A Geographical Detector Study on Factors Influencing Urban Park Use in Nanjing, China

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A Geographical Detector Study on Factors Influencing Urban Park Use in Nanjing, China

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Highlights:

- An urban park use index is proposed to estimate urban park use based on the Baidu heat map data.
- A geographical detector is used to quantify the influence of the internal and external factors and their interactive impact on urban park use.
- Among all driving factors, park-surrounding facilities have the greatest influence on urban park use.
- The interactive effects between each pair of driving factors are manifested as bivariate enhanced or nonlinear enhanced.

Abstract: Even though urban parks are widely recognized to be of immense benefits for urban residents and environment alike, developing a direct and effective method to estimate urban park use and decipher its influencing mechanisms remain to be challenging. In this study, an urban park use index is proposed to quantitatively estimate urban park use based on the Baidu heat map data in Nanjing region. Besides, a geographical detector is applied to quantify individual and interactive influences of the internal and external factors on urban park use. The evidence shows that park-surrounding facilities have the greatest influence among all driving factors. Moreover, compared with the individual influences of driving factors on urban park use, the interactive effects between each pair of driving factors are manifested as bivariate enhanced or nonlinear enhanced. These findings provide an effective means to examine and reveal the influencing mechanisms of urban park use, which can assist urban planners and policy makers to frame more specific policies aimed at successful urban park management and planning.

Keywords: Urban park use; Baidu heat map data; Geographical detector; Influencing factors; Nanjing
1. Introduction

Urban park, which is among the most important public services in urban area, plays an essential role in enhancing public health of urban residents and supporting ecological integrity within urban areas (Barbosa et al., 2007; Bedimo-Rung, Mowen, & Cohen, 2005; Chiesura, 2004; Cohen et al., 2016; McCormack, Rock, Toohey, & Hignell, 2010; Wolch, Byrne, & Newell, 2014). Increasing empirical evidence indicates that urban parks in urban contexts contribute to the quality of human life by providing a range of ecological, social, economic, and health benefits (Cetin, 2015; Chiang & Li, 2019; Chiesura, 2004; Kaczynski & Henderson, 2007; Kim & Jin, 2018; Lachowycz & Jones, 2013; Z. Li, Fan, & Shen, 2018; Millward & Sabir, 2011; Schipperijn, Bentsen, Troelsen, Toftager, & Stigsdotter, 2013; Schnell, Harel, & Mishori, 2019; P. Y. Tan & Samsudin, 2017). Besides, urban parks also offer opportunities to direct contact with urban nature, particularly for inhabitants who are in want of interaction with nature environments (Daniel et al., 2012; S. Zhang & Zhou, 2018). Therefore, assessing urban park use and understanding the determinants of urban park use have drawn increasing attention from both policy makers and urban planners.

Urban park use refers to the actual visitation of urban parks in resident’s lives (Lyu & Zhang, 2019). As multiple health and well-being benefits of urban parks are highly contingent on it being visited in the first place, and therefore, recent studies have investigated various driving factors influencing urban park visitation (Giles-Corti et al., 2005; Grilli, Mohan, & Curtis, 2020; Koohsari et al., 2015; McCormack et al., 2010; Schipperijn, Ekholm, et al., 2010; Schipperijn, Stigsdotter, Randrup, & Troelsen, 2010; J. Zhang & Tan, 2019), which include the internal and external factors (Chen et al., 2018; Guo et al., 2019; F. Li et al., 2017). Internal factors, such as park size, landscape shape index, water area, the provision of park facilities, vegetation coverage, and biodiversity, are positively related with urban park use (Hermy & Cornelis, 2000; F. Li, Li, Li, & Long, 2020; Nielsen, van den Bosch, Maruthaveeran, & van den Bosch, 2013; Palliwsoda, Kowarik, & von der Lippe, 2017; Wright Wendel, Zarger, & Mihelcic, 2012; S. Zhang & Zhou, 2018; W. Zhang, Yang, Ma, & Huang, 2015; Zhu et al., 2020). In addition to these internal factors, population density, services and facilities, and accessibility, which represent the external factors, also have a significant influence on urban park visitation (Donahue et al., 2018; Guo et al., 2019; F. Li et al., 2020). The positive role of accessibility in the promotion of urban park use is often mentioned in present urbanized society, the related factors of which include the number of the road density, the number of nearby bus and subway stations, and the
distance to the city center (Chen et al., 2018; Guo et al., 2019; F. Li et al., 2020; S. Zhang & Zhou, 2018).

In terms of data collection for urban park use, previous work has investigated the characteristics, activities and behaviors of urban park users through questionnaire survey data (Gibson, 2018; Kaczynski, Potwarka, & Saelens, 2008; Neuvonen, Sievänen, Tönnes, & Koskela, 2007; Schipperijn et al., 2013; Schipperijn, Ekholm, et al., 2010; Sreetheran, 2017; W. Zhang et al., 2015) and observation data of Systems for Observing Play and Recreation in Communities (SOPARC) (Chow, McKenzie, & Sit, 2016; Evenson, Jones, Holliday, Cohen, & McKenzie, 2016; Marquet et al., 2019). For questionnaire survey, it is a directly mean to acquire detailed information about individuals’ usage of urban parks via the questionnaire design. However, questionnaire survey data are generally limited by the risk of implicit bias (Donahue et al., 2018), limited samples (Cohen et al., 2016; Schipperijn et al., 2013; D. Wang, Brown, & Liu, 2015), and insufficient response rates. For SOPARC, it was developed to obtain observational data on the visitation frequency and preferences for physical activities of participants (McKenzie, Cohen, Sehgal, Williamson, & Golinelli, 2006). While using SOPARC can collect abundant characteristic information such as gender, age groups, and physical activity levels (Chow et al., 2016; Evenson et al., 2016), spatial and temporal coverage data of urban park users is commonly lacking, particularly at the scale of entire cities (Guo et al., 2019; X. P. Song, Richards, & Tan, 2020). Thus, it is essential to develop new methods derived from geospatial information and sensors to strengthen the available data collection tool for measuring and monitoring the visitation of urban park (Shoval & Ahas, 2016).

With the advancement of technologies such as Information and Communications Technology (ICT) and Web 2.0 technology, there is a burgeoning literature on positioning technologies and social media in urban parks and green spaces from an emerging big data perspective (Chen et al., 2018; Donahue et al., 2018; Hamstead et al., 2018; F. Li et al., 2020; Lyu & Zhang, 2019; Sessions, Wood, Rabotyagov, & Fisher, 2016; X. P. Song, Richards, He, & Tan, 2020; Sonter, Watson, Wood, & Ricketts, 2016). The advantage of big data is that it describes the characteristics of urban residents' spatiotemporal behaviors at different scales which tend to emphasize cost-efficiency and convenience and be economical with time (Heikinheimo et al., 2020; Hu, Shen, Shi, & Zhang, 2020; Niu & Silva, 2020; Y. Song, Huang, Cai, & Chen, 2018; Zhen, Cao, Qin, & Wang, 2017). As a technology built on Web 2.0, many social media platforms (e.g., Twitter, Instagram, Flickr, and Weibo) support a check-in option and are increasingly used to gain insight into the relationships with users’ everyday life behavior or the spatial distribution of users.
Silver, and Lacayo (2013) tried to assess the visitation rates at as many as 836 recreational sites by examining the locations of photographs posted on Flickr. Tenkanen et al. (2017) collected the visitor information from diverse social media platforms, such as Instagram, Twitter, and Flickr, to evaluate temporal visits in 56 national parks located in Finland and South Africa. Hamstead et al. (2018) used geolocated data derived from Flickr and Twitter to analyze the variation in use in all parks across New York City. S. Zhang and Zhou (2018) used Weibo check-in data to measure the recreational visits of different types of urban parks in central Beijing. X. P. Song, Richards, He, et al. (2020) compared between measures of park use derived from geo-located social media and household surveys, and found that social media data reflected residents’ preferences better than the visit frequency of parks. Besides, social media check-in data sources cannot be used to represent urban park use on daily or hourly intervals (Chen et al., 2018).

Compared with social media check-in data, Baidu heat map data is one of another big data sources that it is nearly unbiased and can provide real-time data for population dynamics studies (Fang, Huang, Zhang, & Nitivattananon, 2020). Recent studies have employed the Baidu heat map data in an attempt to measure the distribution of population density in the research of urban park, land use, and urban structure (J. Li, Li, Yuan, & Li, 2019; Lyu & Zhang, 2019; Z. Wu & Ye, 2016). Yuhui Liu, Zhang, and Hou (2018) used Baidu heat map data to investigate the visitation of urban park in Wuhan. Lyu and Zhang (2019) used Baidu heat map data and Weibo check-in data to describe the urban park use in Wuhan, and found that the former data outperformed the latter.

In terms of the methodology, traditional regression model has proved its effectiveness in unveiling the correlations between dependent and independent variables (Cetin, Adiguzel, Gungor, Kaya, & Sancar, 2019; Huang et al., 2019; A. Zhang et al., 2020). Recent studies also have focused on the multiple regression model for determining the factors that associate with urban park use (Chen et al., 2018; Lyu & Zhang, 2019; S. Zhang & Zhou, 2018). However, the traditional regression model often neglects the multicollinearity among the influencing factors and spatial relationships between the driving factors (Luo et al., 2019; R. Zhang, Chen, Zhang, Hou, & Chang, 2020). Geographical detector is a new spatial statistical method that can be employed to detect spatial stratified heterogeneity and identify the relative significance of driving factors, as well as the interactions among these factors (J. Wang & Xu, 2017; J. F. Wang et al., 2010). Although geographical detector has been applied in many fields such as human health (J. F. Wang et al., 2010), land use (Liang & Yang, 2016), housing price (C. Wu, Ye, Du, & Luo, 2017), urban forest (Duan & Tan, 2020), and socioeconomics (Yangsui Liu & Yang, 2012; Yang et al., 2018).
attempts to examine the relationship between urban park use and its influencing factors are still lacking.

Against this backdrop, it is more important to explore the determinant power of the related factors and their interactive impact on urban park use, as these have important practical implications on urban park management and planning. To this end, the Nanjing Central Districts were selected as the study area. An urban park use index is proposed by estimating the value of the Baidu heat map data. Then, the geographical detector is used to quantify the individual and interactive influences of factors on urban park use. Specifically, this study aimed to (1) analyze the spatial characteristics of urban park use based on the Baidu heat map data; (2) explore the determinant power of the related factors and their interactive impact on urban park use using the geographical detector method; and (3) provide meaningful implications for urban park planning and management that could contribute to the sustainable development of a city. With a new perspective and deeper understanding of the urban park use, this study can provide significant insights into urban park management and planning.

2. Data and methodology

2.1. Study area

The city of Nanjing is the capital of Jiangsu Province. According to the Nanjing master planning (2011-2020), the city has a permanent population of nearly 10.6 million in a total area of approximately 6582 km² (Nanjing Planning Bureau, 2017). To ensure the availability of data acquisition, we selected the Nanjing Central Districts as the study area, where the total area is approximately 834 km² (Fig. 1). Over the past decade, urban green space in Nanjing were increasingly improved after a series of urban greening construction programs launched by the local government. We focused on the 178 urban parks within the Nanjing Central Districts (Fig. 1). These parks range in size and type, and represent a diverse sample of parks across the urban core area.
Fig. 1. The study area: Nanjing Central Districts

2.2. Data

2.2.1. Baidu heat map data

Baidu heat map, which is one of the most influential big data sources in China, gathers real-time data based on the geolocated information provided by the smartphone users who use Baidu products (e.g., Baidu map, Baidu search, and Baidu music, etc.). Although the Baidu heat map data cannot directly demonstrate the actual number of population, it has been proven to be a reliable big data source that serves as a proxy for delineating the spatial distribution of the population with real-time dynamics (Fang et al., 2020; X. Tan et al., 2016).

Recent studies have proven that the population conforms to the similar distribution and evolution regularity based on Baidu heat map data from Monday to Friday (weekdays), and on Saturdays and Sundays (weekends) (J. Li et al., 2019; Z. Wu & Ye, 2016). Therefore, the Baidu heat map data of March 29th in 2019 (Friday) as a weekday and of March 30th in 2019 (Saturday) as a weekend in the Nanjing Central Districts were collected in this study. During the period of population activity (from 6:00 to 22:00), a heat map data was collected once every 60 min. Finally, 34 heat maps with 3.5m spatial resolution were adopted totally (Fig.2).
2.2. Other basic data

The other basic data mainly included information on urban parks, water, road networks, bus and subway stations, and points of interest (POIs) in Nanjing. This study acquired the polygon data of 178 urban parks by extracting urban park boundaries based on the *Nanjing Green Space System Planning (2013-2020)* (Nanjing Green and Garden Bureau, 2019). Polygon data of water were also obtained in the same way. The road networks data were obtained from the *Nanjing master planning (2011-2020)* (Nanjing Planning Bureau, 2017). Furthermore, a total of 11,729 bus station and 147 subway station data were collected from the Nanjing public transportation website (http://nanjing.gongjiao.com/). These two types of data in relation to traffic were employed to assess the traffic convenience for an urban park. A total of 264,001 POIs data was derived from the Baidu Map Application Programming Interface (https://lbsyun.baidu.com/), and was employed to represent the commercial prosperity inside and near an urban park.

2.3. Methodology

2.3.1. Urban park use index

Urban park use is an essential indicator to comprehensively understand the relationship between urban parks and people (Lyu & Zhang, 2019). To measure urban park use across the Nanjing Central Districts, the Baidu heat map data collected on March 29th and March 30th in 2019 in the Nanjing Central Districts (Fig. 2).
map data were used to calculate the relative calorific value of human activities, which ranges from 0 to 7, the greater the value, the more human activities. Yuhui Liu et al. (2018) put forward a method to measure the visitation of urban park based on the Baidu heat map data. This study attempts to improve it and propose an urban park use index to quantitatively measure the visits per unit of urban park area, which represents the visiting intensity of an urban park. By summarizing the values of Baidu heat map data within the zones of urban parks dataset using a so-called “Zonal Statistics” in ArcGIS 10.5, the urban park use index of each park were calculated, as shown in Equation (1):

\[
Q_i = \frac{\sum_{t=1}^{n} A_t}{n \times S_i},
\]

Where \( Q_i \) is the average visits of urban park \( i \) at a given day, \( A_t \) is the visits of urban park \( i \) at a given time, \( S_i \) is the area of urban park \( i \), \( n \) is the number of times.

### 2.3.2. Potential influencing factors on urban park use

Based on the literature review (Evenson et al., 2016; Giles-Corti et al., 2005; Guo et al., 2019; F. Li et al., 2020; McCormack et al., 2010; D. Wang et al., 2015), two groups of independent variables that potentially affect the urban park use, namely the internal factors and external ones (Table 1), are selected from a range of available data sources.

Internal factors indicate the attributes of a specific park as its initial design, such as park size, landscape shape index, park facilities, water size, and vegetation coverage (Goličnik & Thompson, 2010; Kaczynski et al., 2008; F. Li et al., 2020; F. Li et al., 2017). The park size was calculated based on the polygon data of the urban park. The park facilities were defined as the number of POIs counted in the urban park. The water size was defined as the area of water within the urban park. The vegetation coverage was defined as the average value of Normalized Difference Vegetation Index (NDVI) within the urban park, it was obtained by measuring the distinction between near-infrared light (which vegetation strongly reflects) and red light (which vegetation absorbs) in ENVI 5.3. The landscape shape index represents the shape of an urban park, whose expression is:

\[
LSI = \frac{2 \sqrt{\pi \times A_i}}{C_i},
\]

where \( A_i \) represents the area of the urban park \( i \) and \( C_i \) denotes the circumference of the urban park \( i \).

External factors are those influencing factors existing around a certain park, without considering the properties
of the park itself, such as road density, traffic convenience, distance from the urban center, and park-surrounding facilities (Guo et al., 2019; Hillsdon, Panter, Foster, & Jones, 2006; F. Li et al., 2017). When measuring the surrounding environment features of an urban park, the 500 m park service area is introduced according to previous work (Chen et al., 2018; F. Li et al., 2020). The road density was defined as the road density counted in the 500 m buffer area of an urban park. The traffic convenience can be interpreted as the number of bus and subway stations counted in the 500 m buffer area of an urban park. The distance from the urban center was defined as the distance from an urban park to the urban center, it was measured by the spatial join tool in ArcGIS 10.5. The park-surrounding facilities were defined as the number of POIs counted in the 500 m buffer area of an urban park.

Table 1. Description of potential influencing factors on urban park use.

<table>
<thead>
<tr>
<th>Factors types</th>
<th>Index</th>
<th>Abbr.</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal factors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Park size</td>
<td>PS</td>
<td>$PS$</td>
<td>Park area</td>
</tr>
<tr>
<td>Landscape shape index</td>
<td>LSI</td>
<td>$LSI$</td>
<td>The shape of a park</td>
</tr>
<tr>
<td>Park facilities</td>
<td>PF</td>
<td>$PF$</td>
<td>The number of POIs in an urban park</td>
</tr>
<tr>
<td>Water size</td>
<td>WS</td>
<td>$WS$</td>
<td>Water area</td>
</tr>
<tr>
<td>Vegetation coverage</td>
<td>VC</td>
<td>$VC$</td>
<td>The average value of NDVI within an urban park</td>
</tr>
<tr>
<td>External factors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road density</td>
<td>RD</td>
<td>$RD$</td>
<td>The road density around an urban park</td>
</tr>
<tr>
<td>Traffic convenience</td>
<td>TC</td>
<td>$TC$</td>
<td>The number of bus and subway stations around an urban park</td>
</tr>
<tr>
<td>Distance from the urban center</td>
<td>DUC</td>
<td>$DUC$</td>
<td>The distance from an urban park to the center of the city</td>
</tr>
<tr>
<td>Park-surrounding facilities</td>
<td>PSF</td>
<td>$PSF$</td>
<td>The number of POIs around an urban park</td>
</tr>
</tbody>
</table>
Fig. 3. (a) park size; (b) landscape shape index; (c) park facilities; (d) water size; (e) vegetation coverage; (f) road density; (g) traffic convenience; (h) distance from the urban center; (i) park-surrounding facilities.
2.3.3. **Geographical detector**

The geographical detector serves as an effective spatial statistics method based on spatial variation analysis of the geographical strata of variables (J.-F. Wang & Hu, 2012), and it comprises as many as four modules, namely factor detector, interaction detector, ecological detector, and risk detector (J.-F. Wang & Hu, 2012; J. Wang & Xu, 2017). In order to explore the determinant power of the related factors and their interactive impact on urban park use, a geographical detector method was used in this study.

(1) The factor detector quantifies the influences of factors on urban park use based on the $q$-statistic. Its formula is:

$$ q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma^2_h}{N \sigma^2} = 1 - \frac{SSW}{SST}, \quad (3) $$

Where $q$ is the explanatory power of determinants associated with the urban park use, $h = 1, \ldots, L$ are the stratification of $y$ or factor $x$, that is, classification or partition; $N_h$ and $N$ stands respectively for the number of units in $h$ and the whole region. $\sigma^2_h$ and $\sigma^2$ are the variance of units in $h$ and the global variance of $y$ over the whole region, respectively. $SSW$ and $SST$ stands respectively for the within the sum of squares and the total sum of squares. The $q$ value ranges between 0 and 1, and the larger the $q$ value is, the stronger the influence of factor $x$ on $y$.

(2) The interaction detector examines whether the factors ($x_1$ and $x_2$) have an interactive effect on urban park use. First, the $q$-statistic of factors $x_1$ and $x_2$ with respect to the urban park use were calculated and marked as $q (x_1)$ and $q (x_2)$. Then, the interactive $q$-statistic of factors $x_1$ and $x_2$ was calculated and marked as $q (x_1 \cap x_2)$. The interactive relationship can be classified into five types by comparing the interactive $q$-statistic of the two factors and the $q$-statistic of each of the two factors (J.-F. Wang & Hu, 2012; J. Wang & Xu, 2017). The five types are described in Table 2.

<table>
<thead>
<tr>
<th>Description</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q (x_1 \cap x_2) &lt; \min (q (x_1), q (x_2))$</td>
<td>Weakened, nonlinear</td>
</tr>
</tbody>
</table>
\[
\text{Min} (q(x_1), q(x_2)) < q(x_1 \cap x_2) < \text{Max} (q(x_1), q(x_2)) \quad \text{Weakened, unique}
\]
\[
q(x_1 \cap x_2) > \text{Max} (q(x_1), q(x_2)) \quad \text{Enhanced, bilinear}
\]
\[
q(x_1 \cap x_2) = q(x_1) + q(x_2) \quad \text{Independent}
\]
\[
q(x_1 \cap x_2) > q(x_1) + q(x_2) \quad \text{Enhanced, nonlinear}
\]

(3) The ecological detector is used to compare whether \(x_1\) has a significantly greater influence or contribution than \(x_2\) based on the \(F\)-value. Its formula is:

\[
F = \frac{N_{s_1} \left(N_{s_1} - 1\right) SSW_{s_1}}{N_{s_2} \left(N_{s_2} - 1\right) SSW_{s_2}}, \quad (4)
\]

\[
SSW_{s_1} = \sum_{h=1}^{L_1} N_h \sigma_h^2, \quad SSW_{s_2} = \sum_{h=1}^{L_2} N_h \sigma_h^2, \quad (5)
\]

where \(N_{s_1}\), \(N_{s_2}\) mean the sample number of two factors, respectively. \(SSW_{s_1}\), \(SSW_{s_2}\) stand respectively for the sum of intra-layer variance formed by two factors. \(L_1, L_2\) represent the number of stratification of factors \(x_1\) and \(x_2\), respectively.

(4) The risk detector is applied to detect whether the urban park use is remarkably different while the area studied is stratified by a variety of factors. If the result of two factors is “Y”, it means the significant differences between the two factors that influence urban park use, whereas if the result of two factors is “N”, it means no significant difference. The risk detection is examined by using \(t\)-test:

\[
t = \frac{\bar{Y}_{h=1} - \bar{Y}_{h=2}}{\sqrt{\frac{\text{Var}(Y_{h=1})}{n_h = 1} + \frac{\text{Var}(Y_{h=2})}{n_h = 2}}}^{1/2}, \quad (6)
\]

Where, \(\bar{Y}_h\) represents the average of \(Y\) in the subregion \(h\); \(n_h\) is the size of samples in subregion \(h\), and \(\text{Var}\) is variance.

In this study, we focus on the relationship between urban park use and its influencing factors. Therefore, the geographical detector method is used to examine the influence of nine potential factors, including park size, landscape shape index, park facilities, water size, vegetation coverage, road density, traffic convenience, distance from the urban center, and park-surrounding facilities and their interaction effects on urban park use. These geographical detectors helped us to investigate what factors and their interactive effects are generally important for urban park use across our study area.
3. Results

3.1. Spatial characteristics of urban park use with Baidu heat map data

In general, the 178 urban parks are calculated with the urban park use index in Nanjing Central Districts, with an average value of 1.13 per park, a standard deviation of 0.95, and a range from 0 to 5.16 (Fig. 4). The urban park use index was divided into five grades by Natural breaks in ArcGIS 10.5.

![Urban park use index map](image)

**Fig. 4. Spatial distribution of urban park use based on Baidu heat map**

Urban park use varied greatly by location (Fig. 4). It is obvious that urban parks located closer to the center of the city have a higher urban park use index. There are 10 urban parks (Zhanyuan Garden, Gulou Park, Chaotian Palace, Zhenghe Park, Dazhongting Park, Zhushan Park, Xu Garden, Xi'an Gate Park, Tianyin Park, and Wulongtan Park) with urban park use index above 3.14 are regarded as the most preferentially visited urban parks in Nanjing.
Zhanyuan Garden (5.16) also has the highest visiting intensity than the other urban parks. Moreover, it is noted that large comprehensive parks, especially for parks such as Zijin Mountain Scenic Area (0.19), Xuanwu Lake (0.96), and Yuhuatai Scenic Area (0.81), have much less urban park use index compared with small ones, this may be related to that the urban park use index represents the visiting intensity rather than the total visits of urban park.

3.2 Analyzing factors influencing urban park use based on geographical detector

3.2.1 The influence of driving factors on urban park use

The factor detector was used to quantify the influences of the nine driving factors on urban park use. As shown in Table 3, it is clear that the nine factors all significantly influence on the urban park use, although the extents of these influences vary. Among all potential driving factors, park-surrounding facilities had the greatest influence on the value of urban park use index \((q = 0.4323)\), followed by another external factor, road density \((q = 0.3750)\). Compared with the external factors, internal factors presented smaller influences on the value of urban park use index. Among the internal factors, park facilities presented as having a dominant influence \((q = 0.2375)\) on the value of urban park use index, while water size presented as having the least influence \((q = 0.0725)\).

Table 3 The factor detector analysis between urban park use and driving factors

<table>
<thead>
<tr>
<th>Factors types</th>
<th>Factor</th>
<th>q-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal factors</td>
<td>PS</td>
<td>0.1355</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>LSI</td>
<td>0.1752</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>PF</td>
<td>0.2375</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>WS</td>
<td>0.0725</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>VC</td>
<td>0.1142</td>
<td>0.00</td>
</tr>
<tr>
<td>External factors</td>
<td>RD</td>
<td>0.3429</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>TC</td>
<td>0.2149</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>DUC</td>
<td>0.3750</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>PSF</td>
<td>0.4323</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: park size (PS), landscape shape index (LSI), park facilities (PF), water size (WS), vegetation coverage (VC), road density (RD), traffic convenience (TC), distance from the urban center (DUC), and park-surrounding facilities
3.2.2. The interactive effects of driving factors on urban park use

In total, 36 pairs of interactions between the nine factors were detected using the interaction detector. Table 4 shows that the interaction relationships among all the interactions between internal factors and external factors. In this study, the synergistic effects between each pair of driving factors are manifested as bivariate enhanced or nonlinear enhanced in influencing urban park use. This demonstrated that the interaction between two driving factors strengthens the influence of each individual factor in urban park use. Among the interactions of internal factors, $q$ (park facilities $\cap$ park size) is the maximum (0.5967), indicating that the interaction between park facilities and park size was the strongest. Also, among the interactions of external factors, $q$ (road density $\cap$ park-surrounding facilities) is the maximum (0.6151), indicating that the interaction between park facilities and park size was the strongest. Additionally, the interaction between park size and park-surrounding facilities ($q = 0.7868$) is the strongest among all the interactions between internal factors and external factors.

Table 4 The interaction detector analysis of driving factors on urban park use

<table>
<thead>
<tr>
<th></th>
<th>$PS$</th>
<th>$LSI$</th>
<th>$PF$</th>
<th>$WS$</th>
<th>$VC$</th>
<th>$RD$</th>
<th>$TC$</th>
<th>$DUC$</th>
<th>$PSF$</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
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<tr>
<td>$RD$</td>
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</tbody>
</table>
3.2.3. Statistical significance of differences among driving factors

The significance of varying influence among the nine factors was examined via the ecological detector. Table 5 showed that upward of half were not statistically significant, but statistically significant differences were observed between road density and other factors, distance from the urban center and other factors, and park-surrounding facilities and other factors. By combining the results from the factor detector, it could be concluded that park-surrounding facilities have a significantly stronger influence on the urban park use than road density and distance from the urban center; and distance from the urban center has a significantly stronger influence on the urban park use than road density.

Table 5 Statistically significant differences in the driving factors influence on urban park use.

<table>
<thead>
<tr>
<th>Stat. Sig. Diff</th>
<th>PS</th>
<th>LSI</th>
<th>PF</th>
<th>WS</th>
<th>VC</th>
<th>RD</th>
<th>TC</th>
<th>DUC</th>
<th>PSF</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>VC</td>
<td>N</td>
<td>N</td>
<td>N</td>
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<td></td>
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<tr>
<td>RD</td>
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<td>N</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TC</td>
<td>N</td>
<td>N</td>
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<td>N</td>
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<tr>
<td>DUC</td>
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<td>PSF</td>
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<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
</tbody>
</table>
Note: Y signals that the difference in the influence of the two factors is significant with the confidence of 95%, whereas N means no significant difference.

4. Discussion

4.1. Methodological contributions

Growing evidence of a positive association between contact with natural and health and well-being has led to calls for improved understanding of the relationship between urban park use and its influencing factors (White et al., 2019; J. Zhang & Tan, 2019). Most of the previous studies adopt questionnaire survey data or SOPARC data to acquire the information of urban park use (Evenson et al., 2016; Kaczynski et al., 2008; Schipperijn, Ekholm, et al., 2010). It is almost impossible to assess urban park use with traditional site surveys at the scale of entire cities. Currently, the emerging urban big data have enabled us to portray citywide urban park use with convenience and low cost (Heikinheimo et al., 2020; Wood et al., 2013). Recent studies have also suggested that the geotagged social media data can be a reasonable proxy for the visitation of parks (Donahue et al., 2018; Hamstead et al., 2018; S. Zhang & Zhou, 2018), while the geotagged social media data may be an effective tool to reflects residents’ favorite parks better than the visitation of parks (X. P. Song, Richards, He, et al., 2020). This study aims to develop an innovative method with Baidu heat map data to measure urban park use, which may be a more convenient, feasible, and replicable method for urban park use researches. As a popular big data application in China, the Baidu heat map data can greatly reflects the spatial-temporal human activities in the exact area (J. Li et al., 2019; Shi, Xiao, & Zhan, 2020), providing a unique insight in what are the spatial characteristics of urban park use. This study suggests, therefore, that the Baidu heat map data can be a reliable and rapid big data source to describe urban park use at the city level.

Besides, the methodology of this study can serve as a model for other rapidly urbanizing cities in evaluating urban park use and factors relating to its use. Contrary to previous studies which explore the determinants of urban park use with the multiple regression model, this study applied a geographical detector to quantify the individual and interactive influences of factors on urban park use. A major strength of the geographical detector is that it can be used to deal with categorical dependent variables, determine the predominant driving force, and examine the interaction between variables without consideration of the multicollinearity among the explanatory variables (J.-F. Wang, Zhang,
The research also verified that the geographical detector can be an effective tool to examine discrepant influences and interactions among factors involved in urban park use.

4.2. The influencing mechanisms of urban park use

Based on the geographical detector analysis, five internal factors are found associate with urban park use, namely park size, landscape shape index, park facilities, water size, and vegetation coverage. Previous studies have reported that characteristics of green space, such as size, landscape, and facilities, have an influencing on its use (Donahue et al., 2018; Grilli et al., 2020; Schipperijn, Ekholm, et al., 2010). Among the five external factors, the presence of park facilities presented as having a dominant influence on urban park use, which means, in our case, promoting park services and facilities is more important than other characteristics of urban parks.

The results showed that external factors are more important than internal factors that influences urban park use. Among four external factors, park-surrounding facilities had the greatest influence on urban park use. Similar results were found in previous studies in other cities (F. Li et al., 2020; Lyu & Zhang, 2019). A study by Chen et al. (2018) in Shenzhen city, showed that urban park use is more intensively in areas with high building density and surrounding services and facilities. Our observation is that resident living in Nanjing has a great need of convenient surrounding services and facilities to provide them with recreation and catering. The distance from the urban center was another external factor that significantly influences urban park use. This finding is consistent with that of previous studies showing the strong association between distance to the city center and park check-in visits in Beijing city (S. Zhang & Zhou, 2018). Also accessibility is regarded as a significant factor that influences the visits of urban parks (Barbosa et al., 2007; Schipperijn et al., 2013). In the present study, both road density and traffic convenience are related with urban park use. These could be attributable to that urban parks are open not only to nearby residents but also to all citizens in Nanjing, especially the larger parks that attracted tourists from all over the country, therefore, it is important to realize that high road density and convenient public transportation will increase more visits to urban parks.

A further examination suggests that the interactive effects between each pair of driving factors are manifested as bivariate enhanced or nonlinear enhanced in influencing urban park use. Looking at our findings from another point of view, we might also speculate that the interaction between two driving factors strengthens the influence of each individual factor in urban park use, it is thus essential for urban planners and park managers to improve urban parks
from a multiple dimension to enhance the efficiency of urban park use.

4.3. Implications for urban park planning and management

Based on an interpretation of a GIS map showing which urban parks are most intensely used (Fig. 4), it seems that smaller parks located in closer proximity to the city center in Nanjing tended to have a higher urban park use index. S. Zhang and Zhou (2018) suggested that the role of small neighborhood parks in the urban green space systems is essential to meet the increasingly needs of the local residents’ urban park use. A study conducted in Latin America also found that small neighborhood green spaces usually provide places for women to relax and socialize and provide amenities for children to play (Wright Wendel et al., 2012). In the urban central area in Nanjing, it is extremely unlikely that additional large parks will be established, a reasonable option would be to increase more “pocket parks” and microgreen spaces on vacated and abandoned land to attract more visits. Additionally, enhancing the quality of small green space in dense city areas can satisfy the need of residents’ daily recreation (Haaland & van den Bosch, 2015; Peschardt, Schipperijn, & Stigsdotter, 2012).

As results in this study, having a better services and facilities within and around parks had a higher urban park use index. Therefore, it is extremely recommended that public service facilities (e.g., restaurants, public toilets, coffee bars, galleries, and sports venues) should be added to better encourage park visitation. Meanwhile, the combination of parks with the surrounding environment should take into account to enhance the use of underutilized parks (Chen et al., 2018; Lyu & Zhang, 2019). Urban planners and park managers also should pay more attention to improve vegetation coverage and landscape aesthetics of parks to attract more people. Besides, as traffic convenience has a significant effect on urban park use, this finding suggests that improving park accessibility via public transport policies could be a feasible and effective way to increase urban park visits in Nanjing.

4.4. Limitations

Although this study proposed to use the Baidu heat map data and the geographical detector method to analyze the determinant power of the internal and external factors and their interactive impact on urban park use, several limitations should be mentioned in this study. First, this study estimated urban park use based on the Baidu heat map data, which could only offer a relative value of urban park use index among different urban parks. The future research focus could consider other big data sources such as Weibo check-in (Lyu & Zhang, 2019; Zhen et al., 2017)
and mobile phone signaling (Guo et al., 2019; Xiao, Wang, & Fang, 2019; Zhai, Wu, Fan, & Wang, 2018) to acquire the information of residents’ preferences and the exact number of population distribution in urban parks.

Second, climate has a great impact on urban environments and human activities (Cetin, 2020; Gungor, Cetin, & Adiguzel, 2020). In this study, the Baidu heat map data in a weekday (March 29th) and a weekend (March 30th) in Nanjing were collected to estimate urban park use, while it cannot reflect urban park use in other climate or seasons because of the limited sample data. Further studies are thus needed to expand and enrich the methods and findings of this study to compare urban park use within various seasons. The discrepancy between weekdays and weekends also deserves exploration.

Finally, this study selected internal factors and external factors to analyze the determinants of urban park use, other potential driving factors such as population density, urban form, biodiversity, and socioeconomic conditions are also not considered (Baran et al., 2014; Palliwoda et al., 2017; S. Zhang & Zhou, 2018). Further research is needed to understand more comprehensive in regard to the potential drivers of urban park use depending on specific context to better promote urban park planning and design.

5. Conclusions

Urban parks encourage physical activity and outdoor recreation that contribute to health and well-being of urban residents, and the extent to which the potential benefits of parks can be realized is highly dependent on a thorough understanding of how urban parks are used. More recently, the advancement of technologies allows urban planners and park managers to gather the spatial-temporal information on how urban parks are used with a set of available big data sources. In this study, we estimated urban park use by using the Baidu heat map data to understand the relationship between urban parks and human activities in Nanjing. Moreover, a geographical detector was introduced to explore the determinant power of the related factors and their interactive impact on urban park use. The findings provided explanations for the urban park use by urban residents in Nanjing, which can enrich and deepen the understanding as to the urban park use on a daily basis.

The findings suggest that smaller parks located closer to the center in Nanjing city have a higher urban park use index. For urban planners and park managers, it is thus essential to pay more attention to the role of small parks in urban green space systems. The results of geographical detector indicated that internal and external factors are all associated with urban park use, and the park-surrounding facilities have the greatest influence on urban park use...
among all factors. This indicating that improving park surrounding environment features are important to attract more visits. The results also indicated that the interactive effects between each pair of driving factors are all higher than those of a single factor, and the interactive effects between park size and park-surrounding facilities have exerted the greatest impact on urban park use. These findings highlight the importance of focusing on urban park use and its influencing mechanisms to improve the public health of urban residents worldwide.

Conflict of interest

The authors declared that they have no conflicts of interest to this work.

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

CRediT authorship contribution statement

Zhengxi Fan: Conceptualization, Methodology, Investigation, Data Curation, Writing - original draft, Visualization, Writing - review & editing. Jin Duan: Funding acquisition, Writing - original draft, Writing - review & editing, Supervision. Yin Lu: Methodology, Investigation, Data Curation, Writing - review & editing. Wenting Zou: Methodology, Investigation, Data Curation, Writing - review & editing. Wenlong Lan: Supervision, Writing - review & editing.

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Reference


Schipperijn, J., Ekholm, O., Stigsdotter, U. K., Toftager, M., Bentsen, P., Kamper-Jørgensen, F., & Randrup, T. B.


least 120 minutes a week in nature is associated with good health and wellbeing. *Sci. Rep.*, 9(1), 7730. doi:10.1038/s41598-019-44097-3


