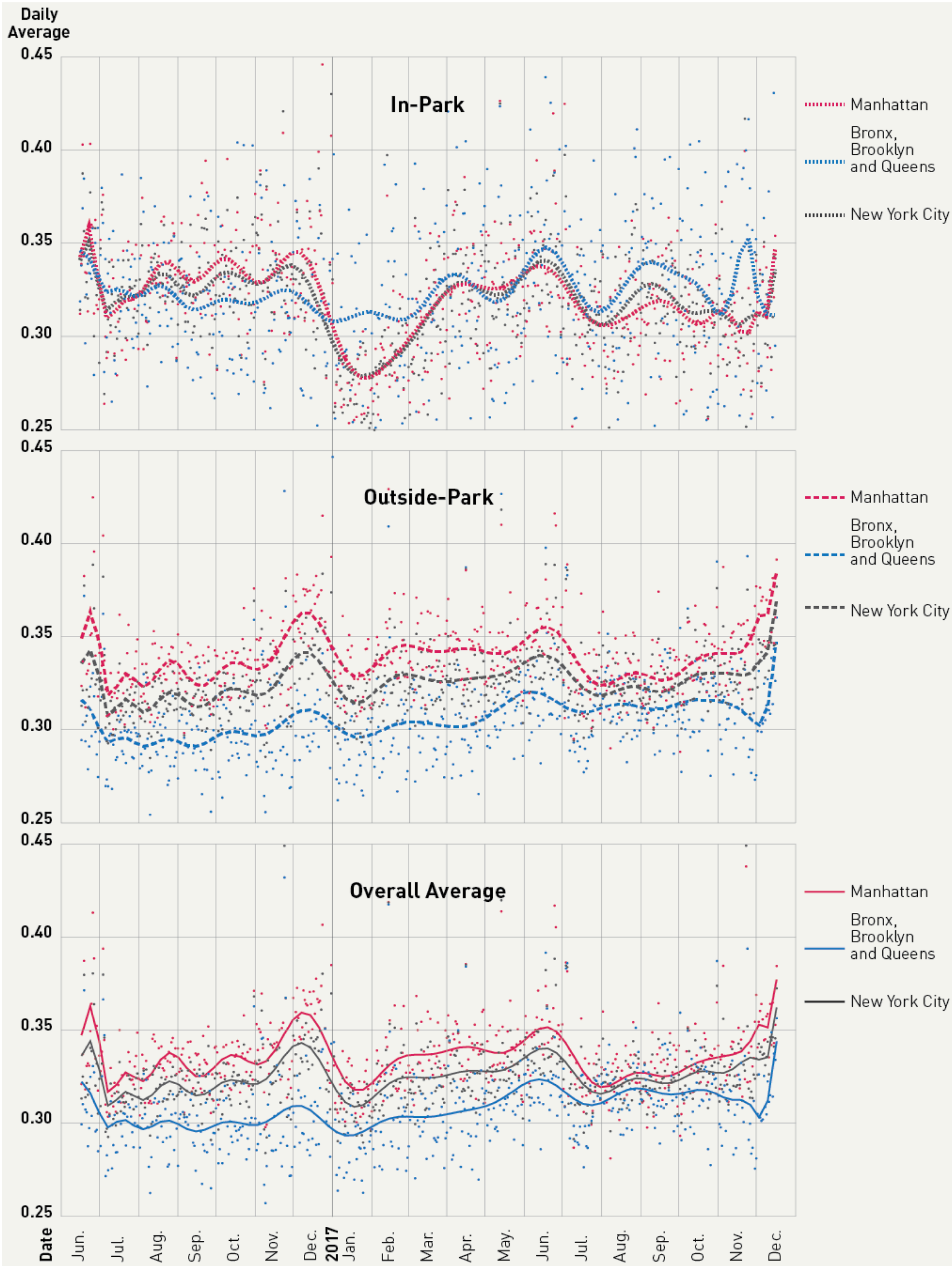

Fig. 5. Average Daily Sentiment Score Trends by In-Park/Outside-Park Location.

70.4% are not residents but daily commuters. In the same way, the daytime population of Manhattan (commuting workers, local residents, visitors, hospitals patients, and commuting students), accounts for 2.45 times of its actual resident population (Moss & Qing, 2012). See Fig. 6. In other words, as compared to the other boroughs, Manhattan has a larger difference in the demographics as well as in usage patterns between its daytime and night time park visitors, because commuters – the working population who does not live in Manhattan – will have a different relationship to Manhattan parks as compared to the local residents during daytime. Consequently, as geolocated tweets generated

Table 3
Results of *t*-test and Descriptive Statistics for Average Daily Sentiment Score by Location.

Manhattan	0.319	0.032	0.340	0.023	−12.142
Bronx, Brooklyn and Queens	0.321	0.048	0.306	0.026	6.3918
New York City	**0.320**	**0.029**	**0.327**	**0.021**	**−4.490**

The bold for NYC represents the cumulative total for all the boroughs.

in Manhattan will reflect the difference in the park experiences of commuters as compared to residents, for Brooklyn, Bronx, Queens the much higher percentage of residential population will also affect the sentiment results. Therefore, the findings call for a further analysis on the mobility patterns of Twitter users in New York City: on how the mobility pattern and sentiment scores of residents will differ from commuters across boroughs; and what other factors are involved influencing sentiment. A pertinent recent study by Kovacks-Györi et al. (2018) explores aspects of these questions using sentiment analysis to further understand spatiotemporal characteristics and user demographics for London, UK parks toward developing a more universally applicable methodology.

In this paper, we have used a sentiment identifier for overall sentiment expressed in the tweet. This tool does not identify what the users are expressing sentiment about. If we look at some of the posts that people made while in the park, we can see that they are expressing opinions about politicians, a restaurant, a snowfall or about a sport event they just attended. In these cases, sentiment does not correspond to their internal state of happiness; it corresponds to their opinion about something else. Future work can refine approaches to capture the target of sentiment so we can determine what feelings people are expressing towards a topic, person, event, place, object. It would be interesting to verify whether the sentiment target differs when a subject is in a park or when not, and if/how parks indicate differing sentiment based on external factors related to urban context.

While twitter users expressing more positive opinions in a park than elsewhere do not express only their mood or the emotions they are feeling, we might consider that when people are in a more relaxed state, are more likely to express a positive outlook on the world. This analysis will be the focus of future social media research.

4.1. Limitations

It should be noted that Twitter users only represent a fraction of the actual park visitor population, and the use of geolocated social media data should not replace traditional survey methods but should rather be treated as a powerful supplement tool provided by modern technology. Moreover, this study aims to research on whether a large group of park visitors might report a different level of positivity in tweets when in and outside of parks, and it should be acknowledged that Twitter sentiment could be influenced by numerous variables such as the user's personal life, political events, as well as events happening in parks. Also, the precision of user location is limited by the accuracy of GPS mobile devices, and the nature of 2D geographic data might lead to measurement errors when it comes to determining the actual location of the user. For instance, a user could be either inside of an underground subway station or sitting in a park. Still, the accessibility and richness of geolocated social media data offers many possibilities when combined with urban planning studies, and this research paper offers a direction for the use of this data source when it comes to the analysis of people's sentiment in parks as compared to when they are in other urban spaces, especially for densely populated metropolitan cities.

5. Conclusions

This paper establishes the usefulness of Twitter-based analytics in comparing user sentiment internal and external to urban parks, with application to New York City and by extension to other spatial urban contexts in a diverse range of cities where sufficient granularity of data is available.

Twitter data is 24/7 and in continuum, providing a conscious stream and a collective picture of social responses to particular situations and contexts. As such it can provide a planning tool for assisting in overall design decisions, as opposed to traditional practice focused on specific issues at specific times. It is fundamentally cognitive in nature and therefore represents a significant advance in our comprehension of how we interact with our environment and vice versa.

Our research indicates that geo-tagged Twitter data can be useful in interrogating the widely-held belief that urban parks contribute to general well-being of residents in cities. Geo-located tweets can help understand people's expressed sentiment as clearly distinguishable within urban park space in comparison to overall sentiment for the city boundaries, with a range of values depending on the particular context of the parks. When integrated with traditional planning tools, geo-tagged Twitter data can be used to identify dysfunction in spatial appropriation and organization of urban parkland to maximum public benefit.

For the first time in planning and urban design practice fine-grain geolocated data can be accumulated at massive scale remotely, to be deployed toward understanding the cognitive characteristics of urban space. More generally, social media shows potential to augment traditional social science methods engaging urban public space characteristics with "ground-sourced" surveys. Over time we anticipate that social media will be essential in producing a new generation of urban design and planning tools that address how to make urban space more environmentally and socially resilient. As sequel to this study, the data collected and the results of the research can serve toward a further analysis of Manhattan's in-park lower sentiment level, specifically directed to topic, person, event, place, object, to further understand the effects of the large non-residential commuter population relative to park usage, as well as for other socio-spatial factors related to public space distribution and appropriation.

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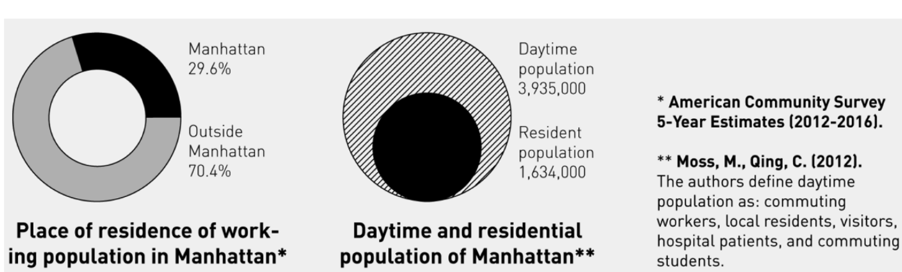

Fig. 6. Average Daily Working and Daytime Populations in Manhattan.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2019.04.024.

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