

Article

Analyzing the Spatiotemporal Patterns in Green Spaces for Urban Studies Using Location-Based Social Media Data

Hidayat Ullah ^{1,2,*}, Wanggen Wan ^{1,2}, Saqib Ali Haidery ^{1,2}, Naimat Ullah Khan ^{1,2}, Zeinab Ebrahimpour ^{1,2} and Tianhang Luo ^{1,2}

¹ School of Communication & Information Engineering, Shanghai University, Shanghai 200444, China; wanwg@staff.shu.edu.cn (W.W.); alisaqib@shu.edu.cn (S.A.H.); naimat@shu.edu.cn (N.U.K.); zeinabe@shu.edu.cn (Z.E.); luoth@shu.edu.cn (L.T.)

² Institute of Smart City, Shanghai University, Shanghai 200444, China

* Correspondence: hidayat@shu.edu.cn

Received: date; Accepted: date; Published: 10 November 2019

Abstract: Green parks are vital public spaces and play a major role in urban living and well-being. Research on the attractiveness of green parks often relies on traditional techniques, such as questionnaires and in-situ surveys, but these methods are typically insignificant in scale, time-consuming, and expensive, with less transferable results and only site-specific outcomes. This article presents an investigative study that uses location-based social network (LBSN) data to collect spatial and temporal patterns of park visits in Shanghai metropolitan city. During the period from July 2016 to June 2017 in Shanghai, China, we analyzed the spatiotemporal behavior of park visitors for 157 green parks and conducted empirical research on the impacts of green spaces on the public's behavior in Shanghai. Our main findings show (i) the check-in distribution of users in different green spaces; (ii) the seasonal effects on the public's behavior toward green spaces; (iii) changes in the number of users based on the hour of the day, the intervals of the day (morning, afternoon, evening), and the day of the week; (iv) interesting user behavior variations that depend on temperature effects; and (v) gender-based differences in the number of green park visitors. These results can be used for the purpose of urban city planning for green spaces by accounting for the preferences of visitors.

Keywords: urban green parks; big data; spatiotemporal; KDE; urban studies; environment; Weibo

1. Introduction

Urban green spaces and public green parks are strategically important for the quality of life in our increasingly urbanized society. Indeed, increasing empirical proof has shown that the existence of natural resources (e.g., parks, forests, and green spaces) and components (e.g., plants and water) in urban environments contribute to living standards in many aspects, including the purification of air and water, the filtration of air and noise, and the stability of the microclimate [1]. Urban areas currently account for half of the global population and are expected to grow to two-thirds of the world's population by 2050 [2]. With this fast urbanization of cities, an emphasis is being placed on ensuring the well-being of urban residents [3]. In response, urban planners are attempting to integrate green places into urban areas since green spaces are believed to enhance the health and quality of life of residents in urban areas. Many urban planners and decision-makers have intended to make residential public spaces livable [4]. Livability, however, is highly dependent on the values of the people and their expectations, so planners must try to understand these expectations on an individual scale [5]. In urban environments, parks play a multipurpose role that offers social, financial, and environmental benefits [6]. In the 19th century, the first public open spaces were developed in the

United Kingdom and the United States with the objective of improving the health and dignity of the working class who were living in miserable conditions [7]. The value of green spaces was also expressed in the latest UN Sustainable Development Goals, which include the specific objective of providing all urban inhabitants with affordable green spaces [8]. Given the significance of green spaces, researchers have also shown interest in this subject, increasingly so in recent years [9].

Every city is special in its features, and this complexity is a fundamental aspect of all cities [10]. One complicating aspect is the continuous mobility of hundreds of thousands or even millions of individuals who are spending more time in public areas, such as green parks. In addition, urban green spaces affect people differently [11], partially as environmental services [12]. It is apparent that access to green spaces or parks is directly linked to the well-being of urban residents in terms of physical and mental health [13]. This influence is evidenced by changes in air quality [14], climate [15], social cohesion [16], and stress mitigation [17]. Features and facilities [18], security and access [19], or even area or perceived greenness [20] are the most appropriate considerations for parks. In designing livable, sustainable, and healthy cities, accessibility to urban green spaces is becoming increasingly relevant [21]. National Recreation and Park Association (NRPA) has stated that parks and recreation have three characteristics that make them vital services in societies: economic value, environmental and health advantages, and social importance [23]. According to Casandra Campbell [24], parks serve eight important functions: rainwater collection, minimization of the urban heat island effect, community center, breathable air, mental health improvement, a place for physical exercise, a place for children to be outside, and protection of natural ecosystems.

Parks or green areas are surely the best way to motivate individuals to become involved in physical activities. In this study, we examined the spatiotemporal behavior of visitors to green parks. We assessed 157 parks with about 30,000 user check-ins using a location-based social network (LBSN) service called Sina Weibo, also referred to as *Weibo* [25]. Established in August 2009, Weibo is among the largest social media platforms and a popular microblogging site in China that enables users to post their day-to-day activities to share with their social group. The word “check-in” indicates that a user voluntarily shares or confirms his or her location on the LBSN by broadcasting where they are—generally through a location-sensing mobile device—while engaging in some activity [26].

In this empirical research, we aimed to investigate the impacts of green space visits on the check-in behavior of users. We used a sample of data to study green park-related check-in behavior, such as liking and disliking, as a representation of the general public’s behavior or interests in certain activities while utilizing park facilities. In the same manner, we aimed to answer the following study questions: (i) What are the spatial characteristics of the selected parks, and how do these characteristics relate to park visits? (ii) How does the time of day and season of visits to green spaces affect the general public’s behavior toward parks? (iii) How does the temperature affect the general public’s behavior toward green park visits? In order to better understand the connection between green space and user behavior, we investigated the spatiotemporal patterns of users in urban green spaces using a large-scale dataset from July 2016 to June 2017. The study was carried out within the municipal boundaries of Shanghai city located to the southeast of China. Our main findings show the check-in distribution of users in different parks and interesting changes in behavior depending on the time of day in 24 h, the interval of the day, and the day of the week. In addition, we explored seasonal effects on the public’s behavior toward green spaces to reflect real-life trends. By studying these factors, the utilization of urban green space and its variation over a range of temporal scales can be examined. This approach to capturing the behavior of visitors in urban green space is an effort to overcome constraints in previous studies. This strategy paves the way for using crowdsourced and social network data in socio-ecological research rather than relying on the outcomes of subjective reporting and observational data.

The rest of this paper is organized as follows. Section 2 presents an overview of studies on green parks. Section 3 describes our study area and the dataset that we used for our research. In Section 4, we discuss the process of dataset collection and the analysis framework, and Section 5 highlights the outcomes of our research using Weibo data. Section 6 provides a discussion on the obtained results, and finally, Section 7 concludes and summarizes the paper and describes future work.

2. Related Work

The population pressure has risen in metropolitan areas worldwide, with individuals thronging the cities in search of a better life. The total population in urban areas in 2019 is estimated to be 2.26 billion, 53% of the world's urban population [27]. There is no doubt that urbanization has an important effect on ecology, economy, and society at local, regional, and global scales. Studies have noted the major effect of urban green areas, including urban forestry, green parks, play areas, domestic gardens, open areas along the road, and urban vegetation [28]. Besides their intrinsic advantage, they also promote the construction of high-quality human settlements since green spaces serve as the city's "lungs" [29]. Given the significance of green areas, they have attracted researchers' interest in recent years [30]. Previous research has addressed the expressive advantages of green spaces in urban regions [31]. These studies have mainly employed user polls, questionnaires, and case studies, which are traditionally either small in scale or require explicit user involvement. Furthermore, these traditional techniques often make it time-consuming and expensive for investigators to conduct a participant-involved longitudinal study or fine-grained research.

Parks also encourage people to experience open spaces for leisure practices that support emotional stability and enhance the standard of life [32]. In other words, the accessibility of affordable and pleasant green spaces is an essential component of urban living standards. In the urban framework, green spaces provide areas such as parks, gardens, urban forests, nature preserves, waterway paths, and playgrounds, as well as other casual green areas [33]. Unplanned and unofficial settlements in most developing cities have led to increased social and spatial inequality, consumption of resources, and environmental destruction [34]. Accessibility can be simply defined by how quickly or far an individual has to travel. In densely populated regions, when park facilities satisfy high requirements for park services, the supply is considered sufficient; therefore, the accessibility in these places is considered convenient. This shows that parks are accessible if they are planned according to the spatial distribution and population of the urban area [35].

Over the past few years, various analytical attempts to use social media data have been made for urban planning purposes, and the fields of application are vibrant and increasing, varying from simple tasks to rather complex analysis, such as urban shape and function identification. In particular, Weibo, Facebook, Twitter, and other big data platforms have been used to evaluate human behavior and mobility, with measurements varying from inter-urban to global [36] since it is almost impossible to identify finer temporal and spatial levels of these two phenomena using traditional techniques, such as survey questions or in-situ observations. In addition, LBSN data can be used for sociospatial analysis [37] with methods such as the extraction of users' tweet content or the exploration of emotions and their differences over time and space [38] while also considering health aspects, such as diet or physical exercise. Campagna [39] proposed the concept of "Social Media Geographic Information" as a means of investigating "people's perceptions" and people's views and interests in time and space to support spatial scheduling and geo-design using spatiotemporal analysis. With data sources other than surveys, such as mobile data, it is possible to more appropriately describe the spatiotemporal aspects of the urban setting [40].

The accessibility of data has been the main obstacle in LBSN studies, mainly because of personal privacy and security. With the capability of LBSNs, sharing the current geolocation of users and their friends introduces major concerns about users' privacy. Privacy is a matter of not only the individual but also organizational or institutional users who share their details in LBSNs. Sometimes, users share their private data voluntarily, while other times, the data can be obtained extrinsically by providing some rewards and advantages to users for their information. The location of a user can be identified through LBSN services such as WeChat Nearby, Google Latitude, and Fire Eagle. Some LBSN services provide features that identify his or her friend's location, as well [41].

The kernel density estimation (KDE) approach has been used for the spatial modeling of geolocation data, and it provides a more general and flexible framework for spatial density estimation. KDE has been used to examine environmental characteristics such as health resources [42], the food environment [43], and park access. It increases the access count or distance measurements by converting point data into something akin to a continuous surface and permitting

the density of a feature to be estimated at any point on the surface of the map [44]. The authors in [45] researched connections between destination allocation, walking speed, and sufficient physical activity using KDE. KDE has also been used to study the allocation of locations such as food shops in relation to variables such as Body Mass Indexing (BMI) [46], obesity [47], and nutritional intake [48]. In [49], the researchers used the KDE method to investigate the comparative significance of external factors linked to the spatial and temporal distribution of users in urban green areas. Given the good spatial and temporal scale, the detection and assessment of incidents or disasters and their impact on regular urban planning routines are another excellent potential use of social media network data [50].

3. Materials

3.1. Study Area

This work used Shanghai City as a case study since it is one of China's fastest-developing cities [51]. Shanghai, China, is situated at the eastern edge of the Yangtze River Delta between 30°40'–31°53' N and 120°52'–122°12' E [52,53]. Regarded as the financial center of China, Shanghai is also known as the world's most populous "city proper", with a population growth rate of 37.53% from 16,737,734 in 2000 and 6.6 million individuals moving to the city every year. With 6000 individuals per square kilometer in 2012, the population of Shanghai is also significantly greater than that of other major cities in the world, such as New York (1800/km²), Paris (3800/km²), and Tokyo (4300/km²) [27]. The migration rate increased from 18.6% in 2000 to 39% in 2010 [54]. The municipal government of Shanghai is placing a strong emphasis on providing the local ecological system with green recreational services and adding important public benefits, including access to clean air, increased recreation, and aesthetic enjoyment. In 2011, the green spaces in the city of Shanghai exceeded 37.1 km², which is twice that in 1997, according to statistical yearbooks of Shanghai (2000–2011). Further, from 2000 to 2011, the green coverage percentage increased from 22.2% to 38.2%, while the green area per capita grew to 13.1 m² from 4.6 m² in 2000 [55].

This research was carried out in the metropolitan city of Shanghai, and the study area comprised 15 districts and 1 county, namely, Baoshan, Changning, Fengxian, Hongkou Huangpu, Jiading, Jingan, Jinshan, Minhang, Pudong New Area, Putuo, Qingpu, Songjiang, Yangpu, Xuhui, and Chongming, as shown in Figure 1.



Figure 1. Study area.

“Urban Green Space Classification Standard China” [56] describes urban green spaces as recreational amenities and facilities available to the public, and they are primarily used for environmental improvement and disaster prevention and minimization. Urban green areas can be categorized into green parks, green spaces on the road, and belt-shaped spaces. Green parks facilitate recreational activities, and they are large in scale and appropriate for outdoor activities. Moreover, green parks primarily offer physical activities to urban residents [49].

3.2. Dataset

The dataset used for our research was collected from the Weibo Chinese microblog. Shortly after its launch on 14 August 2009, Weibo, one of the largest LBSNs in China, saw an exponential boom in activity and awareness and has now reached maturity. We used Weibo data not only because it is one of the most important LBSNs but also because it includes geodata of distinct modalities and offers different social features that encourage individuals to check in constantly and frequently. Weibo declared that, in 2018, they had more than 500 million registered users actively using the platform; in December 2018, the number of monthly active users hit 462 million [57]. Furthermore, we focused on users who frequently use the Weibo service to investigate user activity patterns. The data gathered from the LBSN service involve serious concerns about privacy and limitations. In China, it is very difficult to find open and reliable data that report geolocations. For this research, the LBSN dataset was taken from Weibo during the period between July 2016 and June 2017. Weibo is an open geodatabase and can be accessed using a python-based Weibo application programming interface (API) [58].

The Weibo dataset contains information that includes user ID, time and date of activity, as well as additional data such as geolocations (longitude and latitude) and location names, but no personal information is accessible for the privacy of users. Weibo check-ins record the user’s daily activity patterns and their behaviors, which depict the everyday operations of users. Shanghai was selected as the study area because of the huge number of Weibo check-ins and more active users in this city. Within the administrative boundaries of Shanghai, we gathered 29,890 check-ins in 157 parks using the Weibo API. Weibo data were preprocessed to remove noise, wildcard entries, duplications, and invalid records. For data preprocessing and cleaning, the following criteria were taken into consideration:

- The geographical location of the data must be in Shanghai;
- The minimum number of check-ins per park must be 100 in the study period;
- Each record must be geolocated (latitude and longitude), and the time, day, month, year, and gender must be included.

The temperature dataset was acquired from the U.S. National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center. A global land-based observation station in Shanghai records historical meteorological data that can be downloaded from the NOAA online repository. An example of a temperature dataset can be seen in Table 1.

Table 1. Example of a temperature dataset.

Date	Weather	Air Temperature	Wind Direction	Sunny (Days)	Rain (Days)	Cloudy (Days)	Average (Month)
July 1, 2016	Overcast/cloudy	34/26 °C	South wind 3–4/ south wind 3–4	09	16	09	34/27 °C
August 09, 2016	Shower/thunder shower	33/28 °C	Dongfeng ≤3/ Southeast 3–4	05	12	21	33/27 °C
September 2, 2016	Cloudy/cloudy	35/25 °C	West wind ≤3/ Dongfeng ≤3	01	16	15	28/23 °C
January 05, 2017	Moderate rain/light rain	12/10 °C	Dongfeng ≤3/ Dongfeng ≤3	08	08	19	10/05 °C

March 14, 2017	Sunny/clear	12/5 °C	North wind ≤3/ north wind ≤3	06	09	17	14/18 °C
June 17, 2017	Sunny/cloudy	29/21 °C	Dongfeng ≤3/ Dongfeng ≤3	04	015	17	28/22 °C

4. Methodology

4.1. Data Preparation

Check-in data are available to the public via the Weibo API. Therefore, data downloading and subsequent evaluation do not infringe on the privacy of users. The data collection includes all the check-ins made within the Shanghai boundary from 1 July 2016 to 30 June 2017. The downloaded data are available in multiple JavaScript Object Notation (JSON) files. Figure 2 reflects the process flow of data preparation.

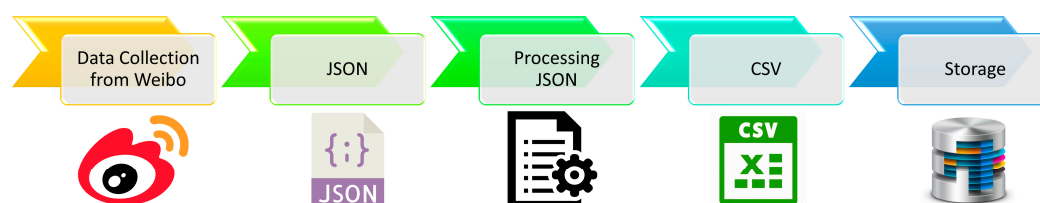


Figure 2. Process flow of data preparation.

JSON is a Java programming platform format that is the most widely used data format, and Java is regarded as the main programming language with open-source public reader and writer modules [59]. The data were processed into a comma-separated values (CSV) format file through MongoDB so that all user information, including geolocations, were listed irrespective of the publication time. The data were stored as shown in Figure 2. For databases and spreadsheets, CSV format is the most common and important format and distinguishes commas as delimiters of different values. Keys (ID, Latitude, Longitude, etc.) in JSON file format are used as headers for the CSV file format, and values (5404478798, 121.544449, 31.268159, etc.) are descriptive data. Table 2 presents an example of “check-in” data in the CSV file.

Table 2. Example of Weibo check-in data.

Building_id	User_id	Month	Date	Day	Time	Year	Gender	Lon	Lat	Address
B2094554D064ABF4429	###	08	24	Wed	0:00:03	2016	F	121.6650	31.14363	ZhaoHang_Park
B2094757D06FA0F8409D	###	11	11	Fri	1:24:45	2016	F	121.5244	31.265614	Jiangpu_Park
B2094757D06FA6FB409B	###	05	29	Mon	3:02:19	2017	M	121.3787	31.34228	Gucun_Park

Given the heterogeneity issue, it was necessary to select only parks with more than 100 check-ins to constitute the sample of users in order to ensure a relatively high level of representativeness. After retrieving all the locations of parks, every park location was found using Google Maps to verify the effectiveness of our data. After checking it through Google Maps, we found some location IDs such as parking areas that were not part of any green park, so we removed these location IDs from our research.

4.2. Social Media Data Analytics

The distribution of Weibo users affects the spatiotemporal distribution of check-in data [60]. In this section, we highlight the general framework of the spatiotemporal heterogeneity of Weibo users' distribution, as shown in Figure 3. We describe the spatiotemporal analysis that was conducted to verify the effectiveness of our study and obtain the temporal and spatial results from our research in this data analytics framework.

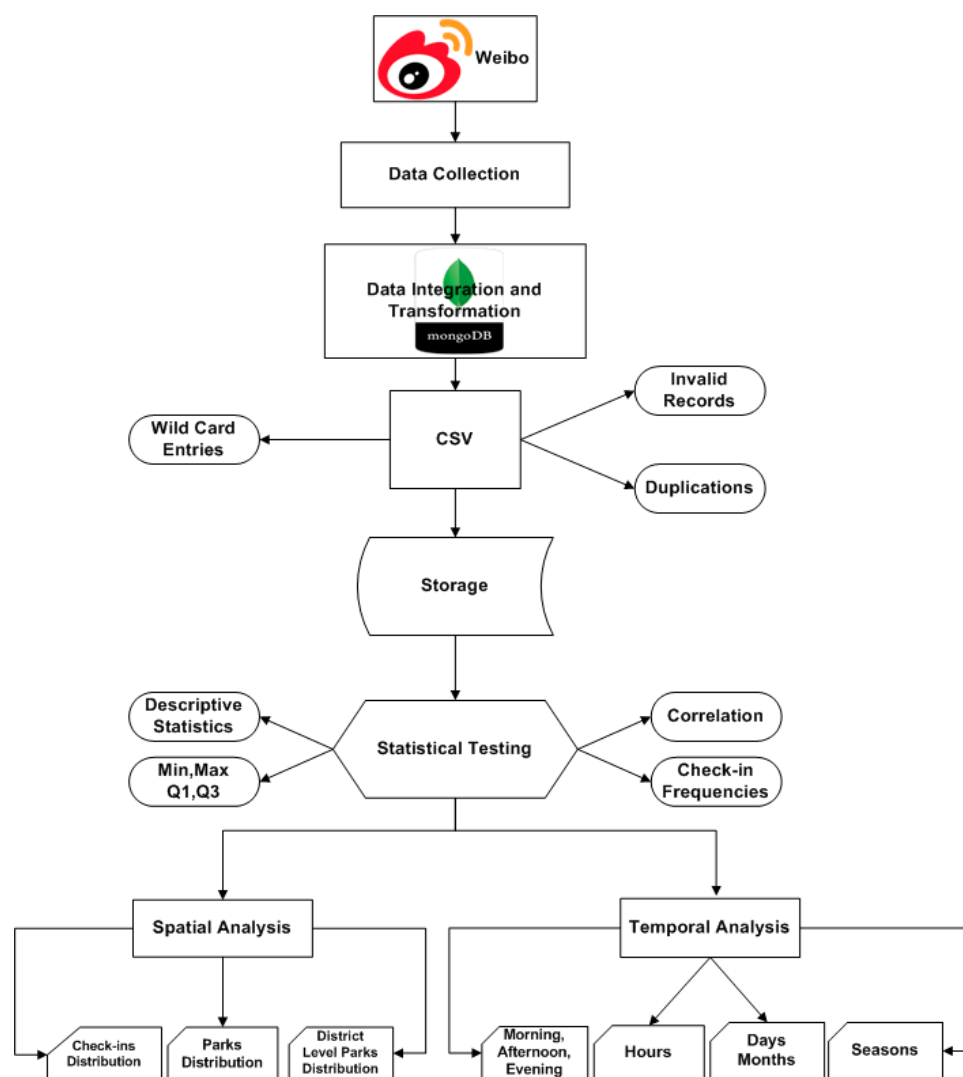


Figure 3. Data analytics framework.

The number of users in urban green areas in one year was gathered as statistical data. From the data, a spatiotemporal analysis was carried out using statistical graphs and tables, and the distribution of check-ins was analyzed by applying the KDE method.

4.2.1. Statistical Analysis

Statistical Package for Social Sciences (SPSS v25) was used to perform statistical analysis. SPSS is a commonly used program in social science for statistical analysis. This statistical software can solve a range of study issues and is used by industry and health researchers, survey firms, government educational experts, marketing agencies, data mining companies, and many others. It offers a variety of functions, including ad hoc analysis, hypothesis checking and reporting, and data management simplification. SPSS Statistics provides a base edition to improve predictive analytic capacities with optional add-ons.

Table 3 shows the correlation between the variables used in this study and reveals that the variables are significant.

Table 3. Correlation matrix.

	Month	Weekdays	Gender	Hours	Date	Year
Month	1	0.004	0.027 **	−0.019 **	−0.028 **	−0.806 **
Week Days	0.004	1	0	0.030 **	−0.037 **	−0.01
Gender	0.027 **	0	1	−0.037 **	0.002	−0.050 **
Hours	−0.019 **	0.030 **	−0.037 **	1	−0	0.006
Date	−0.028 **	−0.037 **	0.002	−0.002	1	−0.017 **
Year	−0.806 **	−0.007	−0.050 **	0.006	−0.017 **	1

** Correlation is significant at the 0.01 level (two-tailed).

Table 4 shows the descriptive statistics for correlated variables and demonstrates that there is no skewness in our data.

Table 4. Descriptive statistics of correlated variables.

	Mean	Std. Deviation
Month	6.17	2.825
Weekdays	4.3	2.111
Gender	0.35	0.478
Hours	14.58	5.648
Date	15.54	8.79
Year	2016.7	0.47

Table 5 shows the descriptive statistics and reveals that there is no irrelevance. The data seem to be normally distributed about the mean.

Table 5. Descriptive statistics.

Mean	Median	Std. Deviation	Min	Q1	Q3	Max
6.17	6	2.825	1	4	8	12

Table 6 indicates the check-in frequencies throughout the year.

Table 6. Check-in frequencies.

Month	Frequency	Percent	Valid Percent	Cumulative Percent
Jan	1212	3.9	3.9	3.9
Feb	1375	4.7	4.7	8.6
Mar	2098	6.9	6.9	15.5
Apr	4488	15.2	15.2	30.7
May	4457	14.9	14.9	45.6
Jun	3840	12.8	12.8	58.5
Jul	4325	14.6	14.6	73.1
Aug	1668	5.6	5.6	78.8
Sep	1510	4.9	4.9	83.7
Oct	1863	6.1	6.1	89.8
Nov	1494	5.1	5.1	94.9
Dec	1560	5.1	5.1	100

4.2.2. Temporal Analysis

In order to trace the changes in visitor behavior, we divided timestamps with check-ins into different temporal categories. Daily trends indicate the hourly distribution of check-ins throughout the day. We aggregated the distribution into three different time intervals, that is, morning, afternoon, and evening. The weekly trend determines whether green parks are more utilized on weekends than during the week on the basis of recorded check-ins. Seasonal patterns and climate factors can affect the functionality of a park. Winter patterns can provide fascinating data because a park works well if it can also attract visitors during the colder seasons. We did not describe seasons

by specific dates in our study but instead used simpler groupings of months: March–May is spring; June–August is summer; September–November is autumn; and December–February is winter.

4.2.3. Spatial Analysis

We used KDE in order to construct a smooth density surface in geographic space for check-in hotspots. KDE is a nonparametric technique for the density estimation of a random data sample [61]. Each data point is smoothed by KDE in a small density bump, and then all these small bumps are combined to achieve a final density estimate. It is an evolving spatial technique that has been implemented in previous studies [62,63] to examine multiple elements of big data analysis, such as human influence and movement patterns [64], check-in behavior [65], the definition of area boundaries [66], and recommended points of interest [67]. It has also been used to analyze characteristics of the environment, such as the food environment, health resources [43], and park access [68]. This approach allows investigators to more intensively identify destinations that are widely distributed and their range of distribution because it examines the distribution of locations in neighborhoods.

KDE is an efficient measurement of the spatial structure of visitor density within the study area. KDE is a statistical approach used to estimate a smooth and continuous distribution from a limited set of observed points [69]. The data considered in our study are in the form of geotagged check-ins. Let “ E ” be a collection of historical check-in data, i.e., $E = \{e^1, \dots, e^n\}$, where $e^i = \langle x, y \rangle$ is a check-in geolocation, $1 < i < n$, of individual i at time “ t ”, where “ E ” represents the dataset that we used. The sum of the functions of the kernel was scaled to create a smooth curve that is an area of the unit. This results in the following form of a KDE bivariate:

$$f_{KD}(e|E, h) = \frac{1}{n} \sum_{i=1}^n K_h(e, e^i) \quad (1)$$

$$K_h = \frac{1}{2\pi h} \exp\left(-\frac{1}{2}(e, e^i)^t \sum_h^{-1}(e, e^i)\right) \quad (2)$$

where “ e ” refers to the check-in location in dataset “ E ”, along with the bandwidth “ h ”. “ h ” is assumed to be dependent on the estimated density “ f_{KD} ”, thereby generating a smooth density surface around “ E ” at the data point “ e^i ”.

ArcGIS 10.0 was used for spatial analysis in order to analyze the spatial distribution of check-ins in space. ArcGIS 10.0 (Environmental Systems Research Institute, Inc., Redlands, CA, USA) software with a Shanghai map generated in 2016 with Geodetic Coordinate System WGS_1984 was used. Base map hierarchical data include the major transport lines (line layer) and administrative units (polygon layer, along with district layers), with the latest subway lines and entrances (point layer) from OpenStreetMap.

5. Results

Shanghai City is among the world’s fastest-growing cities, with a population of 22,125,000 in an area of 4,015 square kilometers [27]. The total number of green spaces in the Shanghai municipal boundaries is 366 [55], which motivates the residents of the city to engage in healthy activities. After filtering the data collected from Weibo, 157 green parks were selected for this study.

The distribution of green parks considered in this study can be seen in Figure 4, which clearly indicates that the parks are sparsely distributed all over Shanghai City, except for the downtown area, which includes the districts Changning, Hongkou, Huangpu, Jingan, Pudong New Area, Putuo, and Xuhui [58].

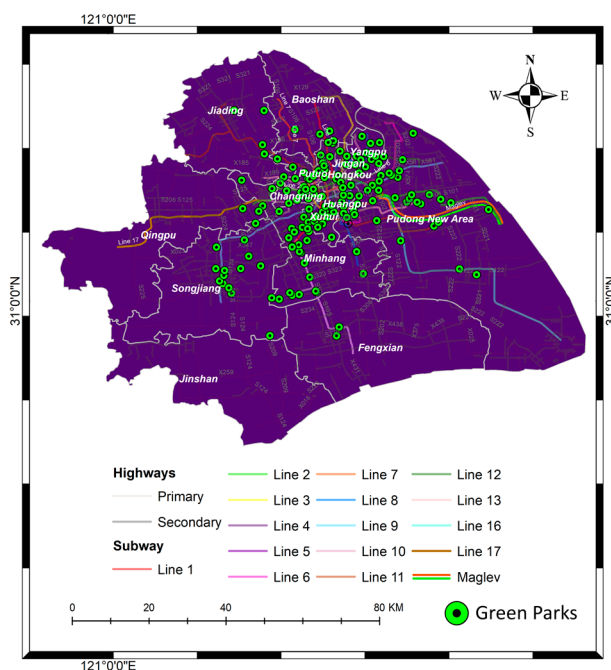


Figure 4. Parks' distribution in Shanghai.

For a more specific overview of green parks' distribution in Shanghai City, the green parks were broken down to the district level. Figure 5 shows that the distribution of parks in the district of Pudong is the highest, followed by the district of Minhang. One reason for such behavior is that these districts are larger in size compared with the other districts. Another point to be noted is that the distribution of parks is higher in the downtown area compared with suburban areas.

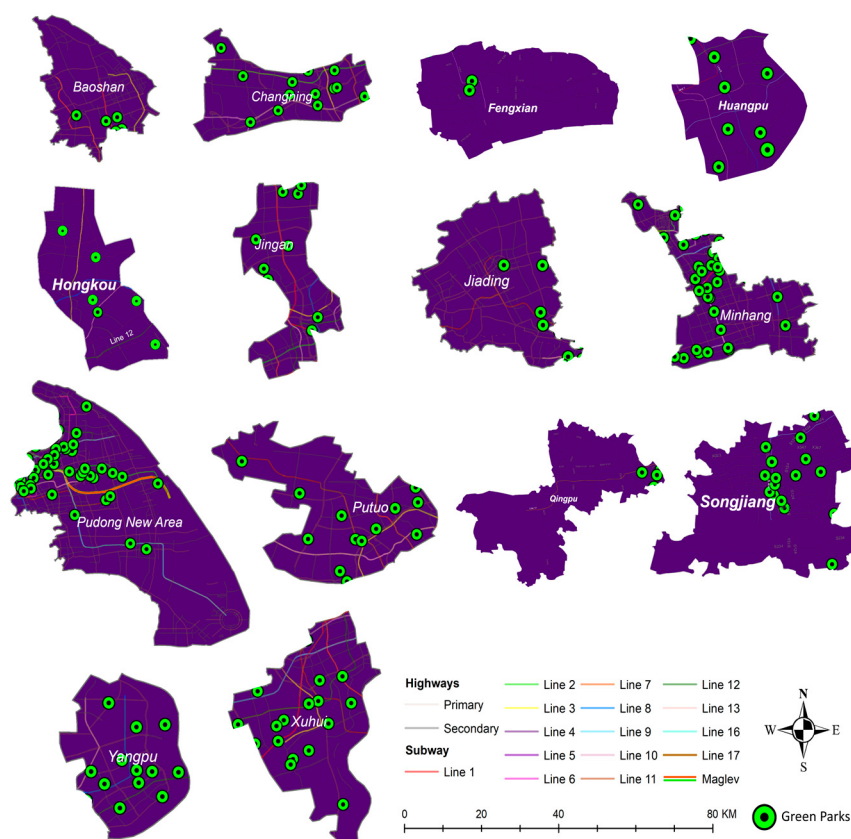


Figure 5. Parks' distribution at the district level in Shanghai.

To examine the Weibo geolocation check-in dataset, we used KDE to analyze the spatial distribution of check-in data, and ArcGIS was used for visualization. Figure 6 shows the overall check-in density in Shanghai from July 2016 to June 2017. The areas shaded in red indicate a higher density of people, higher activity frequency, and higher concentration of social media use. It is no surprise that the green spaces in the city center have large clusters of activity.

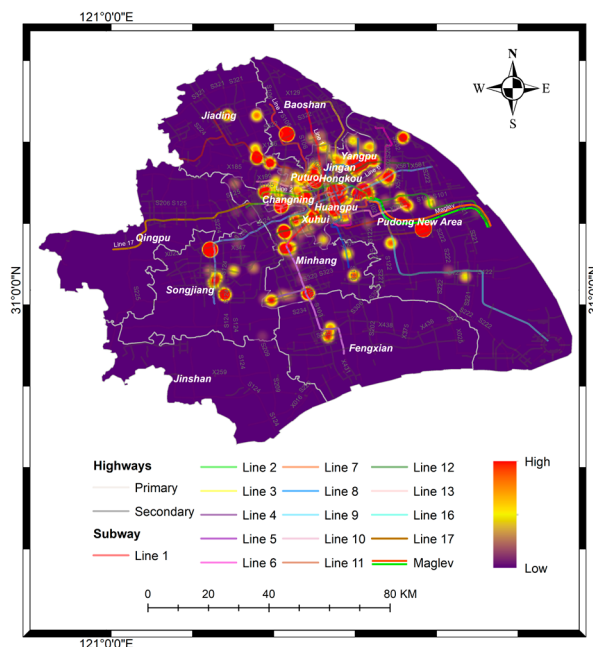


Figure 6. Check-in density of parks in Shanghai.

To analyze visitors' temporal distribution features, we split a day into three intervals according to the rhythms of daily life. In 157 urban green parks, we analyzed the numbers of visitors according to daily time intervals, namely, morning, afternoon, and evening, to measure temporal differences and variations during a 24 h day.

Figure 7 reveals temporal differences in the number of visitors in 24 h and in three intervals of the day. Among the parks considered in the research, visitors were present during all three intervals of the day, but the highest number of check-ins was recorded at 16:00. The trend also continuously increased until midnight. This finding shows that green parks in Shanghai have rapidly become important recreational destinations for Shanghai citizens.

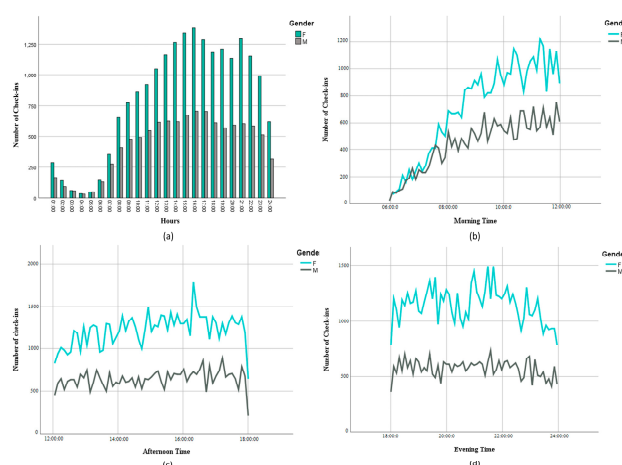


Figure 7. Temporal variations in a day: (a) hourly, (b) morning, (c) afternoon, (d) evening.

The weekly patterns are quite normal, with nearly the same numbers of check-ins for each weekday and a much higher number on weekends. Figure 8a presents the general weekly check-in pattern, which indicates that female users prefer to use Weibo more than male users throughout the week and on weekends.

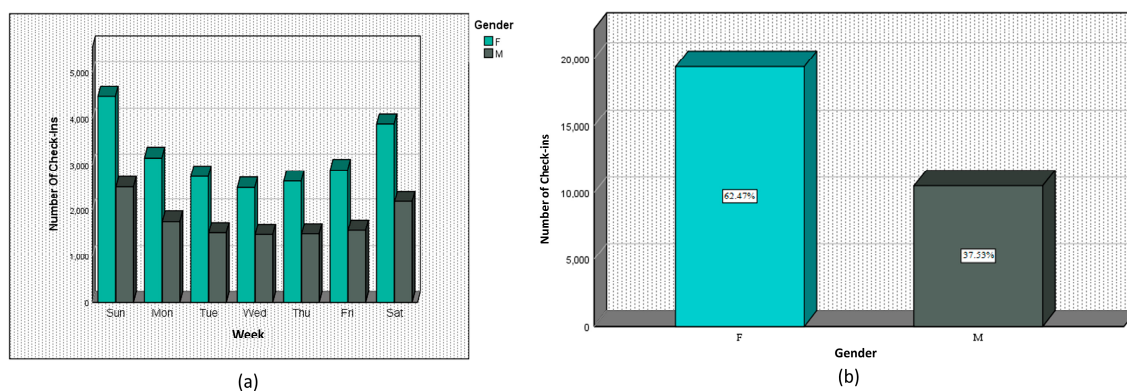


Figure 8. Check-in distribution by (a) the day of the week and (b) gender.

We analyzed gender (male and female) data in Shanghai to explore differences in check-in frequency and behavior. Figure 8b reveals the gender check-in density in Shanghai. It is noted that female visitors prefer to use Weibo compared with male visitors; therefore, the outcome in Figure 8a is supported.

Male and female user check-ins were compared for different days of the week as well as different districts to evaluate the variation between male and female users in Shanghai. We used the relative difference (dr) [70] to calculate gender-based differences for different Shanghai districts and different days of the week. This metric is mostly used as a quantitative indicator of quality control and quality assurance and is determined as follows.

$$d_r = \frac{|P_m - P_f|}{\left(\frac{|P_m| + |P_f|}{2}\right)} \quad (3)$$

Tables 7 and 8 show the outcomes of the relative difference measured by using differences between male and female users for different days of the week and districts. The results are displayed at the cumulative level. We computed the gender differences in the number of check-ins by day of the week and districts as a percentage of total accumulated check-ins generated in the study period. Table 7 shows the relative differences for the days of the week, which were computed using Equation (3). For Tuesday and Friday, the comparative difference values are considerably higher than the values for other days.

Table 7. Gender differences on different days of the week.

Day	Check-in %	Female	Male	dr
Mon	14.26%	9.26%	4.998%	0.597
Tue	12.26%	8.03%	4.232%	0.619
Wed	11.43%	7.22%	4.229%	0.522
Thu	11.75%	7.60%	4.108%	0.596
Fri	12.66%	8.29%	4.365%	0.620
Sat	17.37%	11.23%	6.149%	0.584
Sun	20.27%	13.18%	7.109%	0.598

The results in Table 8 show that the gender difference in the number of check-ins is relatively significant in the districts Fengxian, Qingpu, and Xuhui. The results indicate that female users are much more likely than male users to use Weibo on all days of the week and in all districts. In addition,

as shown in Figure 6, a high concentration of check-ins is located at the district boundaries linked to the center of the city. One of the reasons could be the availability of financial and commercial activities. Finally, all the findings indicate that female users are more likely than males to use Weibo in our study area.

Table 8. Gender differences in districts of Shanghai.

District	Check-in %	Female	Male	d _r
Baoshan	7.06%	4.47%	2.581%	0.540
Changning	6.26%	3.98%	2.287%	0.540
Fengxian	1.45%	0.92%	0.507%	0.579
Hongkou	2.51%	1.45%	1.061%	0.309
Huangpu	7.86%	4.89%	2.970%	0.488
Jiading	4.27%	2.59%	1.694%	0.418
Jingan	2.86%	1.75%	1.110%	0.448
Minhang	10.32%	6.47%	3.855%	0.506
Pudong New Area	29.66%	18.84%	10.823%	0.540
Putuo	8.63%	5.22%	3.424%	0.415
Qingpu	1.67%	1.08%	0.591%	0.585
Songjiang	9.38%	6.23%	3.345%	0.602
Xuhui	3.72%	2.22%	1.504%	0.384
Yangpu	4.35%	2.58%	1.777%	0.368

Table 9 demonstrates the mean and standard deviation among the various district groups and shows the distribution and spread of male and female users around the mean. The number of females in each district is higher than that of males, and significant variation is found in the sample.

Table 9. Summary statistics in districts.

District	Female			Male			Difference
	N	Mean	STD-Dev	N	Mean	STD-Dev	
Baoshan	1195	0.57	0.012	915	0.43	0.052	0.14
Changning	1186	0.63	0.011	685	0.36	0.062	0.27
Fengxian	280	0.65	0.021	153	0.35	0.132	0.30
Hongkou	424	0.57	0.021	326	0.43	0.126	0.14
Huangpu	1444	0.61	0.010	905	0.39	0.054	0.22
Jiading	783	0.61	0.014	493	0.39	0.073	0.22
Jingan	601	0.70	0.012	254	0.30	0.107	0.40
Minhang	1980	0.64	0.008	1104	0.36	0.049	0.28
Pudong New Area	6113	0.69	0.004	2752	0.31	0.032	0.38
Putuo	1588	0.62	0.010	991	0.38	0.051	0.24
Qingpu	378	0.75	0.013	125	0.25	0.156	0.50
Songjiang	1774	0.63	0.009	1029	0.37	0.051	0.26
Xuhui	647	0.58	0.016	465	0.42	0.073	0.16
Yangpu	755	0.58	0.015	545	0.42	0.068	0.16

Seasonal variations in visitors to green parks for autumn, winter, spring, and summer were examined. Prominent seasonal variations in user check-ins were identified, and several factors were explored in an attempt to explain these variations, in accordance with similar studies [5,71]. The seasonal distribution in Figure 9 shows that a greater proportion of check-ins are made in parks during summer and spring. It is interesting to note that winter check-ins are slightly lower than autumn check-ins.

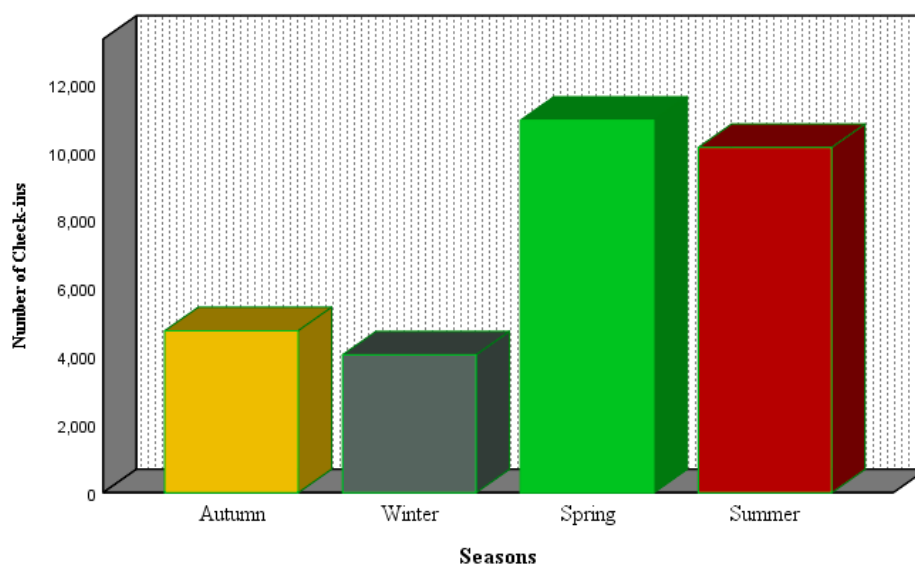


Figure 9. Seasonal variations in the number of park visitors.

Previous research has shown that the influence of temperature varies in relation to park visitors and physical activities. Some studies have identified temperature as an important factor for explaining the variability in park visits between seasons [30].

Figure 10 shows the overall park visiting behaviors during the study period. The temperature has a significant effect on the frequency of check-ins for each month. There are many factors that can influence the determination of an individual's reaction to the climate and its impact on a person's involvement in outdoor activities. The check-ins are much higher during the months of April, May, and June, which supports the results for seasonal variation that indicate that spring and summer have a large number of check-ins.

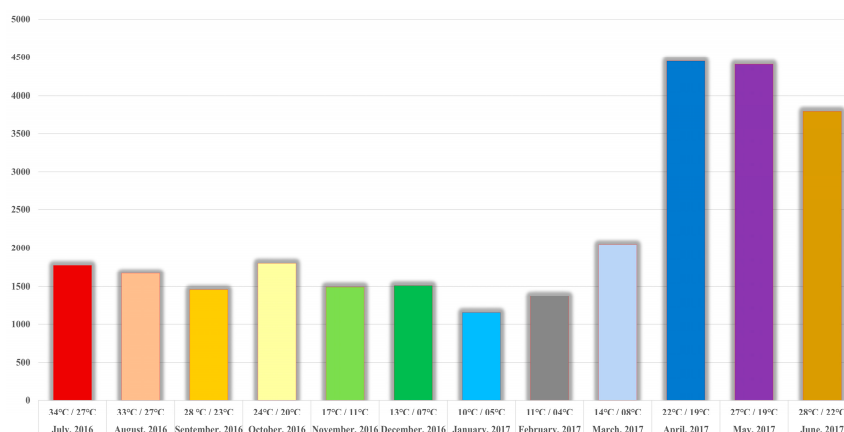


Figure 10. Variation in the number of park visitors with respect to temperature.

6. Discussion

The analysis reveals that Weibo data constitute a useful resource for assessing the features of urban green parks and analyzing spatiotemporal aspects. The benefit of using social media data for analyzing urban green space is that we can extract qualitative and large-scale information for a whole city in more detail.

Some green parks in Shanghai are always crowded, whereas others have fewer visitors. This research aimed to determine the behavioral modifications of park visitors by verifying that the use of green spaces can be influenced by weather or seasons. We investigated the spatiotemporal pattern of the distribution of check-ins in green parks in Shanghai. In this research, we performed an in-depth

empirical analysis of check-in behavior using trend graphs and density maps constructed from LBSN data. The spatiotemporal patterns of check-ins were investigated from different perspectives, including differences based on gender, day of the week, and hour of the day. From the temporal perspective, the number of visitors in green parks varied within the day and among the three intervals of the day. From the spatial perspective, the level of spatial agglomeration in urban green parks was greater in the center of the city because this is also the center of activity for other activities [58]. In particular, spatial agglomeration was the highest in the districts Changning and Hongkou.

This study used geotagged social media check-in data as a proxy to estimate the number of urban park visits in Shanghai, which was used as a case study. This technique is more time-efficient than time- and labor-intensive surveys and can provide exceptional spatial coverage. However, this technique has its own constraints. We did not have access to observed visitor rates, so we were unable to assess whether there was a strong correlation between check-in data and visitations observed in the planning and evaluation of urban areas. The connection between the check-in frequency of Weibo and actual visitation may vary across green parks. A major issue is that, in contrast to traditional census data, social media data generally do not directly provide certain demographic information such as ethnicity and marital status. However, there are ways to extract these variables indirectly [37].

The key reasons for increasing urbanization are the ever-growing population and booming industrialization [72]. Despite the potential of LBSN data to assess the characteristics of urban parks and analyze spatial, temporal, and content-specific aspects, the representativeness of the gathered information does have limitations due to contradictions in the georeferenced locations of the users. However, we can infer that at least the population extremes in age (very young and old) and social situations minimize the use of LBSNs; therefore, their influence on the general public's behavior is minimal in the data. In urban planning and the analysis of urban green parks, geotagged data and demographic data, such as age and ethnicity, are significant factors. It is a problem that social media data typically do not directly provide information that includes names, home addresses, phone numbers, or email addresses—all of which are attainable from conventional census data—but there are ways to collect this information indirectly [37]. In our case, besides the general representativeness issue, the main limitation is the low number of check-ins per user while visiting a park. This resulted in a less than an ideal number of data points per user.

To the best of our knowledge, this research might be the first case study using Weibo data to analyze the use of urban green parks by using check-in behavior for a large number of green parks in Shanghai. The broad spatial coverage of this study provides useful information that could enhance urban green space planning and development in other large cities. The efficient use of urban green areas has substantial potential to encourage moderate to vigorous physical activities among urban inhabitants. These results emphasize the significance of the use of urban green parks in order to improve the health of urban residents around the world.

7. Conclusions and Future Work

Urban green spaces are areas in which people can participate in health-enhancing physical activities. Using geotagged data from social media platforms to evaluate the variation in visitation allows for the coverage of a larger geographical area compared with conventional techniques, such as visitor surveys and on-site counting. We analyzed the spatiotemporal pattern of urban green areas in Shanghai by using a Weibo dataset. In the present research, which used intensity maps and trends using LBSN data, we conducted an in-depth empirical analysis of check-in behavior. The findings reveal the check-in distribution of users in parks, and the results show that the parks located in the downtown area are more crowded than parks in other districts. The analysis of the seasonal effects on the public's behavior toward green parks indicates that the number of check-ins is much higher in spring and summer than autumn and winter. The number of Weibo users based on the hour of day and interval of the day (morning, afternoon, evening) reveals that the peak time of park utilization is from noon to the evening. Interesting variations in user behavior based on temperature effects were observed, and the patterns show that April, May, and June are the most popular months

in terms of check-ins. Finally, gender-based differences in green park visitors were calculated, and results show that female users are more active in their utilization of social media services while visiting green parks. More facilities such as transport and the area of the park can attract more visitors since this study shows that the visitors to parks in the downtown area are denser compared with other regions. These results can be helpful in urban city planning for green spaces by accounting for the priorities of visitors.

Further research can be carried out using the technique and outcomes of this study. Possible future directions for measuring the patterns of recreational visits to urban green parks include the use of geotagged photographic data to establish patterns of recreational activities. The current research approach can provide more informative results for the behavioral transitions of park visitors if user-profile information such as age, income, marital status, and hometown city can be acquired in the future. Similarly, social media content posted by park users can be further interpreted to help recognize the emotions or feelings of visitors and assess the numerous advantages that urban parks provide. Furthermore, similar research can be carried out in other megacities to evaluate common problems that affect the use of urban green spaces.

Author Contributions: Hidayat Ullah and Wan Wanggen conceived the research; Hidayat Ullah and Saqib Ali Haidery designed the research; Hidayat Ullah, Saqib Ali Haidery, Naimat Ullah Khan, Zeinab Ebrahimpour and Tianhang Luo performed the simulations; Hidayat Ullah and Saqib Ali Haidery wrote the article and Wan Wanggen proofread the article for language editing. All authors read and approved the final manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (61711530245) and a project of Shanghai Science and Technology Commission (18510760300).

Conflicts of Interest: The authors declare no conflict of interests.

References

1. Mougiakou, E.; Photis, Y.N. Urban green space network evaluation and planning: optimizing accessibility based on connectivity and raster GIS analysis. *European Journal of Geography* **2014**, *5*, 19–46.
2. UN. *World Urbanization Prospects*; 2018.
3. Hartig, T.; Kahn, P.H. Living in cities, naturally. *J Science* **2016**, *352*, 938–940.
4. Kashef, M. Urban livability across disciplinary and professional boundaries. *Frontiers of Architectural Research* **2016**, *5*, 239–253.
5. Kovacs-Györi, A.; Ristea, A.; Kolcsar, R.; Resch, B.; Crivellari, A.; Blaschke, T. Beyond spatial proximity—classifying parks and their visitors in London based on spatiotemporal and sentiment analysis of Twitter data. *ISPRS International Journal of Geo-Information* **2018**, *7*, 378.
6. Saleem, A.; Kamboh, K. Why people visit parks? The role of gender, age and education among urban park visitors in Faisalabad. *International Journal of Asian Social Science* **2013**, *3*, 2196–2203.
7. Giles-Corti, B.; Broomhall, M.H.; Knuiaman, M.; Collins, C.; Douglas, K.; Ng, K.; Lange, A.; Donovan, R.J. Increasing walking: how important is distance to, attractiveness, and size of public open space? *American journal of preventive medicine* **2005**, *28*, 169–176.
8. UN Sustainable Development Goals. Available online: <http://www.un.org/sustainabledevelopment/cities/> (accessed on 05 April, 2019).
9. Dadvand, P.; Sunyer, J.; Alvarez-Pedrerol, M.; Dalmau-Bueno, A.; Esnaola, M.; Gascon, M.; Pascual, M.D.C.; Basagaña, X.; Morgan, I.G.; Nieuwenhuijsen, M.J. Green spaces and spectacles use in schoolchildren in Barcelona. *Environmental research* **2017**, *152*, 256–262.
10. Batty, M. *The new science of cities*; Mit Press: 2013.
11. Keniger, L.; Gaston, K.; Irvine, K.; Fuller, R. What are the benefits of interacting with nature? *International journal of environmental research public health* **2013**, *10*, 913–935.
12. Costanza, R.; d'Arge, R.; De Groot, R.; Farber, S.; Grasso, M.; Hannon, B.; Limburg, K.; Naeem, S.; O'Neill, R.V.; Paruelo, J. The value of the world's ecosystem services and natural capital. *nature* **1997**, *387*, 253.
13. Sturm, R.; Cohen, D. Proximity to urban parks and mental health. *The journal of mental health policy economics* **2014**, *17*, 19.
14. Wolch, J.R.; Byrne, J.; Newell, J.P. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape urban planning* **2014**, *125*, 234–244.

15. Maimaitiyiming, M.; Ghulam, A.; Tiyyip, T.; Pla, F.; Latorre-Carmona, P.; Halik, Ü.; Sawut, M.; Caetano, M. Effects of green space spatial pattern on land surface temperature: Implications for sustainable urban planning and climate change adaptation. *ISPRS Journal of Photogrammetry Remote Sensing* **2014**, *89*, 59–66.
16. Chiesura, A. The role of urban parks for the sustainable city. *Landscape urban planning* **2004**, *68*, 129–138.
17. Tyrväinen, L.; Ojala, A.; Korpela, K.; Lanki, T.; Tsunetsugu, Y.; Kagawa, T. The influence of urban green environments on stress relief measures: A field experiment. *Journal of environmental psychology* **2014**, *38*, 1–9.
18. Bedimo-Rung, A.L.; Mowen, A.J.; Cohen, D.A. The significance of parks to physical activity and public health: a conceptual model. *American journal of preventive medicine* **2005**, *28*, 159–168.
19. Takano, T.; Nakamura, K.; Watanabe, M. Urban residential environments and senior citizens' longevity in megacity areas: the importance of walkable green spaces. *Journal of Epidemiology Community Health* **2002**, *56*, 913–918.
20. Kothencz, G.; Blaschke, T. Urban parks: Visitors' perceptions versus spatial indicators. *Land Use Policy* **2017**, *64*, 233–244.
21. Transforming our world: The 2030 agenda for sustainable development. Available online: <https://sustainabledevelopment.un.org/post2015/transformingourworld/publication> (accessed on 14 June, 2019).
22. United Nations General Assembly Transforming OurWorld: The 2030 Agenda for Sustainable Development 2015.
23. Brantly, H.B. National Recreation and Park Association (NRPA). *Visions in Leisure Business* **1983**, *2*, 14.
24. Casandra, C. 8 Reasons Why Parks are Important. Available online: <http://www.gardinergreenribbon.com/why-parks-are-important/> (accessed on 14 May, 2019).
25. Weibo. Available online: <https://www.weibo.com> (accessed on 25 June, 2019).
26. Zhen, F.; Cao, Y.; Qin, X.; Wang, B. Delineation of an urban agglomeration boundary based on Sina Weibo microblog 'check-in' data: A case study of the Yangtze River Delta. *Cities* **2017**, *60*, 180–191.
27. Demographia World Urban Area, 2019. Available online: <http://www.demographia.com/db-worldua.pdf> (accessed on 14 June, 2019).
28. Ummeh, S.; Toshio, K. Classification of Urban Parks and their Regional Characteristics in Dhaka City, Bangladesh. *Journal of Environmental Science and Engineering* **2017**, *B 6*, 41–54.
29. Jim, C.Y.; Chen, W.Y. Perception and attitude of residents toward Urban green space in Guangzhou (China). *Environmental management* **2006**, *38*, 338–349.
30. Wang, Y.; de Groot, R.; Bakker, F.; Wörtche, H.; Leemans, R. Thermal comfort in urban green spaces: a survey on a Dutch university campus. *International journal of biometeorology* **2017**, *61*, 87–101.
31. Hartig, T.; Mitchell, R.; De Vries, S.; Frumkin, H. Nature and health. *Annual review of public health* **2014**, *35*, 207–228.
32. Lee, G.; Hong, I. Measuring spatial accessibility in the context of spatial disparity between demand and supply of urban park service. *Landscape Urban Planning* **2013**, *119*, 85–90.
33. La Rosa, D. Accessibility to green spaces: GIS based indicators for sustainable planning in a dense urban context. *Ecological Indicators* **2014**, *42*, 122–134.
34. Gould, P.R. *Spatial Diffusion*, Resource Paper No. 4; Association of American Geographers: Washington, D.C, USA, 1969.
35. Wolch, J.; Wilson, J.P.; Fehrenbach, J. Parks and park funding in Los Angeles: An equity-mapping analysis. *Urban geography* **2005**, *26*, 4–35.
36. Hasan, S.; Ukkusuri, S.V. Urban activity pattern classification using topic models from online geo-location data. *Transportation Research Part C: Emerging Technologies* **2014**, *44*, 363–381.
37. Longley, P.A.; Adnan, M. Geo-temporal Twitter demographics. *International Journal of Geographical Information Science* **2016**, *30*, 369–389.
38. Frank, M.R.; Mitchell, L.; Dodds, P.S.; Danforth, C.M. Happiness and the patterns of life: A study of geolocated tweets. *Scientific reports* **2013**, *3*, 2625.
39. Campagna, M. The geographic turn in Social Media: opportunities for spatial planning and Geodesign. In Proceedings of International Conference on Computational Science and Its Applications, Guimarães, Portugal, June 30 - July 03, 2014; pp. 598–610.
40. Sagl, G.; Resch, B.; Hawelka, B.; Beinat, E. From social sensor data to collective human behaviour patterns: Analysing and visualising spatio-temporal dynamics in urban environments. In Proceedings of In Proceedings of the GI-Forum, Berlin, Germany, July 3–6, 2012; pp. 54–63.

41. Lowry, P.B.; Cao, J.; Everard, A. Privacy concerns versus desire for interpersonal awareness in driving the use of self-disclosure technologies: The case of instant messaging in two cultures. *Journal of Management Information Systems* **2011**, *27*, 163–200.
42. Smiley, M.J.; Roux, A.V.D.; Brines, S.J.; Brown, D.G.; Evenson, K.R.; Rodriguez, D.A. A spatial analysis of health-related resources in three diverse metropolitan areas. *Health place* **2010**, *16*, 885–892.
43. Thornton, L.E.; Pearce, J.R.; Macdonald, L.; Lamb, K.E.; Ellaway, A. Does the choice of neighbourhood supermarket access measure influence associations with individual-level fruit and vegetable consumption? A case study from Glasgow. *International journal of health geographics* **2012**, *11*, 29.
44. Thornton, L.E.; Pearce, J.R.; Kavanagh, A.M. Using Geographic Information Systems (GIS) to assess the role of the built environment in influencing obesity: a glossary. *International Journal of Behavioral Nutrition Physical Activity* **2011**, *8*, 71.
45. King, T.L.; Thornton, L.E.; Bentley, R.J.; Kavanagh, A.M. The use of kernel density estimation to examine associations between neighborhood destination intensity and walking and physical activity. *PLoS one* **2015**, *10*, e0137402.
46. Moore, K.; Roux, A.V.D.; Auchincloss, A.; Evenson, K.R.; Kaufman, J.; Mujahid, M.; Williams, K. Home and work neighbourhood environments in relation to body mass index: the Multi-Ethnic Study of Atherosclerosis (MESA). *Epidemiol Community Health* **2013**, *67*, 846–853.
47. Jones-Smith, J.C.; Karter, A.J.; Warton, E.M.; Kelly, M.; Kersten, E.; Moffet, H.H.; Adler, N.; Schillinger, D.; Laraia, B.A. Obesity and the food environment: income and ethnicity differences among people with diabetes: the Diabetes Study of Northern California (DISTANCE). *Diabetes Care* **2013**, *36*, 2697–2705.
48. Buck, C.; Börnhorst, C.; Pohlabein, H.; Huybrechts, I.; Pala, V.; Reisch, L.; Pigeot, I. Clustering of unhealthy food around German schools and its influence on dietary behavior in school children: a pilot study. *International Journal of Behavioral Nutrition Physical Activity* **2013**, *10*, 65.
49. Li, F.; Zhang, F.; Li, X.; Wang, P.; Liang, J.; Mei, Y.; Cheng, W.; Qian, Y. Spatiotemporal patterns of the use of urban green spaces and external factors contributing to their use in central Beijing. *International journal of environmental research public health* **2017**, *14*, 237.
50. Kovacs-Gyori, A.; Ristea, A.; Havas, C.; Resch, B.; Cabrera-Barona, P. # London2012: Towards Citizen-Contributed Urban Planning Through Sentiment Analysis of Twitter Data. *Urban Planning* **2018**, *3*, 75–99.
51. Li, Z.; Wu, F. Tenure-based residential segregation in post-reform Chinese cities: a case study of Shanghai. *Transactions of the Institute of British Geographers* **2008**, *33*, 404–419.
52. Li, J.; Fang, W.; Wang, T.; Qureshi, S.; Alatalo, J.; Bai, Y. Correlations between socioeconomic drivers and indicators of urban expansion: Evidence from the heavily urbanised shanghai metropolitan area, China. *Sustainability* **2017**, *9*, 1199.
53. Guo, R. *Regional China: a business and economic handbook*; Springer: 2013.
54. NBS National Bureau of Statistics; Sixth national population census of the people's republic of China. Beijing,, 2010.
55. Xiao, Y.; Wang, Z.; Li, Z.; Tang, Z. An assessment of urban park access in Shanghai—Implications for the social equity in urban China. *Landscape urban planning* **2017**, *157*, 383–393.
56. Chiquet, C.; Dover, J.W.; Mitchell, P. Birds and the urban environment: the value of green walls. *Urban ecosystems* **2013**, *16*, 453–462.
57. Weibo Statistics Availabe online: <http://ir.weibo.com/news-releases/news-release-details/weibo-corporation-report-fourth-quarter-and-fiscal-year-2018> (accessed on 10 June, 2019).
58. Rizwan, M.; Wan, W.; Cervantes, O.; Gwiazdzinski, L. Using location-based social media data to observe check-in behavior and gender difference: Bringing weibo data into play. *ISPRS International Journal of Geo-Information* **2018**, *7*, 196.
59. Xie, Z.; Yan, J. Kernel density estimation of traffic accidents in a network space. *Computers, environment urban systems* **2008**, *32*, 396–406.
60. Chen, Z.; Luo, N.; Gao, T. Research of typhoon disaster assessment based on VGI [J]. *Geomatics Spatial Information Technology* **2016**, *10*, 33–34.
61. Silverman, B.W. *Density estimation for statistics and data analysis*; Routledge: 2018.
62. Wu, C.; Ye, X.; Ren, F.; Wan, Y.; Ning, P.; Du, Q. Spatial and social media data analytics of housing prices in Shenzhen, China. *PloS one* **2016**, *11*, e0164553.
63. King, T.L.; Bentley, R.J.; Thornton, L.E.; Kavanagh, A.M. Using kernel density estimation to understand the influence of neighbourhood destinations on BMI. *BMJ open* **2016**, *6*, e008878.

64. Hasan, S.; Zhan, X.; Ukkusuri, S.V. Understanding urban human activity and mobility patterns using large-scale location-based data from online social media. In Proceedings of the 2nd ACM SIGKDD international workshop on urban computing, Chicago, IL, USA, August 11–14, 2013; p. 6.
65. Li, L.; Goodchild, M.F.; Xu, B. Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. *Cartography geographic information science* **2013**, *40*, 61–77.
66. Sun, Y.; Fan, H.; Li, M.; Zipf, A. Identifying the city center using human travel flows generated from location-based social networking data. *Environment Planning B: Planning* **2016**, *43*, 480–498.
67. Li, H.; Ge, Y.; Hong, R.; Zhu, H. Point-of-interest recommendations: Learning potential check-ins from friends. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, San Francisco, CA, USA, August 13–17, 2016; pp. 975–984.
68. Maroko, A.R.; Maantay, J.A.; Sohler, N.L.; Grady, K.L.; Arno, P.S. The complexities of measuring access to parks and physical activity sites in New York City: a quantitative and qualitative approach. *International journal of health geographics* **2009**, *8*, 34.
69. Maia, M.; Almeida, J.; Almeida, V. Identifying user behavior in online social networks. In Proceedings of the 1st workshop on Social network systems, Glasgow, Scotland, UK, April 01–04, 2008; pp. 1–6.
70. Van Iddekinge, C.H.; Lanivich, S.E.; Roth, P.L.; Junco, E. Social media for selection? Validity and adverse impact potential of a Facebook-based assessment. *Journal of Management* **2016**, *42*, 1811–1835.
71. Roberts, H.; Sadler, J.; Chapman, L. Using Twitter to investigate seasonal variation in physical activity in urban green space. *Geo: Geography Environment* **2017**, *4*, e00041.
72. Ramaiah, M.; Avtar, R. Urban Green Spaces and Their Need in Cities of Rapidly Urbanizing India: A Review. *Urban Science* **2019**, *3*, 94.



© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).