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Deciphering the recreational use of urban parks: Experiments using multi-source big data for all Chinese cities

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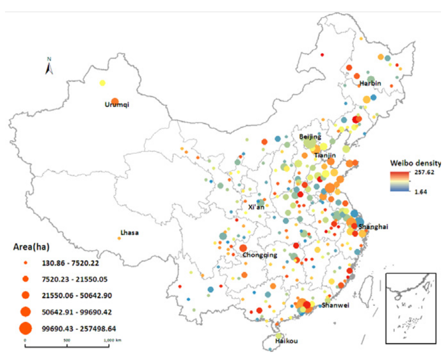
HIGHLIGHTS

- We assessed the recreational use of 13,759 parks across China through check-in data.
- In all cities, the densities of POIs and bus stops was significantly positive.
- The factors with the greatest impact varied according to the administrative tiers.

GRAPHICAL ABSTRACT



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ABSTRACT

China's rapid urbanization process has accentuated the disparity between the demand for and supply of its park recreational services. Estimations of park use and an understanding of the factors that influence it are critical for increasing these services. However, the data traditionally used to quantify park use are often subjective as well as costly and laborious to procure. This paper assessed the use of parks through an analysis of check-in data obtained from the Weibo social media platform for 13,759 parks located in all 287 cities at prefecture level and above across China. We investigated how park attributes, accessibility, and the socioeconomic environment affected the number and density of park check-ins. We used multiple linear regression models to analyze the factors influencing check-ins for park visits. The results showed that in all the cities, the influence of external factors on the number and density of check-in visits, notably the densities of points of interest (POIs) and bus stops around the parks was significantly positive, with the density of POIs being the most influential factor. Conversely, park attributes, which included the park service area and the landscape shape index (LSI), negatively influenced park use. The density of POIs and bus stops located around the park positively influenced the density of the recreational use of urban parks in cities within all administrative tiers, whereas the impact of park service areas was negative in all of them. Finally, the factors with the greatest influence varied according to the administrative tiers of the cities. These findings provide valuable inputs for increasing the efficiency of park use and improving recreational services according to the characteristics of different cities.

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1. Introduction

Green space, which is an important component of an urban ecosystem, plays a critical role in enhancing the sustainability of urban communities and the livability of urban environments by providing a variety of ecosystem services and supporting biodiversity within urban areas (Bolund et al., 1999; Crane et al., 2005; Barbosa et al., 2007). Such spaces also serve to mitigate many urban problems (Heidt et al., 2008; Janhäll et al., 2015; Gidlöf-Gunnarsson et al., 2007), providing urban residents with primary contact with the natural environment (Jorgensen et al., 2002), which improves the quality of their living environment. Urban residents also derive physical and mental health benefits from visiting green space (Dietz et al., 1998; McCormack et al., 2010), such as reduced risks for numerous chronic (Wolch et al., 2014), childhood obesity (Wolch et al., 2011; Kabisch et al., 2014), and cardiovascular diseases (Richardson et al., 2013). Moreover, individuals with greater access to green spaces and recreational facilities are more likely to recover from stress (Woo et al., 2009; Grahn et al., 2010) and gain associated psychological benefits (Fuller et al., 2007). The advancement of society has led to increasing awareness of the importance and value of urban green spaces, with the provision and equitable use of adequate green space considered an important dimension of environmental justice (Jennings et al., 2012; Wolch et al., 2014).

Nevertheless, a disparity between the demand for and supply of urban green space prevails in many cities (McConnachie et al., 2010; Lee and Hong, 2013; Kabisch et al., 2014; Xu et al., 2018). Differences in population densities and distributions of expanding and increasingly urbanized populations have resulted in differing demands for urban green spaces, with a faster growth in green space demand compared with supply. This phenomenon will inevitably lead to greater inequity relating to access and use of urban green spaces (Xing et al., 2018; Xu et al., 2018). Therefore, quantification of urban green space use is an important aid for urban planners in determining whether their use by citizens is equitable and in identifying areas where their supply is not proportional to their demand.

The factors that drive green space use play a critical role in reducing the gap between their supply and demand. A series of studies have proved that city-level characteristics, green space attributes and environmental characteristics are critical influencing factors (Brown et al., 2014; Koohsari et al., 2015). City-level characteristics mainly refer to the size, population and socioeconomic characteristics of a city (Dai et al., 2011). Ibes (2015) found that population density and the built-up area index had a positive influence on park demand. Xing et al. (2018) found that socioeconomic characteristics such as gross domestic product (GDP), revenue from public finance budgeting, and annual per capita living surplus could positively improve the availability of green space for residents. In addition to these city-level characteristics, other researchers have studied the impact on green space use of green space attributes and environmental characteristics. Green space attributes, such as park size and attractiveness. the provision of park facilities, vegetation quality, and entrance fees are positively related to park use (Cohen et al.2010; Wendel et al., 2012; Zhang et al., 2015; Zhang and Zhou, 2018). Moreover, the attributes of the surrounding environment and the accessibility of urban green spaces impact on residents' use of them in different ways and to different degrees. For example, the population density around parks plays an important part in park visits because high population density means more potential users (Mowen et al., 2007). The surrounding environmental features such as services and facilities, points of interest (POIs), building density, and land use are also correlated with park visitation (Donahue et al., 2018; Chen et al., 2018). Accessibility is assumed to be an important factor that influences green space use. Indicators including the number of nearby bus stops and bus lines, the number of metro stops, distance to the city center, road node density, and pedestrian lane density (Zhang and Zhou, 2018; Xing et al., 2018; Chen et al., 2018) are used to represent the accessibility of a green space. Numerous quantitative analyses have been conducted, focusing on the correlation between the above-mentioned factors and green space use.

There is a burgeoning literature on disparities and influencing factors in urban green space use. Most of the studies have entailed the use of questionnaire-based surveys, semi-structured individual interviews conducted on site, and systematic observations of urban residents (Sanesi et al., 2006; Schipperijn et al., 2010; Wendel et al., 2012; Jim and Shan, 2013), providing researchers with accurate knowledge and insights regarding users' subjective evaluations and experiences. However, the application of these methods is usually site-specific and time-consuming, and the use of limited samples constrains data availability for studies of large populations (Chen et al., 2018) and may not accurately reflect an understanding of urban agglomeration (Ettema er al., 1996; Maxwell, 2012). The advancement and global application of Geographical Information Systems (GIS) has led to the widespread use of GIS methods for measuring the distribution (Zhou et al., 2018) and use of urban green spaces (Nicholls et al., 2001; Oh et al., 2007; Brown et al., 2014; Xing et al., 2018). While these methods offer a means of integrating geographic data, in the absence of spatiotemporal population data, they are unable to reveal actual urban green space use (Chen et al., 2018). However, the widespread use of smartphones and diverse applications (apps) has generated vast amounts of data, especially location-based services data, providing new methodological approaches for assessing the spatiotemporal characteristics of human activities (Liu et al., 2015; Wood et al., 2013; Gariazzo et al., 2016). In light of the paucity of available information on urban environments, tools that automatically describe parcels of land and enable them to be grasped using open map services and POIs data, such as Google Maps, OpenStreetMap (OSM), and Baidu Maps (Liu and Long, 2015; See et al., 2016; Guo et al., 2019), can facilitate the extraction of data on urban infrastructure.

Many social media platforms support a check-in option, which allows users to tag their locations on social media. Information from some social media platforms such as Twitter, Foursquare, Flickr, and Weibo, have already been used to study relationships with user behavior or the geographic spatial distribution of users (Fujisaka et al., 2010; Li et al., 2013; Shelton et al., 2015; Li et al., 2017). Previous studies that used check-in data from social media platforms have found significant positive relationships between official visitor statistics and visitation numbers collected by these platforms (Wood et al., 2013). Because of the high degree of correlation existing between the spatiotemporal characteristics of human activities and information provided by social media and open map services, big data have been applied in studies on residents' actual use of green space (Song et al., 2018). The advent of big data offers promising opportunities for mapping urban green spaces, and several studies have applied multiple types of big data within quantitative analyses of the use of specific urban green spaces (Shen et al., 2017; Chen et al., 2018; Zhang and Zhou, 2018), which implies that it is feasible to apply the check-in data to the study of park use. The above-mentioned studies on the use of green space focused primarily on a single city or sub-district scale, because the usage of urban green spaces and the detailed influencing factors in each green space of urban areas was difficult to achieve in a large sample size.

To address the limitations of previous studies, we selected all 287 cities at prefecture level and above in China as the study objects in an investigation of park use and influencing factors with the integration of multi-source big data. In addition to choosing factors at the city level, the influencing factors also include factors on the scale of each green space to ensure a more detailed and comprehensive study of the relationship between green space use and various factors. Our objectives were (1) to quantify park use using check-in data for park visits obtained from the Weibo app for a large dataset of Chinese cities, (2) to explore the relationship between potential influencing factors and check-ins, and (3) to formulate policy recommendations aimed at encouraging park use and improving recreational services in Chinese cities within different administrative tiers.

2. Data and methods

2.1. Study area

To conduct a comprehensive study of urban green space use in China, we included the main parks located in major cities within the scope of study. The central Chinese government categorizes cities under five administrative tiers: municipalities, sub-provincial cities, other provincial cities, prefecture-level cities, and county-level cities. As of 2014, there were a total of 653 Chinese cities covered under all these administrative tiers. Those belonging to the first four administrative tiers, noted above, are more developed and dynamic than county-level cities within the fifth tier. Furthermore, residents living in these cities are more likely to participate in urban activities and to share their experiences online using social networking sites or platforms, such as Sina Weibo, Dazhong Dianping, Jiepang and WeChat's Circles. Accordingly, we excluded county-level cities from our investigation and selected 287 Chinese cities within our sample for assessing park use (Fig. 1). The sample comprised 4 municipalities, 15 sub-provincial cities, 17 provincial cities, and 251 prefecture-level cities. These cities covered all of China's provinces and autonomous regions (excluding Hong Kong, Macao, and Taiwan), with the majority located in northern China and a few cities sampled from the western provinces and from autonomous regions such as Xinjiang, Tibet, and Gansu.

The center of a city is an area of high-density construction, encompassing higher concentrations of people, streets, and public service facilities compared with the suburbs. Therefore, we selected city center areas rather than administrative areas as our study sites. Reasonable determination of the study area is necessary to ensure the validity of an evaluation. We used remote sensing monitoring data on land use status for 2015 with a precision of 30 m. The data include 6 primary types and 25 secondary types, which are derived from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). In this paper, the largest patch of urban construction land in each city (referring to the built-up area of cities above county and town) was identified as the built-up area of the city. The total area covered in the study was 26,152 km^2. Of this area, Beijing accounted for the largest area (2342 km^2) and Haidong accounted for the smallest area (1.31 km^2).

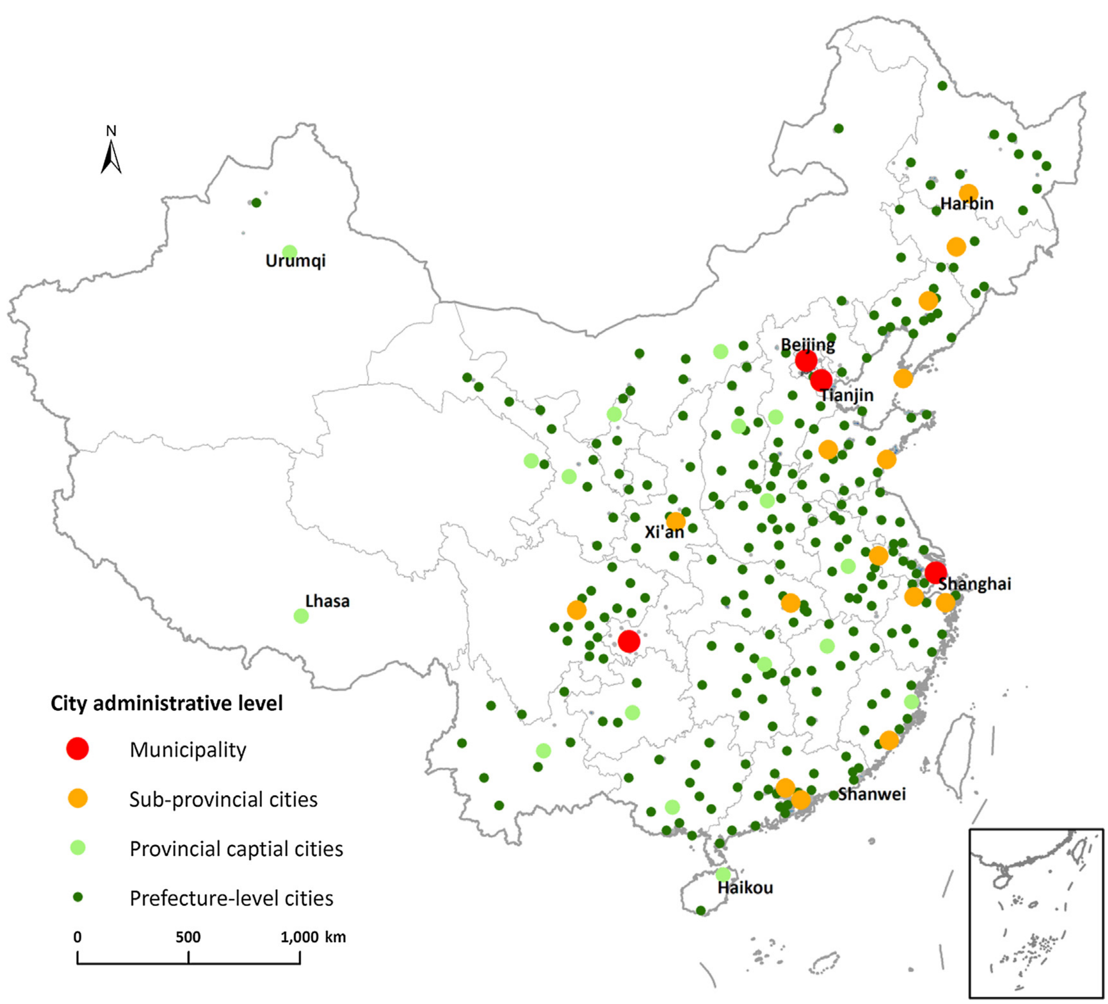

Fig. 1. Chinese cities selected as study samples.

We extracted parks using the Autonavi electronic navigation map (AMAP, https://ditu.amap.com), which offers the advantages of up-to-date data and fine granularity. The data of AMAP come from commercial remote sensing satellites, and AMAP is one of the most popular navigation maps in China. The color of different kinds of park green space in the electronic map has been pretreated, thus green spaces in 287 cities can be identified objectively by color. Subsequently, digitized processing and spatial coordinate system calibration were carried out, which were converted into GIS vector data, and checked by manual identification. Later we merged the same park if its extent was interrupted by roads and deleted the surface elements of non-park green areas. Finally, we assigned the attributes of park green space according to POIs. Our definition of parks included scenic spots, urban parks, and green spaces. We selected 13,759 urban parks that were over one hectare in area for the study using a spatial modeling approach comprising GIS and remote sensing techniques. The total area covered by these parks was 135,769.3 ha.

2.2. Data

2.2.1. Weibo check-in data

To make a comprehensive evaluation of park use and its potential influencing factors, we gathered multi-source big data (Table S1 in Supplementary Materials).

Sina Weibo, which is the one of the most influential social media sites in China, was launched in August 2009. From 2009 to 2010, the number of Weibo users grew by 433.3%. By 2011, there were more than 250 million Weibo users. Between 2011 and 2017, the number of Weibo users fluctuated slightly, but stayed at more than 200 million (Fig. S1 in Supplementary Materials). As of the fourth quarter of 2018, according to the 2018 Weibo User Development Report, the number of active users on Weibo monthly increased to 462 million (Weibo Data Center, 2019). Compared with other apps, Weibo has a much higher degree of user participation. Weibo application program interfaces (APIs) provide convenient free access to data. By contrast, other data are hardly accessible at the national level. Therefore, Wiebo provides statistical evidence for research. According to the data from 2016 to 2018, the number of Weibo users in the third and fourth-tier cities always accounted for more than 50% of the total city population, and this has increased year by year.

Weibo includes a "check-in" feature. Users can upload their real-time locations and share their preferences and activities on the Internet. Previous studies that have used open crowdsourcing data have shown that check-in data obtained from Weibo can be used as an indicator of visits to green spaces (Zhang and Zhou, 2018). The procurement of these data enables urban park use to be measured effectively, without requiring costly and laborious field investigations. Accordingly, we used check-in data from Sina Weibo to estimate actual visits to parks in this study. We introduced two dependent variables, namely the number of check-ins for park visits and their density to estimate urban park use.

We used the location service dynamic reading interface of the Sina Weibo open platform (https://api.weibo.com/2/place/nearby/photos.json) as the data source. After permission to use Weibo has been acquired, data can be obtained for specific temporal and spatial (distance) ranges in relation to a particular spatial location positioned at selected coordinates of latitude and longitude. We used the code to set the data acquisition characteristics, including photographs, text, and locations. We then used the Sina Weibo APIs to obtain data from Sina Weibo's open platform.

2.2.2. Potential influencing factors on park use

Based on previous studies, we selected two categories of variables that may influence park use (Giles-Corti et al., 2005; Schipperijn et al., 2010; Jim and Shan, 2013; Zhang et al., 2015). Then we conducted a correlation analysis of variables to avoid multicollinearity.

The first category of variables was city-level characteristics which represented the urban development vel and economic vitality (Dai et al., 2011; Long and Huang, 2015). Five independent variables were introduced in this study: the area of the city center, the administrative tier of the city, total population of city area, GDP and GDP per capita (Xing et al., 2018). Table 1 shows the city-level data we used in this research.

The second category of variables was park attributes and environmental characteristics. Several studies have confirmed that some characteristics of parks and their surrounding environments had positive or negative effects on park use. We selected key attributes as independent variables to analyze correlations between check-ins for park visits and their potential influencing factors. These included three types of factors that affect the use of parks: park attributes, accessibility, and the socioeconomic environment in their vicinity. These variables are described below and in Table S1.

Landscape shape index (LSI), park size, and the park service area (Cohen et al., 2010; Zhang and Zhou, 2018) have positive or negative effects on park use, so we introduced these three factors as independent variables to study the relation between park attributes and data on check-ins for park visits.

The LSI represents the shape of a park, expressed as follows:

$$LSI = \frac{2\sqrt{\pi * \mathrm{A\_Parkha}}}{\mathrm{P\_Parkm}} \tag{1}$$

where A_Parkha denotes the park size and P_Parkm denotes the circumference of the park.

The park service area relates to its service radius. According to the Classification Standard of Urban Green Space (Classification Standard of Urban Green Space (CJJ/T 85-2017), 2017), the service radiuses of green spaces with areas of 20–100 ha, 2–20 ha, and less than 2 ha are 2,000 m, 1,000 m, and 500 m, respectively.

To describe park accessibility, we selected the following five variables: the distance to the closest urban center (Shen et al., 2017), the relative distance to the closest urban center, the number of bus stops and bus lines, the density of bus stops and bus lines, and the number of bus lines (Zhang and Zhou, 2018; Xing et al., 2018). We used the spatial join tool in ArcGIS 10.2 to calculate the distance to the closest urban center. The formula used to calculate the relative distance to the closest urban center (RelDis_Cen) is shown below:

$$\mathrm{RelDis\_Cen} = \frac{\mathrm{Dist\_Centr}}{\mathrm{Radius}} \tag{2}$$

where Radius is the radius of the city center.

The number of bus stops and bus lines was defined as the total number of bus stops and bus lines within a 500 m buffer zone. The density of bus stops and bus lines was defined as the number of bus stops and bus lines within a 500 m buffer zone per ha. A pedestrian network analysis was conducted to calculate the 500 m buffer zone (Chen et al., 2018). We used the computational geometry, spatial join tool and field calculator tool in ArcGIS 10.2 to calculate the density of bus stops and bus lines.

To evaluate the socioeconomic environment in the vicinity of the park, we collected data from various POIs depicted in the Baidu Map in 2016 (Fig. 2B). For this analysis, two independent variables were introduced: the number of POIs and the density of POIs. The information provided by POIs on attributes and locations have been widely used within urban studies. The number of POIs in this study was defined as the total number occurring within a radius of 500 m, which was calculated using the spatial join tool in the Arc-

Table 1
Descriptive statistics on the number and the density of Weibo check-ins for park visits.

	Number of_parks	Minimum	Maximum	Mean	Std. Deviation
Num_Weibo	13,759	1	31,907	194.177	647.147
Density_Weibo	13,759	0.043983930	96.3	11.120	10.847

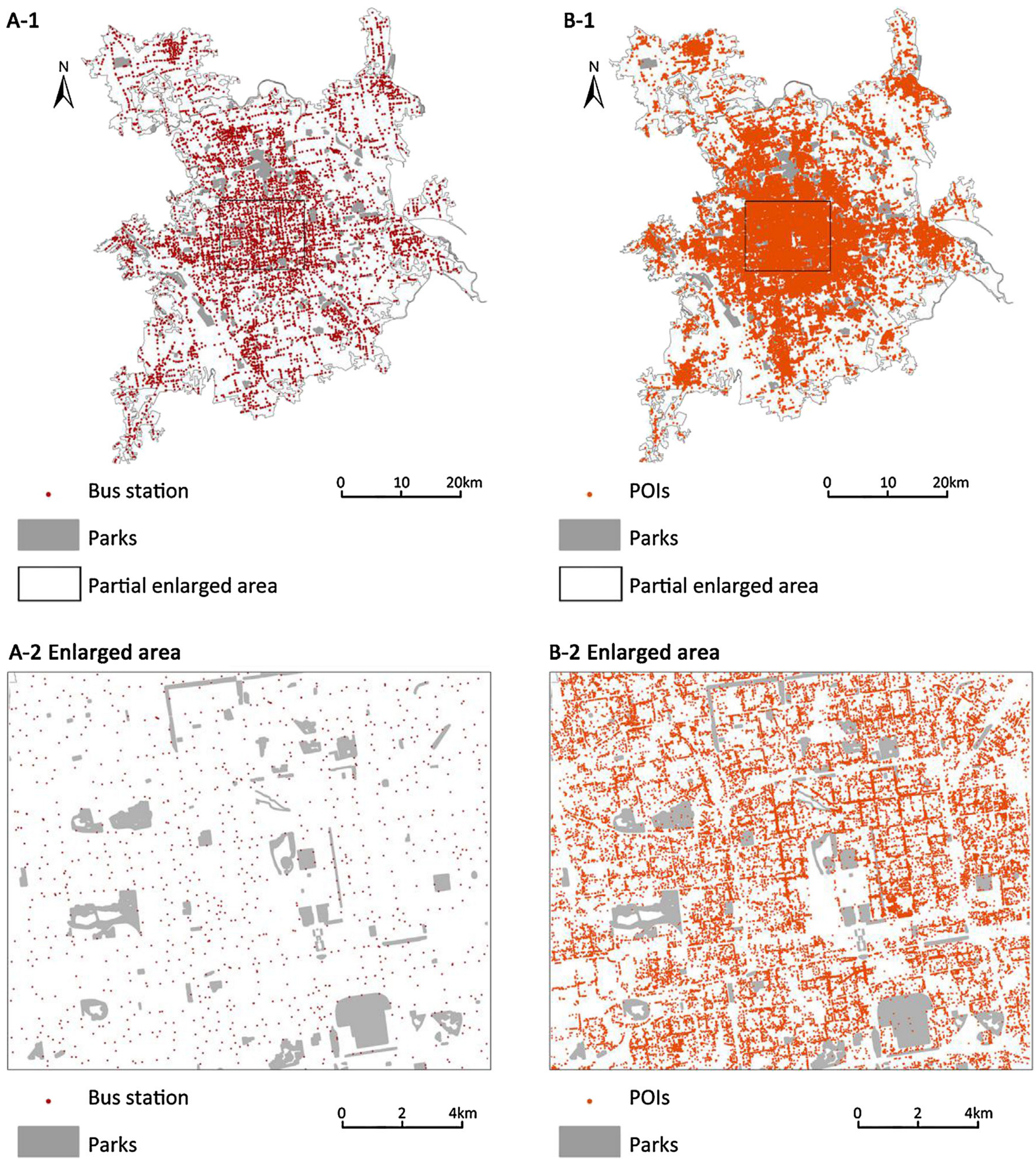

Fig. 2. A-1: Spatial distribution of bus stops in Beijing; A-2: Spatial distribution of bus stops in the enlarged area. B-1: Spatial distribution of points of interest (POIs) in Beijing; B-2: Spatial distribution of POIs in the enlarged area.

GIS 10.2 program. The density of the POIs was indicated by their number within a 500 m buffer zone per ha.

Before conducting the regression analyses, we applied Pearson's correlation and the variance inflation factor to evaluate the level of multicollinearity. A high degree of multicollinearity is evident when two or more variables have a variation inflation factor value above 10, or a Person's correlation above 0.8. The results showed that a high degree of multicollinearity exited between GDP and central city size, so we excluded GDP and conducted both tests on the remaining variables. We found that the variables exhibited no multicollinearity.

2.3. Methods

2.3.1. Mapping of check-in data for park visits

We retrieved millions of park check-in records with locational information (Fig. 3). After checking each of these locations, we deleted those that were not within a park and removed check-in

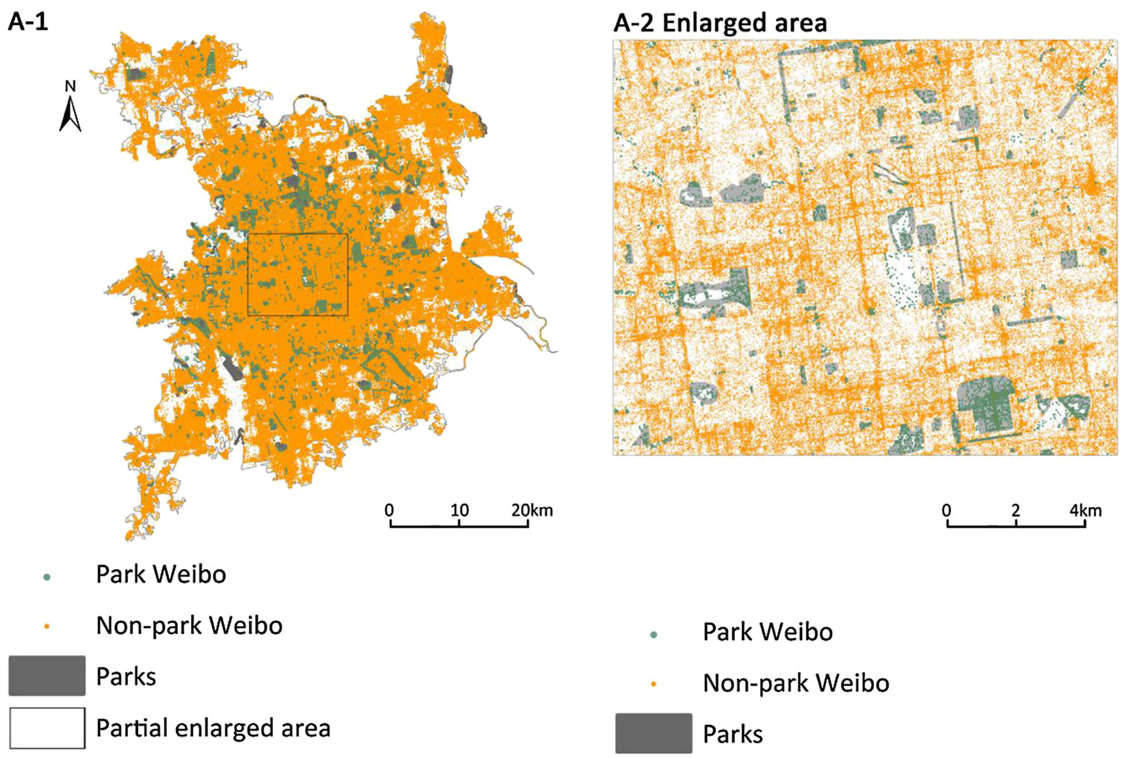

Fig. 3. Weibo check-ins within parks. A-1: Spatial distribution of check-ins in Beijing; A-2: Spatial distribution of check-ins in the enlarged area.

records for restaurants, cafes and other entertainment places within a park. Fig. S2 in Supplementary Materials shows the distribution of check-in points in the Beijing Olympic Forest Park. We collected a total of 2.77 million geotagged check-ins for park visits made during the period 2009–2016 for a nationwide analysis of park use. For data processing, we first excluded the minimum and maximum values, then we removed the duplicate records when the check-in data were released at the same time and place by same user's ID. Ultimately, we had a dataset comprising a total of 2.53 million park check-in records which came from 906,165 IDs. We counted the number of check-in visits of each park, and calculated the number of check-in visits per ha, that is, the density of check-in visits within the park. To map the density of check-in visits, we used Jenks tool and quantile method in ArcGIS 10.2 to classify the data.

To validate the capability of the check-in data to represent the actual visits to parks in the study, we analyzed the bivariate correlation between the Weibo check-in data and the official visitor statistics of urban parks at four cities in different administrative tiers. Due to the different proportion of Weibo users in different administrative tiers of cities, we chose a typical city in each city level, including the Beijing municipality, the provincial capital of Jinan, the sub-provincial city of Qingdao, and the prefectural city Linyi. Then we obtained the official visitor statistics for some parks in a certain year from each city's Landscape and Greening Bureau. Based on the existing data, we selected 22 parks in Beijing, 20 parks in Jinan, 22 parks in Qingdao and 13 parks in Linyi for the research. Then we extracted the number of Weibo check-in visits and normalized official visitor statistics for each park for correlation analysis.

2.3.2. Statistical analysis

Because of the large sample size, we used K-S test, histogram, P-P plot and Q-Q plot to verify the normality of data. Taking the Density_Weibo that were transformed by ln as an example, there were 13,759 Density_Weibo in all cities participating in the calculation, which was a large sample size. The results of K-S test showed that sig = 0.000 < 0.05, which meant that didn't obey normal distribution, however, the histogram, P-P plot and Q-Q plot all showed that the normality of lnDensity_Weibo was good. Therefore, we believed that lnDensity_Weibo in cities are subject to normal distribution. The lnDensity_Weibo at different city levels were also considered to obey normal distribution after testing.

After verification, most of the variables were in normal distribution or similar to the normal distribution. A_Citym2 and Pop_City did not conform to normal distribution, and A_Parkha and A_Serveha did not conform to normal distribution obviously. There were 13,759 samples in all cities involved in the regression analysis, while the sample size of provincial cities was the smallest among different city levels, but there were still 1724 samples. Even if not all variables followed normal distribution, as long as the residual of regression analysis was in normal distribution in the case of large samples, regression analysis could still be carried out.

The normality tests of residuals after regression analysis were showed by histogram and P-P plot. In all cities, when we took lnDensity_Weibo as dependent variable, the residual histogram and P-P plot after regression analysis obeyed normal distribution (Fig. S3 in Supplementary Materials). When we took lnNum_Weibo as dependent variable, the residual histogram and P-P plot after regression analysis also obeyed normal distribution (Fig. S4 in Supplementary Materials). In different city levels, when we took lnDensity_Weibo as dependent variable, the residual histogram and P-P plot after regression analysis obeyed normal distribution (Figs. S5 and S6 in Supplementary Materials). When we took lnNum_Weibo as dependent variable, the residual histogram and P-P plot after regression analysis also obeyed normal distribution (Figs. S7 and S8 in Supplementary Materials). In summary, all the residuals conformed to normal distribution, so regression analysis can be carried out.

The homogeneity test of variance was used to test the homogeneity of variance in different groups. We grouped the data according to the city level, and we tested the variance homogeneity of lnDensity_Weibo and lnNum_Weibo in all cities that participated in the calculation, and tested homogeneity of lndensitwbo and lnnumwbo at different city levels. The results of the homogeneity test showed that the data variances of different city level were uneven and different. The data need to be differentiated according to the city level and analyzed at the same city level.

To determine the relationship between independent and dependent variables, that is, how potential influencing factors affect park use, we applied an ordinary least squares (OLS) model as a conventional regression method for estimating the effects of spatial variables on park use (Tu et al., 2008). The OLS forward selection based on the leave-one-out (LOO) test criteria and local regularization (LR) provided an appropriate algorithm for constructing a sparse kernel model to enable effective generalization. The OLS is expressed by the following formula:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon, \varepsilon \sim N(0, \delta^2) \quad (3)$$

where x_i denotes the model's input variables representing the independent variables, y denotes the dependent variable, β_0 is the intercept, k is the number of independent variables, β_i is the parameter estimate (coefficient) corresponding to the independent variable x_i, and ε is the error term. The parameter estimates, β_i, were assumed to be spatially stationary.

To assess the impacts of different factors on check-ins for park visits in all the cities, we constructed several regression models using the OLS method and considering Num_Weibo and Density_Weibo as separate dependent variables. In Model 1, we chose one factor as the unique independent variable at a time and explored the standardized correlations between dependent variables and the selected factor. Model 2 included all the potential influencing factors needed to develop a more in-depth understanding of the effects of influencing factors on park visits in all the cities under investigation.

We used SPSS 20 for data analysis and explored standardized correlations. When $p < 0.05$ level that the significant level was considered, and significance was divided into 3 levels.

3. Results

3.1. Correlation between the Weibo check-in data and the normalized official visitor statistics

We analyzed the bivariate correlation between the Weibo check-in data and the normalized official visitor statistics for urban parks at four cities in different administrative tiers. The Pearson correlation coefficients were as follows: 0.54 (Linyi) < 0.57 (Jinan) < 0.65 (Beijing) < 0.75 (Qingdao) (Fig. S9 in Supplementary

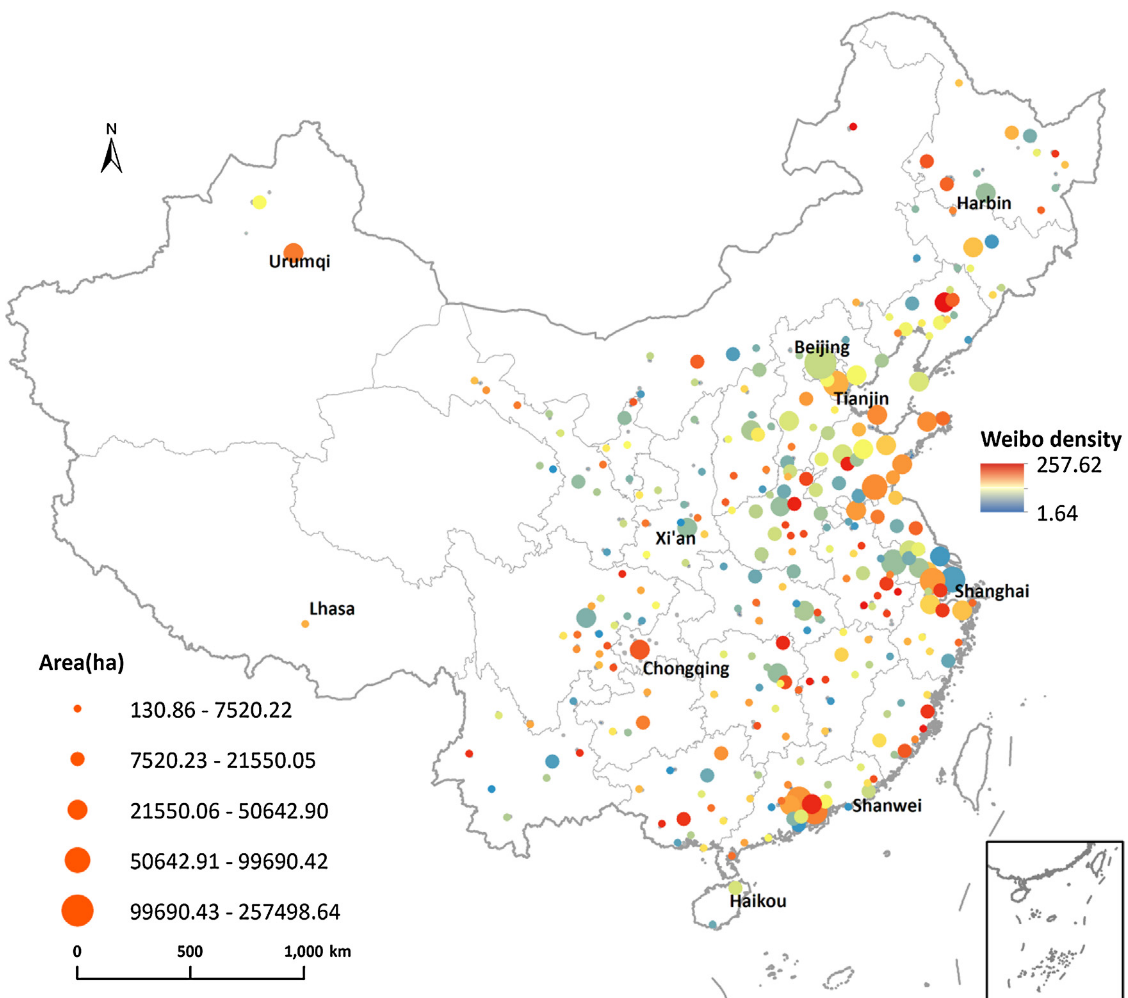

Fig. 4. Urban areas and average density of check-ins for park visits for all selected cities. The circle size denotes the total areas of the extracted urban parks for each city. The stretched colors from blue to red denote the magnitudes of the average density of check-ins for each city. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Materials). The comparison of P values showed that Qingdao had the strongest correlation between the Weibo check-in data and the official visitor statistics while Linyi had the weakest. The P values for four cities were in the range of $0.5<|P|\leq 0.8$, which was a medium correlation. The results indicated that the correlation between the Weibo check-in data and the official visitor statistics in municipalities and sub-provincial cities was stronger, and the correlation in prefecture-level cities was weaker. Overall, there was a correlation between the check-in data and the official visitor statistics in these cities, and we, therefore, assumed that the Weibo check-in data could be used to estimate urban green space visits.

3.2. Differences in numbers of check-ins for park visits and visiting intensities

After we had excluded parks for which no Weibo check-in records were available, we obtained a total of 2.53 million check-ins for visits to the selected urban parks. The average number of check-ins per park was 194.177, ranging between 1 and 31,907, with a standard deviation 647.147 (Table 1). A total of 74.2% of check-ins for park visits were in the range of 1–100, of which 37.7% were in the range of 1–10 visits, 26.5% were in the range of 10–50 visits, and 10% were in the range of 50–100 visits. A further 16% of check-ins for park visits were the range of 100–500 visits, and 9.8% of check-ins were for parks that received over 500 visits, accounting for 73% of the total check-in records. Our calculations of the densities of check-ins for park visits revealed that the average density of check-ins per park was 11.120 (Table 1). The majority (58.9%) of the visiting intensities for the parks were below 10, 34.7% were in the 10–30 range, 1.1% exceeded 50 visits per ha.

Fig. 4 shows the spatial distribution of the density of check-ins for park visits in 287 cities. By comparing the number of cities with high check-in density in different urban agglomerations, we found that cities with high check-in density were mostly concentrated in the Central Henan and Yangtze River Delta urban agglomerations, and the check-in densities of cities within the Harbin–Changchun region urban agglomeration was relatively lower.

Figs. 5 and 6 show the spatial distribution of the density of check-ins for park visits for some typical cities. Whereas each city

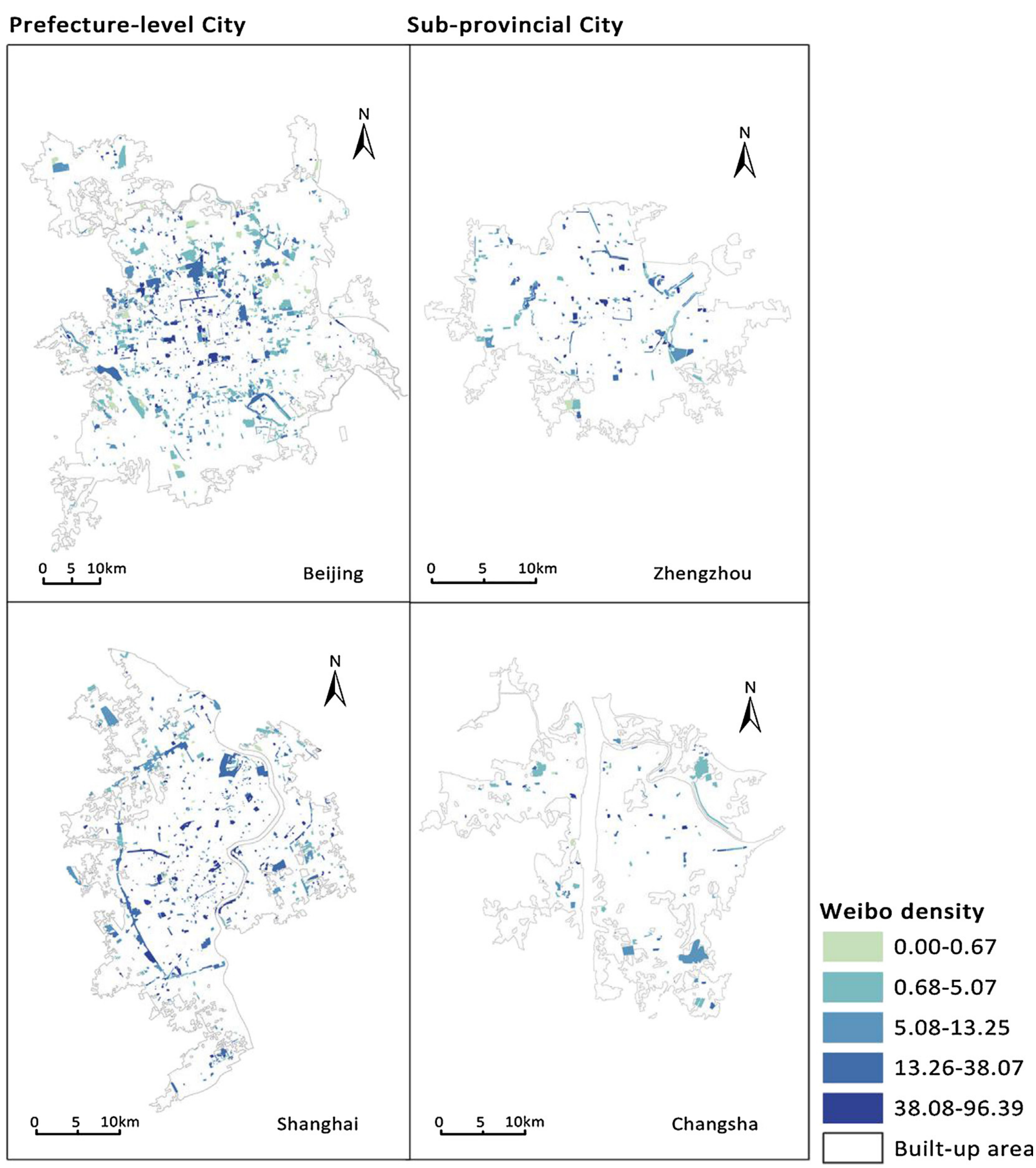

Fig. 5. Depiction of the density of check-ins for park visits in typical Chinese cities at prefecture and sub-provincial levels.

exhibited a unique spatial distribution in relation to Weibo density, there seemed to be common characteristics shared by cities within different administrative tiers. The regression models described in the following section explore this observation in more detail.

3.3. The impacts of different factors on numbers of check-ins for park visits and their densities in all the cities

Table 2 shows the standardized correlations results of Model 1; the higher the absolute value of the standardized correlation, the more important the variable. The results indicated that the park service area, number of bus stops and bus lines, park size, and number of POIs were positively correlated with the number of check-ins for park visits, with the park service area having the greatest positive impact. By contrast, the administrative tier of a city, distance from the closest urban center, the LSI, capita GDP, the relative distance to the closest urban center, and the area of the central city were negatively correlated with the number of check-ins for park visits, with the administrative tier of a city having the greatest impact.

Our assessment of the influence of different factors on the density of check-ins for park visits indicated that the number and density of POIs, the density and number of bus stops and bus lines, and the LSI contributed positively to the density of check-ins for park visits, with the density of POIs being the most significant factor, accounting for about 32.3% of the total density. Conversely, the park service area, the distance to the closest urban center, the relative distance to the closest urban center, park size, and the area of the city center contributed negatively to the density of check-ins for park visits, with the park service area having the most significant negative impact.

We constructed Model 2 with different dependent variables, the results of which are listed in Table 3. Our comparison of R^2 values showed that the number of Weibo check-ins for park visits was better explained by the regression model than the density of Weibo check-in visits. Moreover, the impact of each factor on the number of check-ins for park visits differed significantly from that of its impact on the density of check-in visits.

Our examination of the influence of factors on the number of park check-ins indicated that the number of bus stops and bus

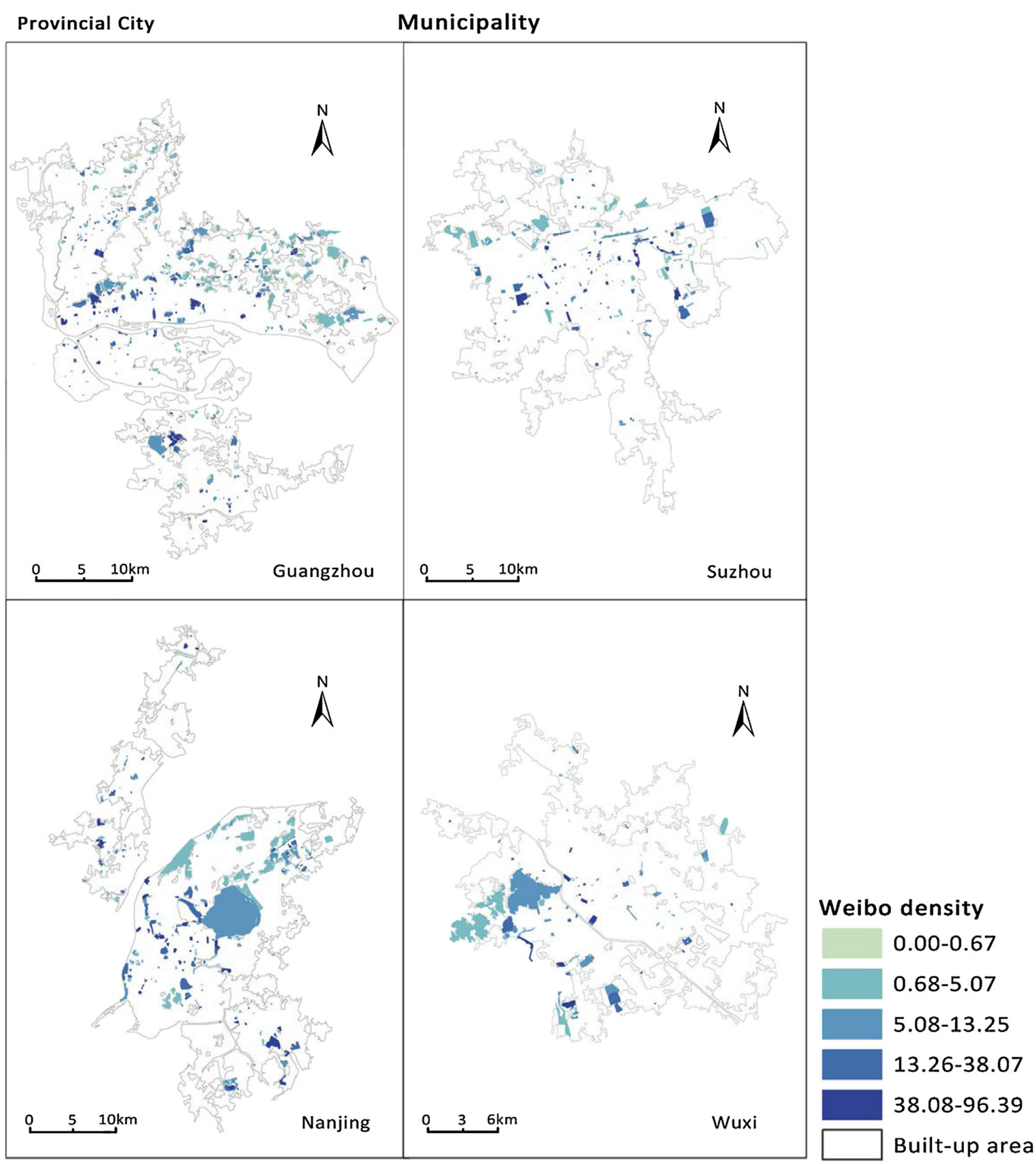

Fig. 6. Depiction of the density of check-ins for park visits in typical Chinese cities within provincial and municipality levels.

Table 2
Standardized correlations between dependent variables and selected factors in the regression models.

	A_Citym2	Level_City	Pop_city	Capita GDP	LSI	A_Parkha	A_Serveha	Dist_Centr	RelDis_Cen	Num_Bus	Density_Bus	Num_POI	Density_POI
Num_Weibo	−0.028**	−0.095***	−0.049***	−0.052***	−0.065***	0.307***	0.531***	−0.069***	−0.050***	0.389***	0.015	0.165***	−0.002
Density_Weibo	−0.062***	0.014	−0.002	−0.017	0.08***	−0.105***	−0.189***	−0.156***	−0.144***	0.168***	0.284***	0.303***	0.323***

Notes: *The coefficient is significant at the 0.05 level.
** The coefficient is significant at the 0.01 level.
***The coefficient is significant at the 0.001 level.

Table 3
Results of the regression for parks in all 287 cities (13,759 parks).

Independent variable	LSI	A_Citym2	A_Parkha	Dist_Centr	RelDis_Cen	Level_City	Num_Bus	A_Serveha	Density_POI	Density_Bus	Population	Capita GDP	R^2
Num_Weibo	0.116***	0.055***	−0.158***	−0.003	0.002	−0.014	0.637***	0.369***	0.086***	−0.449***	−0.040*	−0.021*	0.383
Density_Weibo	0.040***	−0.015	0.004	−0.032	−0.02	0.051***	0.144***	−0.176***	0.211***	0.023	−0.027	−0.003	0.141

Notes: *The coefficient is significant at the 0.05 level.
** The coefficient is significant at the 0.01 level.
***The coefficient is significant at the 0.001 level.

Table 4
Regression results for the number and the density of check-ins for park visits in cities within different tiers.

Independent variable	Prefecture-level cities		Sub-provincial cities		Provincial cities		Municipalities	
	Number of check-ins Beta	Density of check-ins Beta	Number of check-ins Beta	Density of check-ins Beta	Number of check-ins Beta	Density of check-ins Beta	Number of check-ins Beta	Density of check-ins Beta
LSI	0.13***	0.04**	0.104***	0.036*	0.109***	0.025	0.076***	0.041*
A_Citym2	−0.003	0.034*	−0.032*	−0.04*	0.003	0.035	0.076***	−0.032
A_Parkha	−0.182***	−0.033	−0.18***	0.024	−0.082**	0.002	−0.085***	0.042
Dist_Centr	−0.013	−0.018	−0.016	−0.004	0.01	−0.029	−0.021	−0.092***
A_Serveha	0.385***	−0.176***	0.323***	−0.167***	0.281***	−0.153*	0.654***	−0.081**
Density_POI	0.125***	0.222***	0.121***	0.225***	0.099**	0.263***	0.001	0.146***
Density_Bus	−0.473***	0.031	−0.547***	−0.018	−0.518***	0.058	0.156***	0.193***
Num_Bus	0.638***	0.165***	0.691***	0.108**	0.698***	0.066		
Population	−0.016	−0.004			−0.011	−0.097*	−0.003	0.037
Capita GDP	−0.019	−0.01	−0.01	−0.015	−0.036	0.032	−0.07***	0.015
N	4,517	4,517	4,298	4,298	1,724	1,724	3,220	3,220
R2	0.397	0.169	0.38	0.105	0.36	0.157	0.335	0.153

Notes: *The coefficient is significant at the 0.05 level.
** The coefficient is significant at the 0.01 level.
***The coefficient is significant at the 0.001 level.

lines along with the park service area, the LSI, the density of POIs, and the area of the city center positively influenced the number of check-ins for park visits. Among these factors, the number of bus stops and bus lines had the greatest influence, followed by the park service area. Conversely, the density of bus stops and bus lines, park size, population, and capita GDP negatively influenced the number of check-ins for park visits, with the density of bus stops and bus lines being the most significant factor. The results of the model in which the density of check-ins for park visits was the dependent variable indicated that the density of POIs, the number of bus stops and bus lines, the city's administrative tier, and the LSI were all positively correlated with the density of check-ins for park visits, with the density of POIs having the most significant impact. The park service area was negatively correlated with the density of check-ins for park visits.

3.4. The impacts of different factors on the numbers and densities of check-ins for park visits for cities in different tiers

To better understand the impacts of different factors on urban park use, we ran regression models for cities in different administrative tiers. The regression results are listed in Table 4. The results of the regression model conducted for prefecture-level cities showed that the number of bus stops and bus lines, the park service area, the LSI, and the density of POIs all contributed positively to the number of check-ins for park visits, with the number of bus stops and bus lines being the most significant factor, followed by the park service area. The density of bus stops and bus lines, and park size contributed negatively to the number of check-ins for park visits. The density of POIs, the number of bus stops and bus lines, the LSI, and the area of the city center all contributed positively to the density of check-ins for park visits, with the density of POIs being the most influential factor. By contrast, the park service area contributed negatively to the density of check-ins for park visits.

For parks in sub-provincial cities, the number of bus stops and bus lines, the park service area, densities of POIs, and the LSI were positively correlated with the number of check-ins for park visits, with the number of bus stops and bus lines having the most positive impact. By contrast, the density of bus stops and bus lines, park size and the area of the city center was negatively correlated with the number of check-ins for park visits, with the density of bus stops and bus lines being the most influential factor. The regressions for the density of check-ins for park visits indicated that the densities of POIs and the number of bus stops and bus lines as well as LSI were positively correlated with the density of check-ins for park visits, with the density of POIs being the most important factor. The park service area and the area of the city center were negatively correlated with the density of check-ins for park visits.

In provincial cities, the number of bus stops and bus lines, the park service area, the LSI and the density of POIs were positively correlated with the number of check-ins for park visits. The number of bus stops and bus lines had the greatest positive impact on the number of check-ins for park visits, whereas the density of bus stops and bus lines, and park size had a negative correlation. The densities of POIs were positively correlated with the density of check-ins for park visits, whereas the park service area and population demonstrated a negative correlation.

In municipalities, the park service area, the density of bus stops and bus lines, the LSI, and the area of the central city contributed positively to the number of check-ins for park visits. The park service area had the greatest positive impact on the number of check-ins. The results of the regression indicated that factors that positively influenced the density of check-ins for park visits were the density of bus stops and bus lines, the density of POIs, and the LSI, whereas distance to the closest urban center and the park service area negatively influenced check-ins.

In general, the park service area and the LSI had positive impacts on the number of Weibo check-ins for park visits in cities belonging to all tiers, and park size had a negative impact. The densities of POIs positively influenced the density of Weibo check-ins for park visits in cities belonging to all the different tiers, and the park service area had a negative impact.

4. Discussion

4.1. Overall findings for all cities

We applied regression models for all the cities within different administrative tiers. Our overall finding, for all cities, was that park size had a significant negative effect on the number of check-ins. In the urban centers of cities such as Adelaide, Odense, and Beijing, park size had a significant positive influence on the number of check-ins. This may be because, in most cases, large parks have more trees, walking paths and activity facilities which could attract more visitors than smaller parks within a reasonable distance (Cohen et al., 2010; Schipperijn et al., 2010; Brown et al., 2014; Zhang and Zhou, 2018). These findings indicate that the influence of park size on park visits varies in different cities. A previous study found that urban parks that were closer to the urban center tended to have more visits (Zhang and Zhou, 2018), but we did not find that distance from the city center had a significant influence. This may because our dataset was very large and covered many different types of cities rather only one city. It is possible that protection of the natural environment rather than entertainment is the key benefit provided by some parks that are located far away from the urban center. Consequently, these are not the destinations for the residents' daily recreation, which may have influenced the number of check-ins.

Our findings on the impacts of various factors on the density of check-ins for park visits indicated that the density of POIs was closely correlated with the density of check-ins for park visits and had the greatest positive impact on it. The findings of studies focusing on Beijing and Shenzhen are similar (Li et al., 2017; Chen et al., 2018). Therefore, it can be concluded that increased urban vitality around a park leads to more park visits. To quantify park accessibility, we selected the number and density of bus stops and bus lines as potential influencing factors. Our findings indicated that the number of bus stops and bus lines significantly affected the density of check-ins visits. This finding is consistent with that of previous studies which showed that parks with high accessibility had a greater number of visitors (Barbosa et al., 2007; Grow et al., 2008; Lee and Hong, 2013; Li et al., 2017; Xiao et al., 2019), because people can visit parks conveniently. However, studies conducted in Denmark and Shenzhen indicated that improving public transport was not an urgent requirement for increasing urban park use (Schipperijn et al., 2010a; Chen et al., 2018), possibly because the pedestrian system in Denmark and Shenzhen is relatively convenient, which provides easier walking conditions for park visitors. Therefore, urban planning will also affect the results of the study. Differences in the findings of various studies indicate that the selection of potential influencing variables and study subjects could have affected their findings. Thus, conducting regression models for cities in different tiers is essential for understanding the factors that influence visits to urban parks in different cities.

4.2. Findings for cities within each administrative tier

Our comparison of the effects of different factors on cities within each administrative tier in China revealed that there were similarities as well as differences among these cities. For example, the LSI was positively related to the density of check-ins, indicating a greater density of visits to parks with complex shapes. Of the cities categorized in the four administrative tiers, municipalities showed the strongest correlation between urban park use and the LSI, which means that when the city is too big, many citizens prefer to use the boundary spaces of parks rather than to enter them. Our results indicated that well-designed park boundaries had a positive influence by increasing a park's appeal for visitors, improving its vitality, and enhancing the efficiency of its use.

The park service area was negatively correlated with the density of check-ins, with this correlation being more significant in prefecture-level cities. Although parks with large service areas provide services to a correspondingly larger groups of people, this factor had no evident effect on enhancing the appeal of parks.

The results of the correlation between population and the number of check-in visits of cities at all levels indicated that there was no correlation, which meant that cities with a large population did not necessarily have higher park use. This showed that there was an imbalance between supply and demand of recreational services in parks, similar to Daegu, Korea (Lee and Hong, 2013).

4.3. Policy recommendations

In light of our findings, we make the following policy recommendations to encourage park use and improve recreational services. First, our assessment of the factors that influence park use indicates that the construction of "park complexes" is essential for improving recreational services. In all cities, parks should be closely integrated with different service facilities. Improving public transportation around parks would attract more visitors. Pedestrian-focused community life circle construction plans have been proposed in major Chinese cities. In this context, the construction of park complexes with diverse functions would facilitate the establishment of community life circles and lead to improvements in recreational services. Second, given the positive influence of the LSI on check-ins for park visits within municipalities, urban planners should design parks with more complex or changeable shapes to increase park–city interfaces when planning new parks. More attention should be paid to the design of spaces around park boundaries, for example, by enriching the landscape and improving facilities to attract more visitors. Third, to increase the efficiency of park use and improve recreational services, planners designing the green space system should replace single large parks with several small community parks so that residents can use parks located within community life circles.

4.4. Limitations and future research

Although, Weibo check-in data can be used to evaluate park visits to some degree, there are still some uncertainties. First, Sina Weibo check-in data has some biases, such as age, gender, a temporal change and social class bias. We were unable to get the characteristics of check-in users, which means the analysis of recreational use of park based on Weibo check-in data may not be representative of the overall use of urban parks. For example, Weibo users are mainly composed of people between 18 and 40 years old, accounting for 89% of the total number of users (Weibo Data Center, 2019). This age bias indicates that Weibo users do not represent all potential park users. For this reason, using Weibo data alone cannot help us to understand the recreation preferences of people of different ages. In the future, we can use a questionnaire as a comparative study to understand the real characteristics of park use among people of all ages. Second, the proportion of check-in visitors to the real number of park visitors varies among cities of different administrative tiers. Because of the difficulty of obtaining official visitor statistics to parks in each city, we selected four cities that represent four administrative tiers to study the feasibility of using Weibo check-in data to evaluate the use of parks in this paper. Therefore, in future research, the statistics of official data will become extremely important, and will be conducive to more objective and realistic research results. We hope that these limitations can be considered in further studies to enable more accurate and scientific studies of urban park use and studies can focus on the application of new data for optimizing urban park use.

5. Conclusion

In this paper, we examined the relationship between planning indicators and park usage (total potential visits and density) in cities belonging to different administrative tiers across China. This analysis was made possible by the availability of data from social media platforms and other forms of Internet-based data. In contrast to previous studies that have focused on a single city or a small set of cities, we examined a total of 13,759 parks spread across all 287 cities of prefecture level and above in China.

We measured and analyzed the factors associated with check-ins for park visits in the cities under study. Our findings indicated that the park service area, the number of bus stops and bus lines, the density of POIs, and the LSI significantly influenced the density of check-ins in all the cities. Smaller parks in closer proximity to many commercial facilities tended to have more visitors. The number of bus stops and bus lines was positively related to the density of check-ins for park visits, suggesting that increased accessibility through adequate public transportation results in increased park visits. The results of our regression model for cities in different administrative tiers can advance understanding of variations in park use in cities of different types. We have provided policy recommendations to encourage park use tailored to the characteristics of different cities. In particular, we recommend the construction of park complexes that demonstrate high urban vitality and are linked to convenient public transportation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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