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Temporal and spatial assessment of urban park visits from multiple social media data sets: A case study of Shanghai, China

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ABSTRACT

To inform ways of developing urban parks in rapidly urbanizing metropolitans, park use patterns need be explained and understood. The objective of this study was to assess urban park visitation in temporal and spatial domains using multiple social media data (SMD) sources. It focused on 300 urban parks in Shanghai, quantified their visit number and intensity, and characterized park visitation patterns for the city. The findings showed that park visit patterns in Shanghai had uneven spatial and temporal distribution. In general, people preferred parks in downtown districts in space and preferred visiting parks in the season of spring and on non-workdays temporally. Spatio-temporally, parks in downtown have higher visitation at all seasons and days, especially for non-workdays. Locating parks with good star ratings outside downtown may not decrease attraction but reduce the downtown congestion. Moreover, this study compared park visitation assessing performances among different SMDs. The similarities and differences in park visit patterns represented by different SMDs indicated that using multiple SMD sources may help obtain more comprehensive and systematic results and achieve better understanding of park usage. Through this study, methods of using SMD were also developed to assess urban park visitation patterns in temporal and spatial domains to achieve more comprehensive and systematic results. The results inferred explanations and advices for more reasonable park distribution regulation and better green space management and urban development, and would offer a starting place for urban planners, landscape designers, and policy-makers.

1. Introduction

1.1. Backgrounds

As primary green spaces for recreation and social interactions, urban parks offer multiple benefits to the quality of life in a metropolis (Larson et al., 2016; Liang et al., 2017c). The number of visits and visit density in urban parks indicate urban park use patterns in daily life and reflect residents' preferences, desires, and habits when they visit urban parks (Donahue et al., 2018). It is essential to understand the relationship between people and parks through spatial and temporal measures of park visitation to analyze park use patterns (Liang et al., 2017b; Zhang and Zhou, 2018). Moreover, it is vitally important for urban park planning and management to evaluate urban park use and to understand the patterns of urban park visits (Ghermandi and Sinclair, 2019; Liang and Zhang, 2018).

1.2. Literature review

Traditional survey methods that focus on field investigations, such as site observations, surveys, questionnaires, interviews, and counters, could have been used to obtain data and information about park visitation, but were found to be laborious, time-consuming, and costly (Heikinheimo et al., 2017). With the use of social media increasing dramatically worldwide (Smailhodzic et al., 2016), it had been proved that social media data (SMD) have become one of the most popular forms of data for green space studies and could be used to understand and study human behavior of park usage, or precisely park visits (Li et al., 2018; Lyu and Zhang, 2019). For example, with SMD, park attributes and surrounding landscape features were incorporated into ArcGIS for spatial analysis to determine what factors may be associated with visit density in urban parks (Chen et al., 2018; Li et al., 2019; Sonter et al., 2016;

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Zhang and Zhou, 2018). With more and more applications of data mining for the issues of sustainability for environments and cities (Du et al., 2020; Pampoore-Thampi et al., 2014; Pathak et al., 2020; Puri et al., 2018; Varghese et al., 2020), sentiment analysis was used to quantify and analyze SMD to interpret the distribution characteristics of varying levels of visit feelings in parks to study park satisfaction or popularity (Kovacs-Györi et al., 2018; Plunz et al., 2019; Sim and Miller, 2019).

Most of the previous studies focusing SMD park visits often used the sources from the platforms widely used in Western counties, such as Flicker, Instagram, and Twitter (Donahue et al., 2018; Hausmann et al., 2018; Heikinheimo et al., 2017; Levin et al., 2017; Sessions et al., 2016; Sim and Miller, 2019; Sonter et al., 2016; Tenkanen et al., 2017; Yoshimura and Hiura, 2017). With multiple statistical methods, these SMD resources were proved and used as a good proxy for empirical park visit information. However, the SMD could and need to be used in park visit research has gone far beyond these databases, especially in China. Unlike Western countries, the popularly used SMD in other countries like China include various SMD sources, such as Weibo, Ctrip, and Dazhong Dianping (DZDP). The previous studies focusing on park visits with these Chinese SMD were very limited. Fortunately, an increasing number of studies focusing on these Chinese SMD sources have proved that these SMD can be a reliable data source for green space or park visit studies (Dai et al., 2019; Ghermandi and Sinclair, 2019; Li et al., 2019; Lyu and Zhang, 2019; Wang et al., 2018). Considering importance and probability of park visit studies using SMD, it is in great need moving forward to use widely used SMD sources to study park visit patterns of cities, especially those in non-western countries.

For park visit pattern analysis with SMD, park visit need to be estimated first. Wood et al. (2013) proposed the metric of the user-day to calculate visitation rates at recreational sites using Flickr SMD. Widely approved and used as a proxy for empirical visitation rates (Ghermandi and Sinclair, 2019), it was a good metric for SMD park visit estimation and could be used in our study. By estimating SMD visits with this metric, many previous studies have temporally and spatially investigated visit patterns of parks, green spaces or natural environments. They analyzed park or green space visitation patterns in city areas to make their usage understood for further studies of site popularity (Kovacs-Györi et al., 2018), equitable distribution (Hamstead et al., 2018; Shen et al., 2017), or facility location exploration (Barros et al., 2019), and used the SMD visitation estimation results to analyze the factors or drivers influencing park or environment use or to predict the intensity and spatial patterns of public use (Ghermandi, 2016; Li et al., 2019; Lyu and Zhang, 2019; Sonter et al., 2016; Zhang and Zhou, 2018). Although different SMD sources might give different results for park visitation, few of these studies on spatial and temporal analysis of visitation distribution used multiple SMD sources for results comparison. The previous studies comparing park or green space usage patterns among various SMD sources from popular platforms, did not make spatial and temporal analysis (Norman and Pickering, 2017; van Zanten et al., 2016). To obtain more observations and comprehensive park visit pattern results, analysis of space-time dimension and SMD sources from multiple popular platforms are all needed. As to research methods of park visit pattern, previous studies often took single study method of descriptive statistics (Barros et al., 2019; Kovacs-Györi et al., 2018) or spatial analysis (Clemente et al., 2019; García-Palomares et al., 2015), instead of systematic and detailed temporal and spatial visit analysis for study sites. Different dimensions of study methods could obtain results for different aspects of park visitation. Therefore, park visit studies need to furtherly use more systematic and detailed temporal and spatial visit analysis with multiple SMD sources to obtain more comprehensive and systematic results.

1.3. Objectives

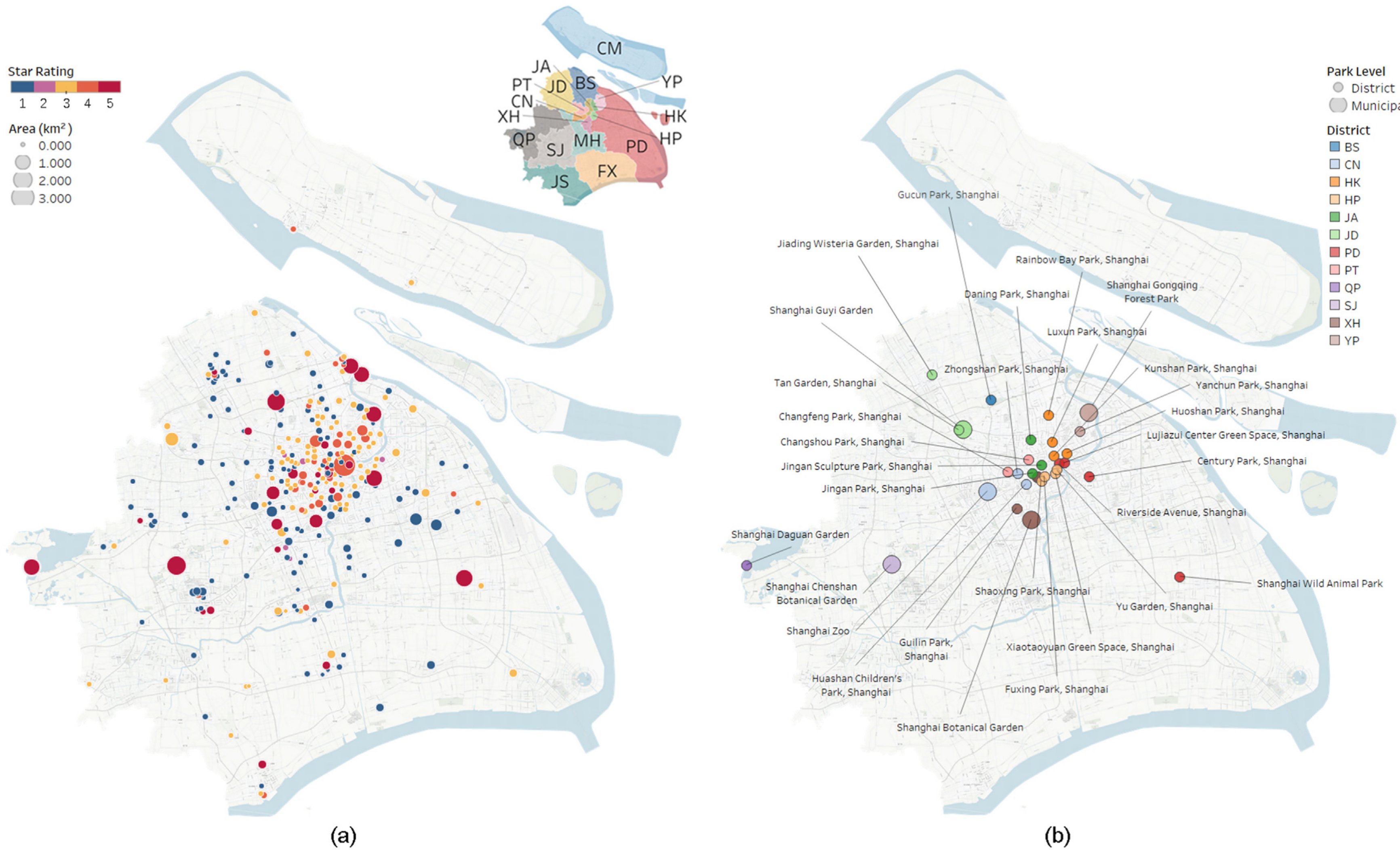
This study aimed to assess urban park visitation in both the temporal and spatial domains using multiple SMD sources. To achieve this research purpose, the city of Shanghai, China was chosen as the study site. The city was investigated to answer the questions and accomplish the objectives as follows: (1) How are the visit patterns of parks in metropolitan on base of SMD? The number of visits and visit density of urban parks in Shanghai were assessed using multiple popularly used SMD sources; (2) How are the park visit characteristics in different spaces or times? How do the spatial characteristics vary over time? Multiple spatial and temporal analysis methods were developed to analyze if there is any significant difference in different spaces or during different time periods to obtain more comprehensive and systematic results of park visit patterns; (3) How did SMD from different platforms perform when assessing park visit pattern? The performance of SMD sources used in this study were compared and analyzed in terms of assessing urban park visitation. This research would improve the methods of SMD application using more efficient and advanced measures for park visit pattern assessment and to promote and inspire more comprehensive and systematic results from park usage assessment in temporal-spatial domains. And these results of park visit patterns would help to achieve better urban park planning and management and urban development in the future.

2. Methods

2.1. Study site

The study focused on all 300 urban parks in Shanghai and quantified and characterized park visits and visiting intensity with data from various popular Chinese social media platforms such as DZDP, Weibo, and Ctrip. Shanghai (121°50′E, 31°40′N) is the largest, most densely populated, and most highly developed city in China, with 16 administrative districts covering an area of 6,340 km^2 and 24,237,800 permanent population (Statistics, 2019). Belonging to the subtropical moist marine climate zone, it has four distinct seasons, large amounts of sunshine, and abundant rainfall. There were 300 urban parks in this famous metropolis in 2019. With a per-capita park green space area of approximately 7.6 m^2 in 2015 and 8.2 m^2 in 2019, Shanghai is congested and rapidly urbanizing, but has an ever-improving green space coverage rate (Liang et al., 2017a), a good and beautiful city environment and appearance, and a favorable modern urban image. Moreover, it is economically developed, with a high level of urban digital information penetration, and was selected as one of the first batch of 5G commercial cities on October 31, 2019. Because of its reasonably good mobile network coverage and very high popularity of social media, Shanghai was an ideal choice for the study site in this research.

The 300 urban parks listed in Shanghai were variable in area, ranging from about 700 m^2 to 3 km^2 (Fig. 1). They are given a star rating with five levels (5, 4, 3, 2, and 1), which is published every year on the official website of the Shanghai Administration Department of Afforestation and City Appearance (http://lhsr.sh.gov.cn/). According to the published park rating standards, the parks were rated with rational and comprehensive considerations based on varies factors, such as park classification, area, facilities, security, service, landscape and scenic, maintenance and management. The urban parks visited by the population are of various types, such as street gardens (like Xiaotaoyuan Green Space, Shaoxing Park, and Donghu Green Space, Shanghai), scenic parks (like Shanghai Gongqing Forest Park, Gucun Park, and Shanghai



No. Abbreviation (District): Huangpu (HP); Xuhui (XH); Changning (CN); Jiang'an (JA); Putuo (PT); Hongkou (HK); Yangpu (YP); Pudong (PD); Minhang (MH); Baosha (BS); Jiading (JD); Jinshan (JS); Songjiang (SJ); Qingpu (QP); Fengxian (FX); Chongming (CM).

Fig. 1. Distribution of urban parks in the metropolitan area of Shanghai, China. (a) all the 300 urban parks; (b) most visited (with Sum(SUD_i) > 1000) and intensively visited (with Sum($SUDPA_i$) > 5000) parks within the study time period (2018.5.1–2019.4.31).

Daguan Garden), and themed parks (Shanghai Botanical Garden, Shanghai Zoo, and Shanghai Wild Animal Park).

2.2. Data sources and visitation calculation

In this research, SMD from the Chinese platforms of Weibo, Ctrip and Dazhong Dianping (DZDP) were chosen and used to study visitation patterns of urban parks in Shanghai (Table 1). These three SMD sets come from the most popular SMD channels in China for tourist attraction data sharing and media access, where people can record and comment on the park they are visiting with text, pictures, and videos. The park SMD from Weibo, Ctrip, and DZDP used in this study were obtained between May 1, 2018 and April 31, 2019 and were collected by Application Programming Interfaces (APIs).

SMD park visitation was calculated by the number of active social media users on each day (SUD), which was defined as the total number of users taking photographs or making posts (whether one or several) on one day within each park (Tenkanen et al., 2017). This approach has been acknowledged earlier as a good surrogate for estimating visit numbers at sites (Sessions et al., 2016; Wood et al., 2013). Park visit intensity or visit density (visit number per unit of park area, SUDPA) was obtained on the basis of SUD and the park area (PA). For park i, day d, $SUDPA_{id}$ was calculated by Equation (1):

$$SUDPA_{id} = SUD_{id} \,/\, PA_i \tag{1}$$

For park i, with the SUD and SUDPA on each day (SUD_{id} and $SUDPA_{id}$), the sum of SUD_{id} and $SUDPA_{id}$ during the studied time period (2018.5.1–2019.4.31), i.e. $Sum(SUD_i)$ and $Sum(SUDPA_i)$, would be obtained by simply summing up and used later to do temporal statistical analyses of park visit number and visit density to study park visit distributions.

For day d, with the SUD and SUDPA for each park (SUD_{id} and $SUDPA_{id}$), the sum of SUD and SUDPA for all the 300 parks in Shanghai on each day, i.e. $Sum(SUD_d)$ and $Sum(SUDPA_d)$, would be obtained by simply summing up and used later to do temporal statistical analyses of park visit number and visit density to study the park visit patterns in temporal domain.

For different temporal categories, such as season and workday/weekend/holiday, the sum of SUD_d and $SUDPA_d$ for season s or workday/weekend/holiday w during the studied time period, i.e. $Sum(SUD_s)$, $Sum(SUDPA_s)$, $Sum(SUD_w)$ and $Sum(SUDPA_w)$, would be calculated by simply sum up the SUD_d or $SUDPA_d$ with the same temporal unit. Since the number of days for different seasons, workdays, weekends, or holidays within the studied time period were different, we used the average SUD_s and $SUDPA_w$ per day in corresponding season or workday/weekend/holiday, i.e. $Mean(SUD_s)$, $Mean(SUDPA_s)$, $Mean(SUD_w)$ and $Mean(SUDPA_w)$, for temporal descriptive statistical analyses later. The equations were as below:

$$Mean(SUD_s) = Sum(SUD_s) \,/\, D_s \tag{2}$$

$$Mean(SUDPA_s) = Sum(SUDPA_s) \,/\, D_s \tag{3}$$

$$Mean(SUD_w) = Sum(SUD_w) \,/\, D_w \tag{4}$$

$$Mean(SUDPA_w) = Sum(SUDPA_w) \,/\, D_w \tag{5}$$

where D_s is the number of days for season s during the studied time period; D_w is the number of days for workday/weekend/holiday w during the studied time period.

For park i, season s and workday/weekend/holiday w, we used the average SUD_i and $SUDPA_i$ per day in corresponding season or workday/weekend/holiday, i.e. $Mean(SUD_{is})$, $Mean(SUDPA_{is})$, $Mean(SUD_{iw})$ and $Mean(SUDPA_{iw})$, for spatial statistical analyses of park visit number and visit density to study the park visit patterns in spatio-temporal domain. The equations were as below:

$$Mean(SUD_{is}) = Sum(SUD_{is}) \,/\, D_s \tag{6}$$

$$Mean(SUDPA_{is}) = Sum(SUDPA_{is}) \,/\, D_s \tag{7}$$

$$Mean(SUD_{iw}) = Sum(SUD_{iw}) \,/\, D_w \tag{8}$$

$$Mean(SUDPA_{iw}) = Sum(SUDPA_{iw}) \,/\, D_w \tag{9}$$

For park i, workday y and non-workday n, visit intensity difference between workday and non-workday, i.e. $DV(SUDPA_{iw})$ was calculated by equation (10) for spatial analysis of park visit pattern difference between workday and non-workday.

$$DV(SUDPA_{iw}) = Sum(SUDPA_{in}) \,/\, D_n - Sum(SUDPA_{iy}) \,/\, D_y \tag{10}$$

where D_y is the number of days for workday y during the studied time period; D_n is the number of days for non-workday n during the studied time period; $Sum(SUDPA_{iy})$ is the sum of $SUDPA_i$ for workday y; and $Sum(SUDPA_{in})$ is the sum of $SUDPA_i$ for non-workday n.

2.3. Statistical analysis

In this research, basic statistics were used in SPSS Version 26 (IBM, Armonk, NY, USA) to study the visit distribution using SMD from Weibo, Ctrip, and DZDP. We used K–S test to verify the data

Table 1
Data and characteristics of the SMD sources used in this study.

Contents	SMD Sources		
	Weibo	Ctrip	DZDP
URL	https://weibo.com	http://you.ctrip.com	http://www.dianping.com
Characteristics	It is core social media and the most used microblog product in China (CIC, 2018). It has check-in data and could well reflect the use of parks in Chinese cities (Zhang and Zhou, 2018).	It is the largest and most popular travel website in China, and has the most travel users and the largest number of travel comments (Guo et al., 2019).	It is the earliest and leading website in the world providing independent consumer review of local services. It has a massive user database of parks and green spaces with travel and review records and is an efficient, professional, and trustworthy travel data website (Wang et al., 2018).
Field contents of information captured	park name; check-in microblog; user ID; microblogging time	park name; travel record and comment; user name; post time	park name; travel record and comment; user name; post time

Abbreviation: Social media data (SMD); Dazhong Dianping (DZDP).

and proved that they did not obey normal distribution. Then Kruskal-Wallis H test was used to respectively compare park visit number and visit intensity calculated from the three SMD sets.

For park i and the days within the study time period, maps of points with different color shades representing Sum(SUD_i) and Sum($SUDPA_i$) were drawn in ArcGIS 10.7 (ESRI, Redlands, CA, USA) to provide an initial visual overview of the geographic distribution of Shanghai park visit number and visit density from the SMD platforms of DZDP, Ctrip, and Weibo. To interpret park spatial visit density furtherly, spatial autocorrelation analysis with ArcGIS was used to determine the areas with higher park visit intensity and the spatial concentration of tourists' visits in the city studied. With global spatial autocorrelation analyses using Global Moran's I and Getis-Ord General G statistics, the Moran's I index measured whether the dependent variables (Sum($SUDPA_i$) from the three SMD platforms) were spatially autocorrelated, and the General G index measured the degree of clustering for either high or low values. Local spatial autocorrelation analysis using the Getis-Ord Gi* statistic (Getis and Ord, 2010) was then performed to identify local trends in spatial distribution patterns with statistically significant hot and cold spots of park visit density from the SMD in the study area.

Using the results of SUD_d and $SUDPA_d$ calculated from the DZDP and Ctrip posts and the check-in microblogs from Weibo, park visit number and visit intensity were divided into various temporal categories, including seasonal, weekly, and workday/weekend/holiday. Mean visit number and visit density per day during each temporal category (different seasons and days of workday/weekend/holiday) for the average urban park in Shanghai, i.e. Mean(SUD_s), Mean($SUDPA_s$), Mean(SUD_w) and Mean($SUDPA_w$), were used to analyze the temporal distribution characteristics of SMD park visits and how they varied over time. After verification of data non-normal distribution with K–S test, Kruskal-Wallis H test was used to compare and identify trends between park visit number and visit intensity by each temporal group. In order to analyze time series of SUD_d and $SUDPA_d$ to study temporal patterns of SMD park visit number and visit density, wavelet analysis was used with MATLAB R2019b (Mathworks, Natick, MA, USA) to compute the wavelet coefficients of SUD_d and $SUDPA_d$ obtained from the SMD from DZDP, Ctrip, and Weibo. Contour maps of the real part of wavelet coefficients were used to illustrate the multi-time-scale characteristics of change in SUD_d and $SUDPA_d$ according to SMD. The variance of the time series in its oscillating components was then decomposed and plotted to detect and demonstrate significant periodicities for park visit number and density in the city as studied using the three sets of SMD.

How do the spatial characteristics vary over time? Are there any significant differences during the year by season or in workday/weekend/holiday periods among the SMD? According to results of the above analysis for spatial and temporal patterns of park visit number and visit density, spatio-temporal park visitation patterns from DZDP, Ctrip, and Weibo SMD were studied through geographic distributions of park visit intensity of seasonal and workday/weekend/holiday periods with ArcGIS maps of points with different color shades representing the average visit intensity per day in corresponding period for each park, i.e. Mean($SUDPA_{is}$) and Mean($SUDPA_{iw}$). Moreover, ArcGIS maps with different color shades representing visit intensity difference between workday and non-workday, i.e. DV($SUDPA_{jw}$), were used to interpret geographic distributions of park visit pattern difference between workday and non-workday from the three SMDs in the study area.

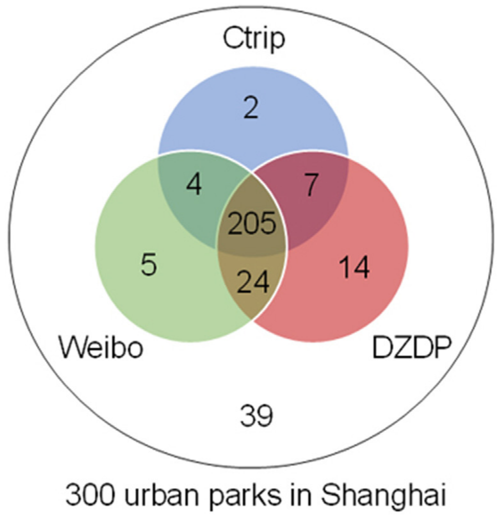
3. Results

3.1. Park visit distributions from SMD

Not all the 300 urban parks in Shanghai have data on the studied SMD platforms in the study periods (2018.5.1–2019.4.31). There were 39 parks, most being newly built, were not checked-in, recorded or commented on DZDP, Ctrip or Weibo. Among the 261 parks with data covering at least one platform, data of DZDP, Weibo and Ctrip covered 250, 238 and 218 parks, respectively (Fig. 2a). Comparing the park lists of SMD for urban parks in Shanghai, these three platforms were in high similarity – with up to 205 parks having data covering all platforms and only 21 parks having data covering one platform.

For park i with SMD, there were significant differences among the Sum(SUD_i) distributions obtained from the three platforms ($p < 0.001$). According to SMD in the study periods, DZDP was the most popular, with 61,212 total visit number (Sum(SUD)) and an average of 245 visit number per park (Mean(SUD)) identified on the platform, much more than either Ctrip (with Sum(SUD) of 21,411 and Mean(SUD) of 98) or Weibo (with Sum(SUD) of 33,123 and Mean(SUD) of 139) (Fig. 2b). For the parks with Sum(SUD) more than 1000 (Sum(SUD) > 1000), DZDP had the greatest park number proportion at 7%, more than Ctrip and Weibo at 3% and 1%, respectively. Although with fewer parks in this scope, Ctrip had higher proportion of total visit number at 80%, more than DZDP at 66%. For the parks with total visit number no more than 1000 but no less than 100 ($100 \leq$ Sum(SUD)≤ 1000), Weibo had the highest park number proportion – 74% of the parks with data on Weibo belongs to this park visit scope, which was far more than the other platforms. With regards to park visit intensity, similar situation happened. It also differed significantly among the three platforms ($p < 0.001$). DZDP had the highest visit intensity, with Mean(SUDPA) of 3,144, more than either Weibo (Mean(SUDPA) of 2,370) or Ctrip (Mean(SUDPA) of 1,390) (Fig. 2b). For the parks intensively visited with more than 5000 visit number per km^2 (Sum(SUDPA) > 5000), DZDP had the greatest park number proportion at 12%. And Ctrip still had higher proportion of visit intensity at 71% with fewer park number proportion at 2% in this SUDPA scope. For visit intensity between 1,000 visits/km^2 and 5,000 visits/km^2 ($1000 \leq$ Sum(SUDPA)≤ 5000), Weibo still had higher park number proportion than the other platforms.

DZDP, Ctrip, and Weibo showed similarities in highly and intensively visited urban parks in Shanghai (Table 2, Fig. 1b). For all three SMD platforms, Shanghai Wild Animal Park was the most visited park, and Yu Garden, Shanghai was the park with the highest visit density. In particular, Yu Garden, Shanghai, was also among the 10 most visited parks according to DZDP and Ctrip. Most highly visited parks had large areas (more than 0.5 km^2) such as Shanghai Chenshan Botanical Garden (2.0700 km^2), Riverside Avenue, Shanghai (3.0000 km^2), and Gucun Park, Shanghai (1.8000 km^2). On the other hand, parks with higher visit density had smaller areas (mostly less than 0.1 km^2), such as Shaoxing Park, Shanghai (0.0024 km^2), Kunshan Park, Shanghai (0.0030 km^2), and Huoshan Park, Shanghai (0.0037 km^2). Moreover, most of the highly visited and high visit density parks had high star ratings of greater than 3, such as Shanghai Chenshan Botanical Garden, Gucun Park, Shanghai, and Shanghai Wild Animal Park, which all had 5-star ratings.



(a)

SUD

All parks

	Ctrip	DZDP	Weibo
Sum(SUD)	21,411	61,212	33,123
Mean(SUD)	98	245	139
Min.(SUD)	1	1	1
Max.(SUD)	4,448	7,162	1,368
Std. dev. (SUD)	510	724	231
PN.	218	250	238

Parks of Sum(SUD)>1000

	Ctrip	DZDP	Weibo
PN.	6	17	3
PN. Pro. (%)	3	7	1
Sum(SUD)	17,222	40,665	3,763
Sum(SUD) Pro. (%)	80	66	11

Parks of 100≤Sum(SUD)≤1000

	Ctrip	DZDP	Weibo
PN.	6	53	70
PN. Pro. (%)	3	21	29
Sum(SUD)	1,629	16,137	24,428
Sum(SUD) Pro. (%)	8	26	74

Parks of 0<Sum(SUD)<100

	Ctrip	DZDP	Weibo
PN.	206	180	165
PN. Pro. (%)	94	72	69
Sum(SUD)	2,560	4,310	4,932
Sum(SUD) Pro. (%)	12	7	15

SUDPA

All parks

	Ctrip	DZDP	Weibo
Sum(SUDPA)	303,059	785,887	564,173
Mean(SUDPA)	1,390	3,144	2,370
Min.(SUDPA)	5	7	10
Max.(SUDPA)	182,789	128,526	35,632
Std. dev. (SUDPA)	12,407	9,950	4,058
PN.	218	250	238

Parks of Sum(SUDPA)>5000

	Ctrip	DZDP	Weibo
PN.	5	30	26
PN. Pro. (%)	2	12	11
Sum(SUDPA)	215,812	536,847	296,202
Sum(SUDPA) Pro. (%)	71	68	53

Parks of 1000≤Sum(SUDPA)≤5000

	Ctrip	DZDP	Weibo
PN.	19	86	101
PN. Pro. (%)	9	34	42
Sum(SUDPA)	39,344	195,597	224,369
Sum(SUDPA) Pro. (%)	13	25	40

Parks of 0<Sum(SUDPA)<1000

	Ctrip	DZDP	Weibo
PN.	194	134	111
PN. Pro. (%)	89	54	47
Sum(SUDPA)	47,902	52,443	43,602
Sum(SUDPA) Pro. (%)	16	7	8

No. Abbreviation: Minimum (Min.); Maximum (Max.); Standard deviation (Std. dev.); Park Number (PN.); Proportion (Pro.)

(b)

Fig. 2. Shanghai urban parks with SMD (2018.5.1–2019.4.31): (a) park number; (b) distribution of SUD and SUDPA.

Table 2
Ranking of the ten most visited and highest visit density urban parks according to SMD in Shanghai (2018.5.1–2019.4.31).

Rank	Park name					
	For visit from DZDP	For visit from Ctrip	For visit from Weibo	For visit intensity from DZDP	For visit intensity from Ctrip	For visit intensity from Weibo
1	Shanghai Wild Animal Park	Shanghai Wild Animal Park	Shanghai Wild Animal Park	Yu Garden, Shanghai	Yu Garden, Shanghai	Yu Garden, Shanghai
2	Gucun Park, Shanghai	Changfeng Park, Shanghai	Luxun Park, Shanghai	Jiading Wisteria Garden, Shanghai	Changfeng Park, Shanghai	Yanchun Park, Shanghai
3	Shanghai Zoo	Yu Garden, Shanghai	Changfeng Park, Shanghai	Rainbow Bay Park, Shanghai	Tan Garden, Shanghai	Jingan Park, Shanghai
4	Century Park, Shanghai	Shanghai Zoo	Shanghai Chenshan Botanical Garden	Jingan Sculpture Park, Shanghai	Xiaotaoyuan Green Space, Shanghai	Kunshan Park, Shanghai
5	Yu Garden, Shanghai	Century Park, Shanghai	Daning Park, Shanghai	Tan Garden, Shanghai	Donghu Green Space, Shanghai	Xiangyang Park, Shanghai
6	Daning Park, Shanghai	Gucun Park, Shanghai	Jingan Sculpture Park, Shanghai	Jingan Park, Shanghai	Kunshan Park, Shanghai	Jingan Sculpture Park, Shanghai
7	Shanghai Chenshan Botanical Garden	Riverside Avenue, Shanghai	Gucun Park, Shanghai	Shaoxing Park, Shanghai	Shaoxing Park, Shanghai	Huoshan Park, Shanghai
8	Shanghai Gongqing Forest Park, Shanghai	Shanghai Chenshan Botanical Garden	Shanghai Botanical Garden	Kunshan Park, Shanghai	Shanghai Zoo	Changshou Park, Shanghai
9	Shanghai Botanical Garden	Shanghai Daguan Garden	Fuxing Park, Shanghai	Guilin Park, Shanghai	Shanghai Wild Animal Park	Guilin Park, Shanghai
10	Jingan Sculpture Park, Shanghai	Lujiazui Center Green Space, Shanghai	Zhongshan Park, Shanghai	Shanghai Guyi Garden	Huoshan Park, Shanghai	Huashan Children's Park, Shanghai

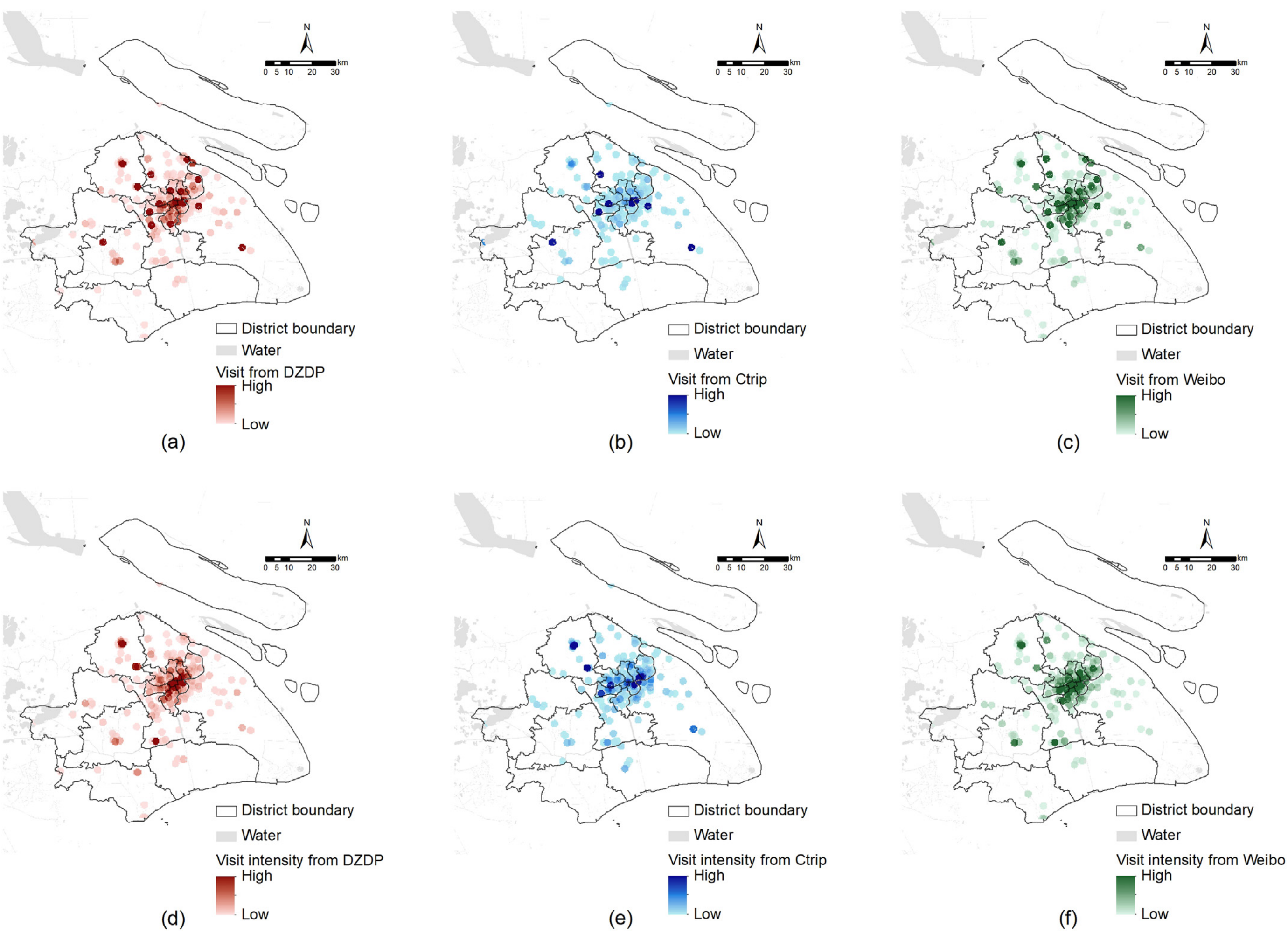


Fig. 3. Geographic distribution of park visit number and visit density (2018.5.1–2019.4.31) in Shanghai: (a) visit number from DZDP SMD; (b) visit number from Ctrip SMD; (c) visit number from Weibo SMD; (d) visit intensity from DZDP SMD; (e) visit intensity from Ctrip SMD; (f) visit intensity from Weibo SMD.

3.2. Spatial park visit patterns from SMD

As showed in Fig. 3, the geographic distributions of both visit number and visit intensity within the study time period obtained from SMD showed similarities among the DZDP, Ctrip, and Weibo SMD platforms. For all the three SMD, the distributions for both park visit number and visit intensity showed downtown area concentration distribution citywide. Higher park visit numbers were apparent in downtown districts such as Huangpu, Jiangan, and Zhabei, which generally had parks with smaller area, but with large park numbers and high park density. Such uneven distribution showed more obvious for park visit intensity. Parks with high park visit intensity were more concentrated in the downtown area. Between distributions of visit number and intensity, the suburb areas far from city center, such as Jinshan, Fengxian and Chongming District, showed a reverse consistency with fewer visit number and less visit density. Together with less quantity and lower density of parks, the suburb areas looked like less sightseeing attractive. But there were some exceptions − some parks of good star rating in areas far from downtown, such as Shanghai Wild Animal Park in Pudong District, Shanghai Chenshan Botanical Garden in Songjiang District and Jiading Wisteria Garden in Jiading District, attracted numbers of visits. Jiading Wisteria Garden was small in area and highly intensified visited. But visit intensity of Shanghai Wild Animal Park and Shanghai Chenshan Botanical Garden, both of large areas were not such distinct high compared to other parks. Moreover, some parks locating outside of but not far from downtown area, such as Gucun Park in Baoshan District, Shanghai Gongqing Forest Park in Yangpu District and Shanghai Zoo in Changning District, showed inconsistency of visit number and intensity. These parks were often large in area, highly visited, but with no such distinct high visit intensity.

According to the results of global spatial autocorrelation analyses, Moran's Index indicated a positive autocorrelation with a strong spatial clustering tendency for all three SMD ($p < 0.001$), and the Getis-Ord General G statistic revealed a marked trend toward concentration of large clusters with high statistical significance for all three SMD ($p < 0.001$). With the Getis-Ord Gi* statistic, the spatial distribution patterns of statistically significant hot and cold spots for park visit intensity from DZDP, Ctrip, and Weibo were obtained (Fig. 4). The distributions of hot and cold spots seem different among the figures of the three SMD. But the differences appeared in local areas, such as within the downtown area. The distributions of hot and cold spots for the whole citywide revealed similarity. For all three SMD, especially Weibo, hot spots were identified in the downtown area, which has a dense population and a high density of small and medium parks with longer history. Cold spots tended to be concentrated along the western edge of downtown, where population and park density are lower and fewer visits occur.

3.3. Temporal park visit patterns from SMD

Fig. 5 shows the temporal distribution of urban park visit number and visit density in Shanghai in season and workday/weekend/holiday periods. The correlations between the average park visit number and intensity per day showed significant positive trends ($p < 0.01$) for each SMD in the temporal categories of seasonal and workday/weekend/holiday. This indicated the similarity of temporal distributions between urban park visit number and visit density. The SMD from DZDP and Weibo gave similar distributions of park visit number and visit density, which were slightly different than those from Ctrip. The seasonal distribution clearly reflected a higher proportion of visit number and a higher visit density occurring in urban parks during spring for all three SMD sets. However, the SMD from DZDP and Weibo showed fewer park visit number and lower visit density in summer than in fall and winter, which was contrary to the situation in the SMD from Ctrip. The number and intensity that the average park was visited per day in the SMD from DZDP and Weibo on weekdays than were higher than on workdays, but lower than on holidays. In the SMD from Ctrip, the differences among the three periods were not obvious.

The results of wavelet analysis proved the multi-time-scale characteristics of time series for visit number and visit density of urban parks in Shanghai using SMD from DZDP, Ctrip, and Weibo. The multi-time-scale characteristics presented in wavelet coefficient real part contour maps showed no fewer than three scales of period change for both park visit number and visit density for all three SMD sets (Fig. 6a). Fig. 6b shows wavelet variance plot maps of the distribution of time-series wave energy for park visit number and visit intensity with period scale "/a". This indicates the major periods of temporal change in park visit number and visit density according to the SMD from DZDP, Ctrip, and Weibo. The major periods for park visit number and visit density presented similarity for the first or even the second major period for the three SMD sets. Moreover, the first and second major periods of visit number and visit density according to the SMD from DZDP and Weibo all appeared to be identical, with the first major period lasting about 90 days and the second major period about 128 days. Interestingly, Ctrip data had the same peak period scales in the major periods, but opposite values for the first and second major periods, with the first major period lasting about 128 days and the second major period about 90 days.

3.4. Spatio-temporal park visit patterns from SMD

Visualized as geographic distributions of park visit intensity by seasonal and workday/weekend/holiday periods, the spatio-temporal visit patterns of Shanghai urban parks derived from DZDP, Ctrip, and Weibo SMD were showed in Fig. 7. The geographic distributions of park visit intensity by both seasonal and workday/weekend/holiday periods obtained from SMD showed similarities from citywide among the DZDP, Ctrip, and Weibo SMD platforms. For all the three SMDs, the areas with the highest park visit density are mostly concentrated in the more developed areas of Shanghai: the downtown, covering the areas of Lujiazui, the Bund, and the North Bund at all seasons and on the days of workdays, weekends or holidays. Moreover, the distributions of park visit intensity were changed by both periods of seasonal and workday/weekend/holiday. In spring and autumn, the perfect time for outside in Shanghai, urban parks, especially those concentrated around downtown and those of good star rating far away from downtown area, had more visit density than in other two seasons. In non-workdays, especially the days of festival and holiday, more intensively visit density appeared than in workdays in Shanghai urban parks, especially for those concentrated around downtown and a few with good star rating far away from downtown area. In spite of these similarities, the geographic distribution change with workday and non-workdays periods seemed not that distinct as with seasons periods as showed in Fig. 7. With the help of Fig. 8, park visit intensity difference distributions between workday and non-workday were presented more clearly. More visit intensity differences were showed for the parks in downtown area and a few of good star rating far away from downtown. It indicated that these parks attracted more tourists in workdays had bigger amount of tourist increase in non-workdays. Consequently, the distributions of park visitation were more uneven in non-workdays for more concentration of park tourists in downtown area. The parks in city center and those locating outside of but not far from downtown area were not distinct different in visit intensity for seasons or workday/

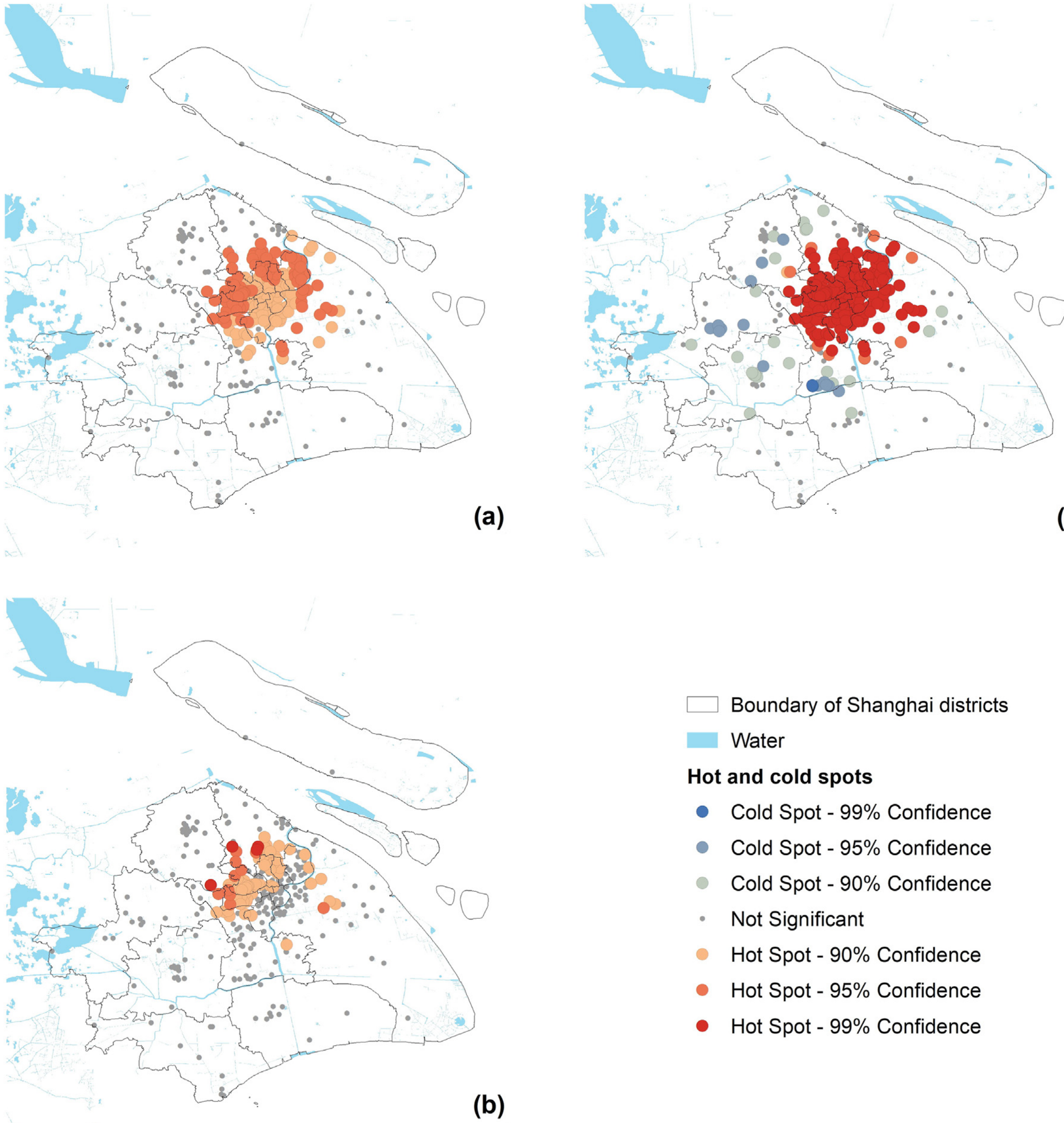


Fig. 4. Hot-spot maps of park visit intensity in Shanghai: (a) from DZDP SMD; (b) from Ctrip SMD; (c) from Weibo SMD.

weekend/holiday periods. Different from the city center parks highly density visited, the parks outside of but not far from downtown area had modest visit intensity for any period. Overall, for any season or day for workday, weekend or holiday, the parks in downtown districts, especially those in city center, were more intensively visited than those in suburbs.

4. Discussions

4.1. SMD comparisons

Because of the big differences between SMD widely used in the cities of east and west and the lack of relative researches focusing on non-western cities, we took the eastern metropolitan of Shanghai as the study site and the Chinese widely used SMD from the platforms of DZDP, Ctrip and Weibo as data sources. Compared to similar studies taking built-up or old town areas of Shanghai as study site for significant researches (Shen et al., 2017; Zhang and Zhou, 2018), this study had larger research area covering the whole city territory. With numerous residents, large area and rich resources and environments, the areas outside of old town in Shanghai, have parks covering nearly half in number and over half in area in total of all the parks of city. Therefore, it is important to take the whole city territory as the study area for comprehensive observations and results. As for data sources, this study was conducted on the basis of multiple popularly used SMD sources in various fields instead of only one SMD source since we found that a single SMD source may not cover all types of users or parks. Despite high similarity in coverage of parks, urban parks in Shanghai with data on Ctrip were still fewer than on other two platforms. It might because of their website characteristics. As described in Table 1, Weibo and DZDP were social media products served for people's everyday life. Ctrip was developed for traveling, and might not be used as popular as other two platforms when citizens take a walk in

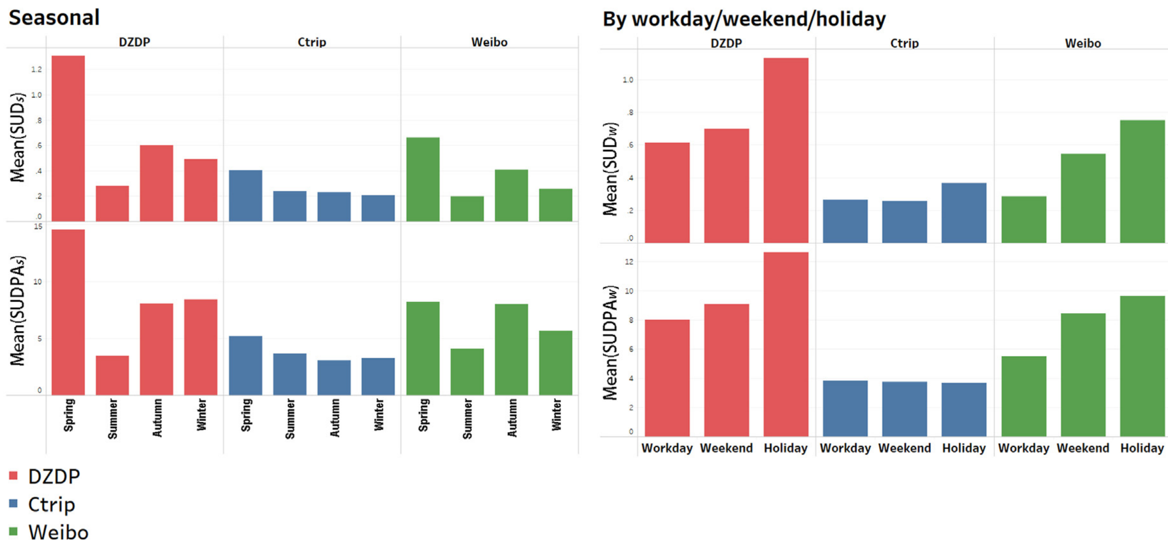


Fig. 5. Temporal distribution of SMD park visit number and visit intensity in Shanghai by seasonal and workday/weekend/holiday periods.

the parks in their neighborhoods. For the parks with total SMD visit number more than 1000 (Sum(SUD) > 1000) and SMD visit intensity more than 5000 (Sum(SUDPA) > 5000) (Fig. 2b), Ctrip had lower park number proportion but higher total park visit proportion. This indicates that Ctrip was used more unevenly and had more accesses than the other platforms for parks more SMD visited. It might because the urban parks more visited on website were famous and popular tourist attractions. And as described in Table 1, Ctrip is the most travel users and the largest number of travel comments. Compared to DZDP or Weibo, Ctrip had much more commented for those well-known destinations than those roadside green spaces with less attractions due to its travel website product feature. In addition, from the park visit number and visit density patterns obtained from the three SMD sets used in this study, similarities and differences were found to exist among the data sources. This finding was surprisingly consistent with other studies using the SMD widely used in western countries, such as Flickr, Panoramio and Instagram (Levin et al., 2017; Lyu and Zhang, 2019; van Zanten et al., 2016). Then, we analyzed these differences and try to find which SMD platform was considered best to assess the number of visits and visit density of urban parks. But it might indicate that multiple popularly used SMD sources may be better. With multiple SMD sources, more comprehensive park visit patterns could be obtained for better park usage understanding.

4.2. Park visit patterns

Being consistent with results obtained in other studies (Hamstead et al., 2018), many of the most visited and most intensively visited parks were similar. Interestingly, we further found that these parks were usually with high star ratings, such as Shanghai Yu Garden, Gucun Park and Jiading Wisteria Garden. This might show that the star rating of the parks in Shanghai by the government was roughly consistent with park attractions for visitors. As measures and directions of construction and management for urban parks, the published park rating standards in Shanghai could be considered reasonable on the whole and are suitable to be used in the future. As for visit attraction, it was widely believed by previous studies (Chen et al., 2018; García-Palomares et al., 2015; Ghermandi, 2016; Hamstead et al., 2018; Kovacs-Györi et al., 2018; Zhang and Zhou, 2018) and proved again by our study that cities presented inequality spatial, temporal, and spatio-temporal distributions for park visitation. In space, being consistent with some previous studies (Shen et al., 2017), we found relatively high numbers of park visits were concentrated in more developed areas of the city, such as the downtown covering the areas of Lujiazui, the Bund, and the North Bund. Temporally, we found relatively high numbers of park visits were concentrated in more clement seasons and at favorable times for traveling, such as spring, weekends, and holidays, which was consistent with results obtained in other studies (Chen et al., 2018; Kovacs-Györi et al., 2018). Moreover, in this study, we further found the parks with high visit number also have high visit intensity and the uneven distribution of park visit intensity were more obvious. And interestingly, the obvious city center concentration of park visit density were more intensively in non-workdays, especially the days of festival and holiday, than in workdays in Shanghai urban parks. It demonstrated that touring might be one of the reasons for crowded and congestion for downtown in Shanghai. Rational planning and distribution for varies urban parks might be a vital practice of city development for such a metropolitan with so many parks and such rapid development. It could not only alleviate uneven usage of park, but also relieve extreme congestion in local areas for the city. Our results also obtained that some parks with high star rating and high visit number, such as Shanghai Wild Animal Park, Shanghai Chenshan Botanical Garden and Gucun Park, Shanghai, were located outside of even far away from downtown. As illustrated in Section 2.1, the parks rated with high star ratings were not owing to location, but good performances on varies factors, such as good landscape, management and facility. It indicated that locating in downtown is absolutely not the requirement for park attraction increasing. Improving the construction and management level of the park itself might be the effective actions for high park visit. We might be inspired that locating attractive parks outside of downtown might be an effective way to alleviate the crowd of downtown and the uneven of park visit distribution for Shanghai.

4.3. Methods innovations

This research also had innovations for study methods with temporal and spatial dimensions to be more systematic. Most previous studies used one or two analyses, and few applied spatial, temporal, and spatio-temporal analysis at the same time to achieve a better understanding of visit patterns. Besides visual overviews of

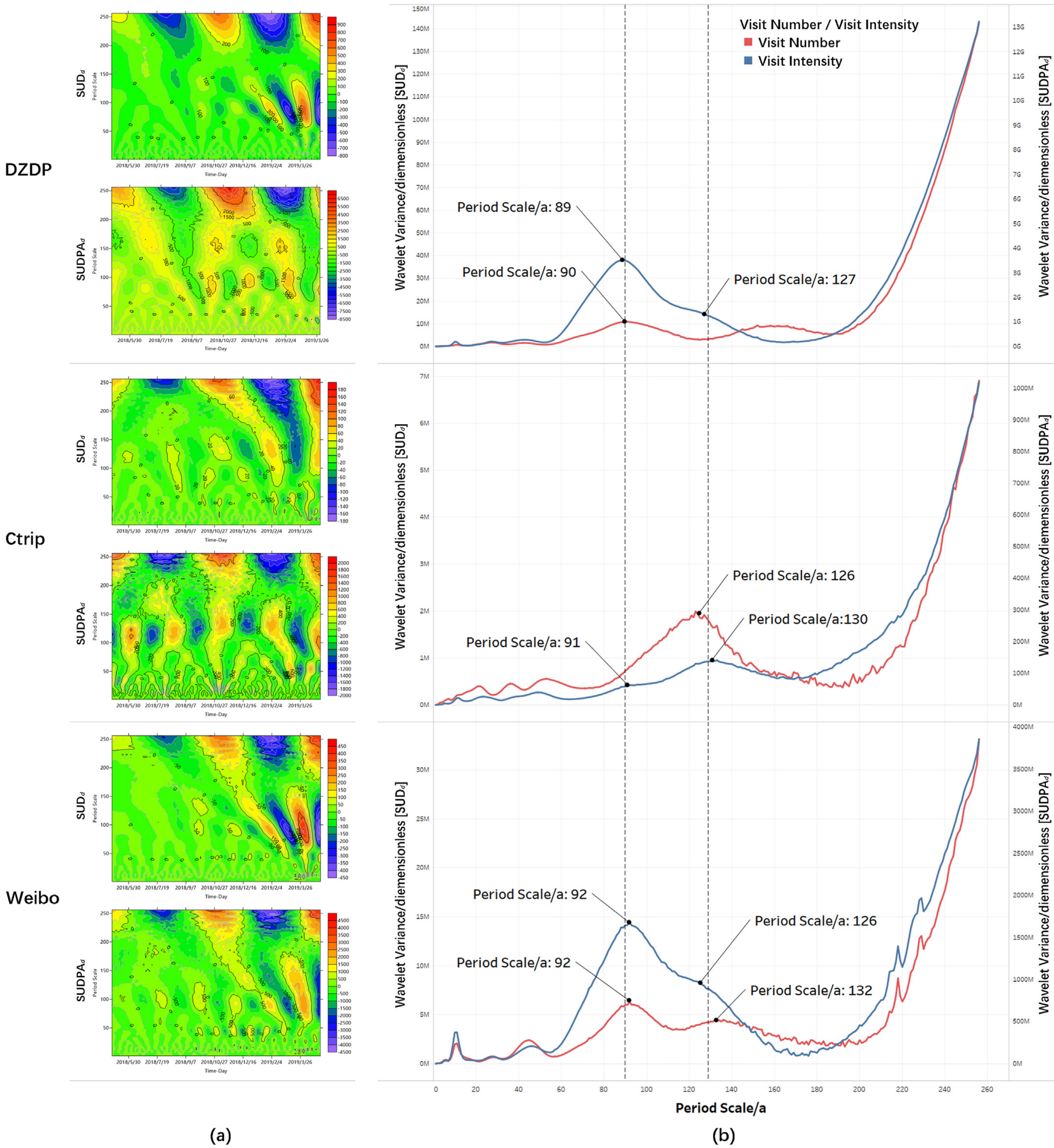


Fig. 6. Maps of wavelet analysis of visit number and visit intensity according to SMD from DZDP, Ctrip, and Weibo for urban parks in Shanghai: (a) wavelet coefficient real part contour; (b) wavelet variance.

the geographic distribution of Shanghai park visit number and visit density, the method used in this study took spatial autocorrelation into consideration, and a positive autocorrelation with strong tendency towards spatial clustering for all three SMD sets was apparent from spatial autocorrelation analysis. In addition, most previous studies used descriptive statistics to analyze temporal visit patterns (Barros et al., 2019; Kovacs-Györi et al., 2018). Few have used wavelet analysis to study the multi-time-scale characteristics of time series for park visit number and visit density, or to obtain the major periods of temporal change in park visit number and visit density patterns from SMD. Moreover, few previous studies used the results obtained from temporal and spatial

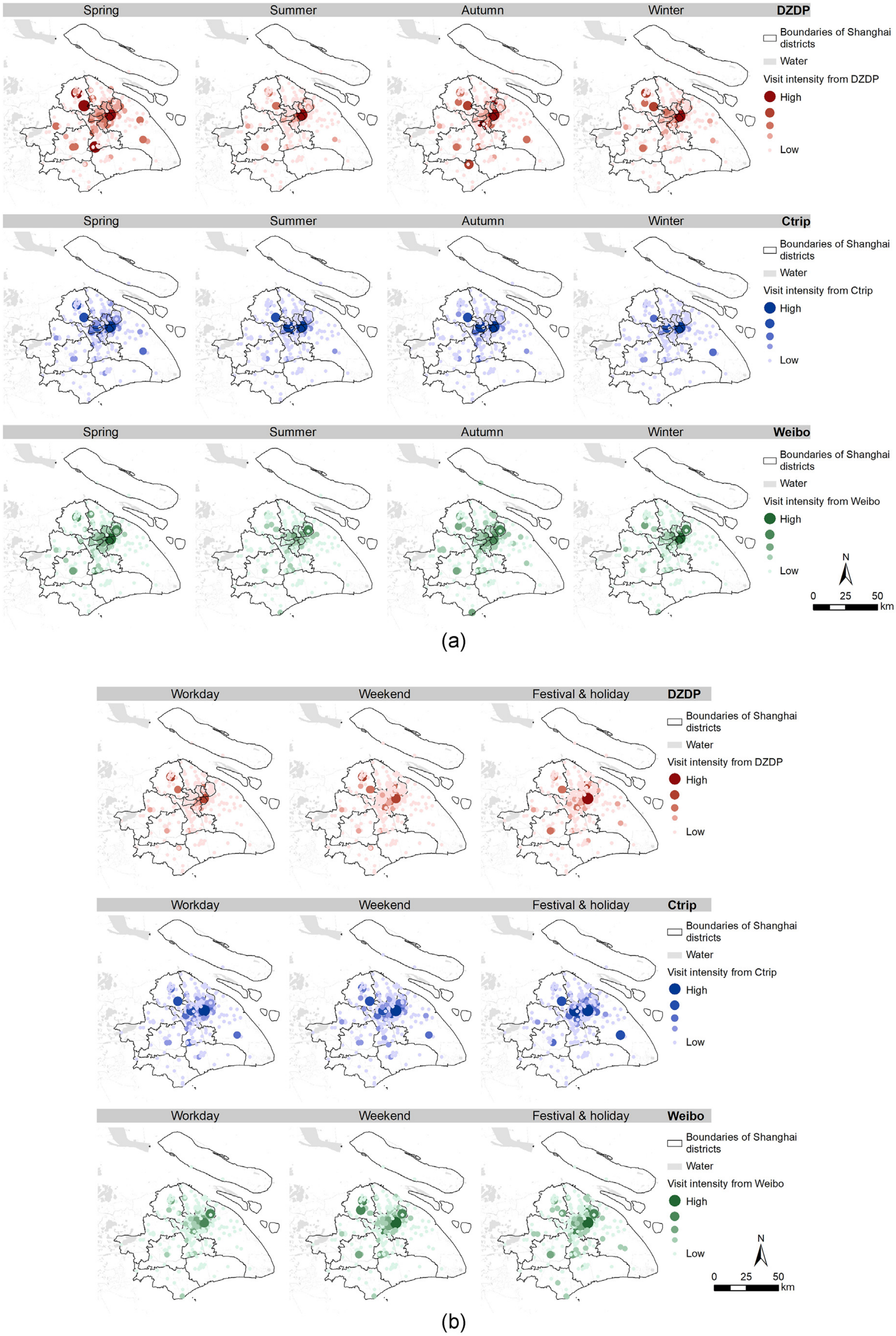


Fig. 7. Geographic distribution of park visit intensity according to DZDP, Ctrip, and Weibo SMD: (a) by season; (b) by workday/weekend/holiday.

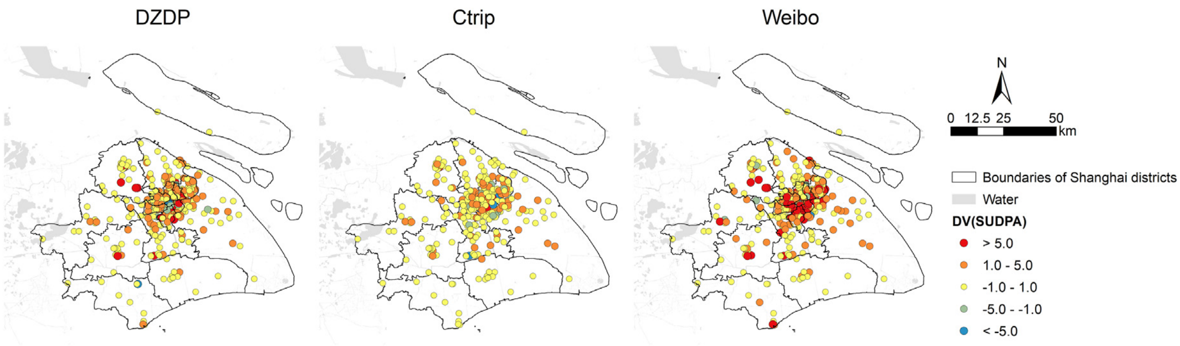


Fig. 8. Maps of park visit intensity difference between workday and non-workday according to DZDP, Ctrip, and Weibo SMD.

analysis as a basis for spatio-temporal analysis. As for the improvements and innovations we took for study area, data and methods, more comprehensive and systematic results were obtained. This study also had some limitations. To achieve a better understanding of park usage, it made analyses with multiple SMD datasets and comparisons among them. But the results obtained from different SMD sources were not combined into a synthesis one. There is a lot of overlapped users and data between different SMD platforms (Yan et al., 2015). It is unreasonable to directly combine data from different SMD platforms. There is a lot of problems needed to be solved, such as filtering overlapped data through highly sophisticated data analyses and using data combining methods involving some specific algorithms, coefficients or weights. These need a large amount of complicated and detailed studies, and would be done in the future. Moreover, the current study only used SMD sources from three platforms and collected the data for only one year. Clearly, using more SMD from different sources would made the results more comprehensive and richer. And more SMD data of longer time span could be taken in future study to better understand the park visit patterns for such a metropolitan with so many parks and such rapid development. Every year, not only the number of the parks is increasing, but also many of the parks are expanded and improvement in Shanghai. The changing of park visit patterns with new parks construction and old parks reconstruction could be assessed on the base of several years SMD. Planning and management of parks and city would be better inspired and guided.

5. Conclusions

Social media data, as a reliable proxy for empirical park visit information, could be used as a low-cost and effective way for park visit pattern research. However, most of the previous studies focusing SMD park visit patterns often used single study method and were on the base of SMD from single platform and widely used in Western counties. Therefore, it is time to furtherly use both temporal and spatial visit analysis with multiple SMD sources, especially those widely used in non-western countries, to obtain more comprehensive and systematic results of park visit pattern. To achieve this research purpose, the city of Shanghai, China, a world-influential eastern metropolitan with high popularity of social media, was chosen as the study site. And we used three of the most popular SMD in China as data source and multiple methods of descriptive and spatial statistics for analysis of both temporal and spatial dimensions. With this study, (1) the methods of SMD application for more efficient and advanced measures in park visit pattern assessments could be improved to enlighten other cities with regard to systematic evaluation of park visit estimation and usage patterns; (2) the lack of park visit pattern study for SMD out of non-western countries would decrease; (3) based on the results in the temporal, spatial, and spatio-temporal domains in this research, park usage in such metropolitan could be systematically and comprehensively studied; (4) this could lead to more reasonable park distribution regulation and better green space management and urban development, and offer a starting place for urban planners, landscape designers, and policy-makers.

CRediT authorship contribution statement

Huilin Liang: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, and, Writing – review & editing. **Qingping Zhang:** Conceptualization, Writing – review & editing, and, Supervision.

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