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Spatiotemporal Analysis to Observe Gender Based Check-In Behavior by Using Social Media Big Data: A Case Study of Guangzhou, China

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Abstract: In a location-based social network, users socialize with each other by sharing their current location in the form of "check-in," which allows users to reveal the current places they visit as part of their social interaction. Understanding this human check-in phenomenon in space and time on location based social network (LBSN) datasets, which is also called "check-in behavior," can archive the day-to-day activity patterns, usage behaviors toward social media, and presents spatiotemporal evidence of users' daily routines. It also provides a wide range of opportunities to observe (i.e., mobility, urban activities, defining city boundary, and community problems in a city). In representing human check-in behavior, these LBSN datasets do not reflect the real-world events due to certain statistical biases (i.e., gender prejudice, a low frequency in sampling, and location type prejudice). However, LBSN data is primarily considered a supplement to traditional data sources (i.e., survey, census) and can be used to observe human check-in behavior within a city. Different interpretations are used elusively for the term "check-in behavior," which makes it difficult to identify studies on human check-in behavior based on LBSN using the Weibo dataset. The primary objective of this research is to explore human check-in behavior by male and female users in Guangzhou, China toward using Chinese microblog Sina Weibo (referred to as "Weibo"), which is missing in the existing literature. Kernel density estimation (KDE) is utilized to explore the spatiotemporal distribution geographically and weighted regression (GWR) method was applied to observe the relationship between check-in and districts with a focus on gender during weekdays and weekend. Lastly, the standard deviational ellipse (SDE) analysis is used to systematically analyze the orientation, direction, spatiotemporal expansion trends and the differences in check-in distribution in Guangzhou, China. The results of this study show that LBSN is a reliable source of data to observe human check-in behavior in space and time within a specified geographic area. Furthermore, it shows that female users are more likely to use social media as compared to male users. The human check-in behavior patterns for social media network usage by gender seems to be slightly different during weekdays and weekend.

Keywords: social media big data; lbsn; check-in density; spatiotemporal analysis; KDE; GWR; SDE; Guangzhou

1. Introduction

In recent years, social media has dramatically expanded in popularity around the world and became an integral part of the information ecosystem in both application and research perspectives due to its unprecedented reach to masses (i.e., users, consumers, businesses, governments, and nonprofit organizations) [1]. Historically, traditional data sources (i.e., survey, census) [2,3] are analyzed to observe human activity behavior [4,5], lifestyle patterns [6], and gender differences [7], but these data sources are considered to be more expensive both in the collection and the analysis. This, in turn, requires more processing time and results in data sparsity. Policymaking and delivery of services are closely intertwined with city planning and human mobility. However, due to the limitations highlighted above, these traditional methods are considered to be less effective in policy-making and delivery of services [8].

A considerable amount of previous research [9–14] studied the demography of social media users and discussed reasons that influence people to use LBSN. These recent research studies highlighted the motivations for social media network use among both male and female users. Smith [9] argued that female users tend to use online social media to interact with families and friends rather than male users. Muscanell and Guadagno [15] put forward that male users mostly use online social media for making new relationships while female users utilize social media more for the maintenance of the relationship. Moreover, the pattern and motivation to use the social media network by both male and female users seems to be slightly different. Hwang and Choi [16] explored the online usage behavior of Weibo by college students and the motivations of usage by gender. Lastly, it was suggested that online usage behavior of Weibo acts as a platform to search for information on social issues and interests. Rossi and Musolesi [17] proposed methodologies to identify the unique users from check-in data and characterized the users by the spatiotemporal trails from the check-ins made over time and the frequency of visit to specific locations [16,18].

As part of online social interaction in LBSN's [19,20], users [21] can announce their geo-location [22], announce the activity performed [23], and discuss places they visit (referred as "check-in" [24]). By the third quarter of 2017, Weibo [25] amounted up to 376 million monthly active users (MAU), 172 million daily active users (DAU). Among the active users, 93% were accessing Weibo through mobile devices [26,27]. This enormous number of users were attracted worldwide due to fast information sharing and check-in phenomenon [28], which generates high volumes of data (referred to as "Big Data" [29,30]). Irrespective of fundamental limits to demonstrate human check-in behavior [31], i.e., prejudice of gender, frequency sampling prejudice, and location type prejudice. Check-in reveals human check-in behavior in space and time. The motivations for using Weibo may differ between male and female users. Statistics show that 50.10% of Weibo users are male, 49.90% are female [32], and it is considered one of the most popular social media platforms in China [33] due to the unavailability of Facebook and Twitter. According to the China Internet Network Information Center (CNNIC) [34], 72% of the total Sina Weibo users were 20 to 35 years of age. Among them, the majority of users are in their 20s and constitute the heaviest users [16,35].

Currently, LBSN data are obtainable at a relatively cheap cost with information such as timestamps, location, and gender [36], and can be analyzed to perceive human check-in behavior as equated to the previously stated traditional datasets. Intrinsically, LBSN data offers new dimensions to help and create new techniques and methods to observe human check-in behaviors [37] and differences in gender. In the current study, we explore the LBSN data to observe human check-in behavior and intensity of check-ins during the period within a city at an individual level. Moving toward this direction, the research presented in the current study aims to investigate the spatiotemporal information related to the check-in to identify and determine human check-in behavior. The simple hypothesis is that people follow a typical daily routine: e.g., go to work, eat at some preferred restaurant, go shopping, and go back home.

Consequently, if we have enough data to observe distinctive human behaviors, such knowledge can be analyzed to understand human behavior by using LBSN check-in information as a proxy measure. Recent research [38–42] explored the LBSN datasets to examine people's daily check-in behavior and mobility patterns in different cities rather than Guangzhou, China. However, most of the existing literature focused on Facebook and/or Twitter rather than Weibo. Therefore, this study will also serve to fill a research gap by focusing on the most popular Chinese local social network site, Sina Weibo, and study area as Guangzhou, China. Moreover, previous studies [16,18] explored gender-based check-in behavior analysis in Sina Weibo and suggested that women are more likely to use Sina Weibo to provide help and information to others. However, studies to date have not fully investigated gender-based check-in behavior analysis in Sina Weibo usage especially in Guangzhou, which also motivated the current study. The primary objective and contribution of the paper are twofold and can be summarized as follows.

1. The primary objective of the research is to characterize behavioral differences between male and female using the "check-in" function of the Sina Weibo (launched by Sina Corporation [43] in 2009).
2. The main contribution of our work consists of examining the check-in density by using KDE. The GWR method was applied to observe the relationship between check-in and districts with a focus on gender during weekdays and weekend. Lastly, the standard deviational ellipse (SDE) analysis is used to analyze the orientation, direction, spatiotemporal expansion trends and the differences of check-in behavior by male and female in Guangzhou, China, which was missing in the existing literature regarding gender-based check-in behavior analysis.

Moreover, this line of research can help improve our understanding of human check-in behavior and consider LBSN data (a source of big data) as a supplement to than a substitute of traditional data sources while taking a decision on policy making [44–46] associated with urban planning [47,48] and city functionalities [49].

The organization of the rest of the paper is as follows. Section 2 presents the literature review. Section 3 defines the study area and dataset. Section 4 presents the methodology. Section 5 presents the results and discussion for the experimental results performed on the dataset. Lastly, Section 6 concludes the paper and proposes some further research issues.

2. Literature Review

The research on spatial analysis has significantly progressed toward observing human behavior, which has long been constrained by traditional data sources with improved abilities to capture, analyze, and process LBSN data [50,51]. The terminology "social network site" (SNS) [52] denotes to web-based services [53] and is a social structure made up of individuals connected by one or more specific types of interdependency, such as friendship, common interests, and shared knowledge [54]. It allows users to (1) construct a profile, (2) articulate users' social links, and (3) track and view shared social ties within the system [55–57]. Moreover, it reflects the real-life social networks among people through online platforms such as a website, providing ways for users to share ideas, activities, events, and interests over the Internet.

SNSs first emerged in the mid-1990s [56,58–60] as a simple mode of communication to interact with people over the Internet by using personal computers only [61]. Recent technological advancements of "smart" mobile devices empowered users in a variety of ways in existing social networks by adding location dimension and providing a potential benefit to access social network accounts on personal computers along with mobile devices [21]. Primarily, desktop computers were the modes to use, connect, and share information on SNSs [62], but, with the introduction of smartphones, the access to SNSs became convenient to use, connect, and share information with their "friends" [63] on the move [64,65]. With this rapid development of mobile phone technology, users can easily communicate and share information (i.e., text, audio, and video) progressively by using the geo-location [66]. The development of LBSNs progressed with the integration of communication technologies [67], which, in turn, provide fast sharing of information about what, where, why, and with whom users share information. LBSNs include geographic services (i.e., geo-location) and capabilities (geo-tagging) to assist in exploring social dynamics and make it an essential type of social networking [20,68], which allows the sharing of users' current geolocation and discovering their friends' location, which, in turn, raises users' privacy concerns [69,70]. Privacy in LBSN primarily depends on legislative and business-oriented actors involved in data sharing even though privacy is not an individual issue. Yet, some of the personal data is shared unintentionally or willingly by the user [71–74]. Sometimes, the location is deliberately shared by users for the sake of benefits (i.e., customers can enter competitions, donate to charities, or earn additional loyalty credit) in exchange of information, branded hashtags, check-ins, or experiences on LBSN [75].

Various studies based on LBSN datasets to observe human check-in behavior under domains like privacy [73,76,77], gender differences [78], geographic spaces [56], urban emotions [79], activity location choice, lifestyle patterns [6,80–82], and operations and production management [83] have been conducted. Li and Chen [63] studied location sharing by the users in the real world, and presented data analysis results over user profiles, update activities, mobility characteristics, social graphs, and attribute correlations. Benevenuto et al. [84] analyzed the frequency and duration of social network connectivity, as well as the users, conduct of different activities on these sites differentiated by types and sequences. Chang and Sun [85] analyzed the LBSN dataset to point out the influence of factors where users check-in, including historical check-ins, similarity to historical places, where their friends check-in, time of day, and demographics. Lei et al. [86] spatiotemporally analyzed the LBSN dataset to observe the human dynamics regarding differences in gender, behavior in check-in, and online time duration in Beijing's Olympic Village. Moreover, it argued that female users are more likely to interact in social media in comparison to male users. Hu and Zhang [87] utilized clustered spatiotemporal data and suggested a selection method. Moreover, exploratory spatial data analysis (ESDA) is performed to acquire the datasets with the prospects of quick grouping by mining the Weibo check-in data. Saleem et al. [88] explored the prominent locations and introduced a method of location influence with the ability to reach out geographically by using LBSN data. Furthermore, a memory-efficient algorithm was proposed, which resulted in efficient and scalable diverse sets of locations with a broad geographical spread. In addition, previous research [89–92] focused on observing human mobility patterns and analyzing check-in data for location prediction and venue tagging in the city by using LBSN datasets. While References [37,93] mainly focused on examining the factors that can predict the uses and patterns of using LBSN.

Many applications utilized the concept of automatic venue tagging to observe spatial differences [94,95]. While Gao and Liu [96] argued that temporal features and ranking of a user's geo-location history are considered to be irrelevant with the integration of human mobility in LBSN. Yang et al. [97] explored check-in behavior and mobility patterns by analyzing the spatiotemporal distribution of geotagged social media data messages and activity patterns. Moreover, References [92,98,99] analyzed the large LBSN datasets to study the variation of urban spaces and observed the spatial characteristics of the social networks, which may arise in LBSN users. Muscanell and Guadagno [15] examined the impact of gender and personality on the use of Facebook and MySpace and reported that male users use social media for relationship formation while female users use social media for relationship maintenance. Moreover, female users are reported low in agreeableness while using instant messaging more often than male users is high in agreeableness, whereas male users are reported low in openness while playing more online games compared to female users are high in openness. Rzeszewski and Beluch [100] addressed the gap (representation and representativeness) in data by investigating the LBSN users, based on the spatiotemporal distribution of the content produced (demographics of the user population). While Guan et al. [101] studied the concentration and significance of users' thoughts on Sina Weibo and Feng et al. [102] analyzed China's city network based on users' friend relationships and check-in behavior on Sina Weibo.

LBSN datasets have been exploited in various research studies for the urban development and its environmental hazards [103], expansion and exploration [104–106], travel and activity patterns [107,108], and disaster management [109–111], emergency mapping [112], Special Event Population [113], and urban sustainability [114]. Hong [115] highlighted various factors to observe the payment patterns and willingness of buyers by utilizing the LBSN dataset. Mazumdar et al. [116] proposed a prediction model, which gathers surreptitiously visited locations from an available user trajectory. Moreover, the relationship between a user's checked-in data for predicting the unchecked or hidden locations was investigated. Dokuz and Celik [117] proposed a method to discover the user's historical data and measures based on communally important locations for each user's (individual's) preferences. Furthermore, an algorithm was proposed that was compared with a naïve alternative using real-life Twitter dataset. Fiorio et al. [118] developed a methodology for parsing the population-level migration signal from individual-level point-in-time data using flexible time-scales. Moreover, a stochastic model was proposed for simulating patterns in digital trace data and test it against three datasets: geo-tagged Tweets and Gowalla check-ins. Wu et al. [119] analyzed the impact on housing prices when neighborhood land uses are mixed. By using geographic information system data, three quantitative measures of the land-use mix were created, and these measures were computed for various neighborhoods in Beijing's central city. The research base on check-in behavior analytics is useful to know about gender-based human check-in behavior, but, under the scope of the current study, the connection with other indicators of gender equality [120,121] are not considered.

3. Dataset and Study Area

The dataset mined in this study was obtained from Sina Weibo. It covered the Guangzhou area for the period between January and May 2016, which contains 852,560 check-ins from 20,634 users. Guangzhou is considered to be one of the most attractive destinations in China due to its heterogeneous population and job opportunities regarding demographic characteristics [122], socioeconomic status [123,124], and place of origin [28]. Guangzhou, China (longitude from 112°57′ to 114°3′E and latitude from 22°26′ to 23°56′N [125]) is located on the south coast of Pearl River Delta (PRD) with a 14.5 million population [126] and had a total area of 7434.4 km^2 [127]. In 2015, Guangzhou was divided into 11 districts (Baiyun, Conghua, Haizhu, Huadu, Huangpu, Liwan, Nansha, Panyu, and Zengcheng) [128]. Six of the districts (Baiyun, Huangpu, Haizhu, Liwan, Tianhe, and Yuexiu) are denoted as the center of the city [129,130], as shown in Figure 1.

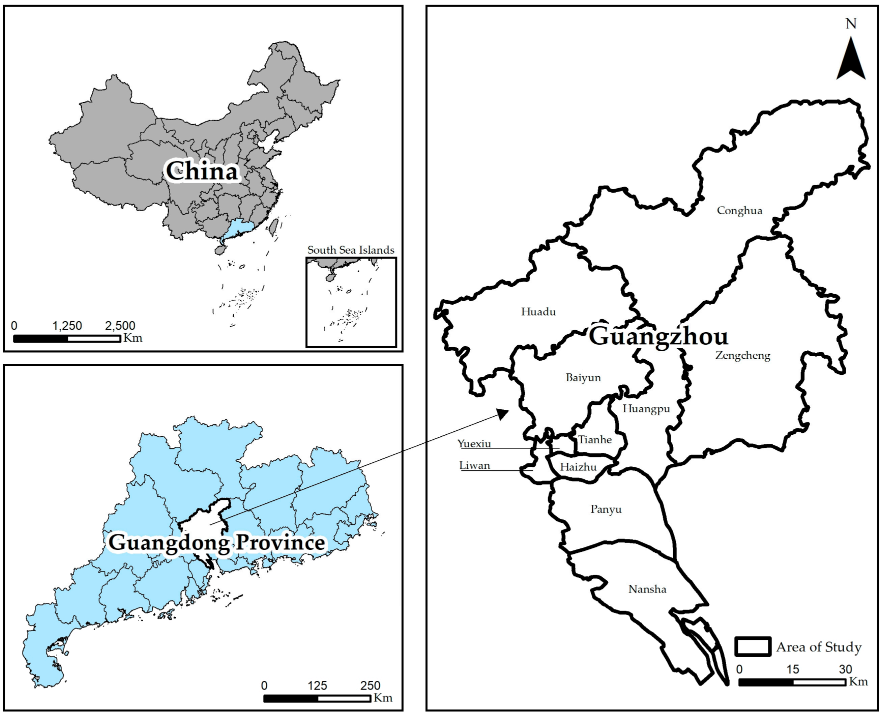


Figure 1. Map of Guangzhou, China.

The Weibo dataset used in the current study contains information like the unique id of user id, time, and date of the check-in. Additionally, geo-location (longitude and latitude), venue type, venue category, and gender collected via the web or mobile applications [131]. Therefore, it is assumed that the LBSN dataset archives the day-to-day activity patterns, usage behaviors toward social media, and presents spatiotemporal evidence, which is related to the daily routines of users [114]. A typical Weibo "check-in" is represented as: check-in (1305141104 006810) = {5503767214, ####, 1305141104 006810, Fri Apr 22 09:37:03 +0800 2016, m, 113.854085, 23.527322}. Where 1305141104 006810 denotes "status_id," 5503767214 denotes "user_id," #### denotes the "user_name," Fri Apr 22 09:37:03 +0800 2016 denotes "day, month, date, time and year," m denotes "gender" and 113.854085, 23.527322 denotes geo-location.

4. Methodology

In the current study, we analyzed the Weibo based geo-location dataset (Jan-May 2016) from Guangzhou, China. Figure 2 presents the check-in behavior analytics framework, where the LBSN data analysis methodology involves the two stages: collection, storage, and analysis of LBSN data. The download of Weibo data is the significant step of Weibo data collection and storage stage. To collect check-in data, we implemented a multi-threaded crawler to access the Weibo API. In turn, the crawler collects the check-in data filtered by gender, and the results are processed with entries that have geolocation. The outcome is in single JSON (JavaScript Object Notation) file by utilizing a python-based Weibo API (an open interface of Sina Weibo) [132,133], which is considered an extensively used data format [134,135]. To be adequately analyzed, the dataset is converted into a distinct file in the CSV (Comma-Separated Values) format so that the check-ins could be listed regarding their publishing time. However, the critical task in the data analysis stage is to mine and investigate the features of LBSN data. Moreover, during data pre-processing, invalid records are excluded by considering four criteria points: (a) availability of information i.e. user id, date, time, gender, geo-location, (b) location of the records must be in Guangzhou, China, (c) the range of record is within the date and time, and, (d) as a minimum, each user checked-in twice a month. After pre-processing (noises, void records, and bogus users) of 903,008 anonymized check-in records, 852,560 check-in records associated with the geographical area are picked up between January to May, 2016. Lastly, the task in the data insight stage is to analyze and investigate the features of LBSN check-in data by considering location, time, and gender and visualize data by using ArcGIS [136] to produce density maps [137] and trends [138,139].

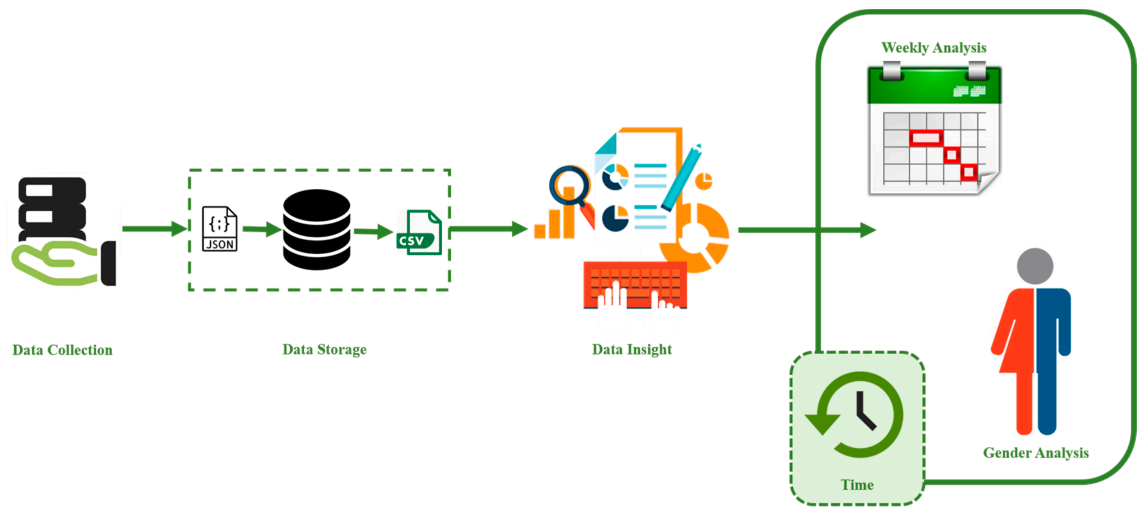


Figure 2. Check-in behavior analytics framework.

4.1. Kernel Density Estimation

In order to detect hot-spots and observe gender differences in check-in behavior, we estimated the density function of check-in using a kernel density estimation (KDE) [140–142]. KDE is considered a popular spatiotemporal investigation practice that is used to observe the features of location (i.e., destination, time) comparative to each other. KDE is an evolving spatiotemporal means that has earlier been used [143–146] to examine several characteristics of the social media (but not limited to LBSN) data analytics such as users' online activity and movement patterns [38], check-in behavior [147], city boundary definitions [148,149], and point-of-interest recommendations [150]. Moreover, it examines the diffusion of destinations in neighborhoods, allows investigators to see where destinations are densely distributed, and where they are more intensely dispersed. Lastly, it attempts to produce a smooth density surface of spatial point events in the geographic space [151].

The goal is to produce a smooth density surface that signifies the density of the point group. The algorithm is functioned by setting the search scope (window). The central grid of the window gives the weight of each grid unit to an outward grid, according to the principle of anti-distance weight. Moreover, in the window, the weights and density values are the sum of kernel density value that belongs to the central grid.

To measure the density of historical check-ins at point "*x*," let $f_i(x)$ be a density function at geo-location "*x*."

$$f_i(x) = k(x,h) = \frac{1}{xh}\sum_{j=1}^{X} K\left(\frac{\|x - x_j\|}{h}\right) \tag{1}$$

where "*x*" represents the geo-location (longitude and latitude) of check-in dataset "$1 < i < n$" at which density estimation with bandwidth "*h*" is calculated. In KDE, bandwidth is considered an important parameter. If the bandwidth is too large, then the point density surface will become too smooth, while too small will change point density distribution abruptly. Therefore, the optimal bandwidth is determined by repeatedly setting the bandwidth and comparing the smoothness of the point density surface. Bandwidth "*h*" is dependent on the resulting density estimate "$f_i(x)$". "X" is the total number of check-ins in the dataset, "*j*" points to a signal geo-location, "K" is a standard normal density function, "$\|.\|$" denotes the Euclidean norm [152–154], and "x_j" is the geo-location of check-in "*j*."

The log-probability data-driven option is used to assess the value of bandwidth "*h*" in constructing the density estimate below.

$$L(h) = \frac{1}{x_t}\sum_{j=1}^{x_t} log\ f_i\left(x^j \middle| X, h\right) \tag{2}$$

where the "x_t" events "x^j" are data points in the dataset X. Higher value of *L(h)* is ideal since it shows that the higher probability is being allocated to new but invisible data. Hence, a simple method for bandwidth selection is to perform a grid-search on "*h*" using a validation set.

4.2. Geographically Weighted Regression (GWR)

GWR is a spatial regression technique that considers spatial nonstationarity and allows local parameters to be estimated. It is considered an extension of a traditional linear regression framework, and is, accordingly, easy for the specification. Unlike the complex mechanism of the Bayesian spatial model, the GWR method is easier for researchers to understand and is widely used in a practical application. In particular, in the GWR models, the coefficients of variables can be visualized in an easily identifiable manner, which could provide insightful suggestions for city planners and check-in behavior analysis [155]. A typical GWR model takes the following form.

$$\mathrm{y}_i = \beta_0(\mathrm{u}_i, \mathrm{v}_i) + \sum_{\mathrm{k}} \beta_k(\mathrm{u}_i, \mathrm{v}_i)\mathrm{x}_{\mathrm{ik}} + \varepsilon_i \tag{3}$$

where $(\mathrm{u}_i, \mathrm{v}_i)$ represents the geo-coordinates (longitude, latitude) of observation *I*, β_0 $(\mathrm{u}_i, \mathrm{v}_i)$ represents the intercept value, β_k $(\mathrm{u}_i, \mathrm{v}_i)$ represents the estimated parameter for the kth variable of observation *I*, and ε_i represents the error term.

This means that the estimated coefficients are allowed to vary in space. One assumption of GWR is that the observed data near the observation *i* have more influence in estimating β_k $(\mathrm{u}_i, \mathrm{v}_i)$ than the data farther from *i*. The parameter β_k $(\mathrm{u}_i, \mathrm{v}_i)$ is estimated below.

$$\beta_k(\mathrm{u}_i, \mathrm{v}_i) = \left(\mathrm{X}^\mathrm{T}\mathrm{W}(\mathrm{u}_i, \mathrm{v}_i)\mathrm{X}\right)^{-1}\mathrm{X}^\mathrm{T}\mathrm{W}(\mathrm{u}_i, \mathrm{v}_i)\mathrm{Y}. \tag{4}$$

where the weighting matrix W(u_i, v_i) is a diagonal matrix, and the off-diagonal elements are all zero. The estimation of GWR is part depend on the bandwidth selection for observation i neighbors. For areas with more data points, the bandwidth of the kernel will be lower, while, for areas with few data points, the bandwidth of the kernel will be larger. In the current study, an appropriate bandwidth is selected based on the minimum Akaike information criterion for the GWR model (AIC) [156].

4.3. Standard Deviational Ellipse (SDE) Analysis

The standard deviation ellipse (SDE) [157] analysis is often used to depict the spatial characteristics of a geographical entity, such as central tendency, dispersion, and directional trends. SDE not only is an abstract expression for individual spatial distribution, but it also builds more comprehensive and realistic models of human mobility and online behavior [158]. It is quite effective for a discrete description of anisotropic events in the spatial point pattern analysis, which has been widely used in extensive research such as urban structure analysis [159]. This useful tool is chosen in this study to analyze the check-in behavior at a more detailed level.

There are four parameters of SDE that include the ellipse center, major axis, minor axis, and azimuth. The major and minor axes of the SDE are calculated according to Equation (5), and their proportional relations denote the degree of flattening the SDE. The rotating azimuth is calculated according to Equation (6), which reflects the main trend directions [160,161]. The standard deviations of the major and minor axes of the SDE are calculated according to Equation (7). The major and minor axes of the SDE form the spatial region of the check-in distribution, and the direction of the major axis is defined as the dominant direction of the variation trend [162]. The ellipse center of SDE $(\overline{X}_w, \overline{Y}_w)$ is calculated below.

$$\begin{cases} \overline{X}_w = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \\ \overline{Y}_w = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \end{cases} \tag{5}$$

The azimuth α of SDE is calculated using the equation below.

$$\tan\alpha = \frac{\left(\sum_{i=1}^{n} w_i^2 \widetilde{x}_i^2 - \sum_{i=1}^{n} w_i^2 \overline{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n} w_i^2 \widetilde{x}_i^2 - \sum_{i=1}^{n} w_i^2 \overline{y}_i^2\right)^2 + 4\sum_{i=1}^{n} w_i^2 \widetilde{x}_i^2 \overline{y}_i^2}}{2\sum_{i=1}^{n} w_i^2 \widetilde{x}_i \overline{y}_i} \tag{6}$$

The standard deviations of the ellipse σ_x and σ_y in the x and y directions are calculated using the formulas below.

$$\begin{cases} \sigma_x = \sqrt{\frac{\sum_{i=1}^{n}\left(w_i \widetilde{x}_i \cos\alpha - w_i \overline{y}_i \sin\alpha\right)}{\sum_{i=1}^{n} w_i^2}} \\ \sigma_y = \sqrt{\frac{\sum_{i=1}^{n}\left(w_i \widetilde{x}_i \sin\alpha - w_i \overline{y}_i \cos\alpha\right)}{\sum_{i=1}^{n} w_i^2}} \end{cases} \tag{7}$$

where (x_i, y_i) in Equations (5)–(7) denote the deviation between coordinates of an element and the geometric center coordinates of an element set, which represents the spatial location of the object. In addition, w_i is the corresponding weight and $\left(\widetilde{x}_i, \overline{y}_i\right)$ denote the coordinates deviation from the spatial location of each object to the ellipse center of SDE $(\overline{X}_w, \overline{Y}_w)$.

5. Results and Discussion

5.1. Density Variations and Distribution of Check-Ins

In the current study, the geo-location-based check-in dataset, which comes from Weibo, is utilized and analyzed the check-in density by using KDE. Figure 3a shows the main highways, water channels, and vegetation of Guangzhou, where Figure 3b presents the overall check-in density in Guangzhou. However, by comparing Figure 3a,b, it can be observed that the city center has a relatively dense check-in distribution. Generally, it is considered that more and more people prefer to live near the communities where they have easy access to services, i.e., transport, healthcare, and entertainment [163,164]. Even from the current study, high check-in density is found nearby subways and highways. Historically, the density of the Guangzhou city population rose abruptly, and the attraction of the port mainly influenced population distribution. After the reforms in China, suburban areas were covered by mega-factories, which attracted more people from the areas outside of Guangzhou for the development of mega-factories. However, a small proportion of these people preferred to live in suburban areas while the majority preferred to reside within the city center [165–167]. Hence, the result of the current study also shows the same pattern of population density in Guangzhou.

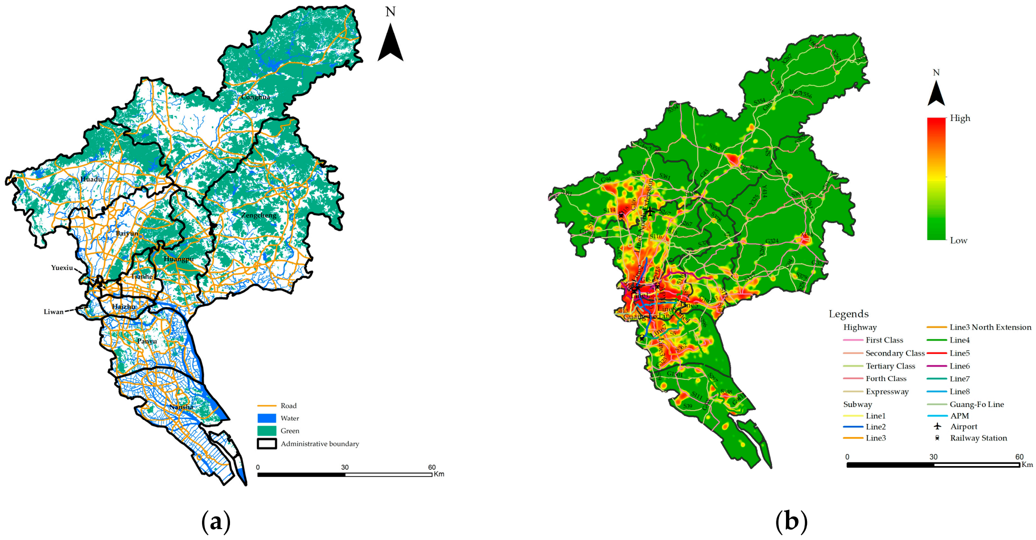


Figure 3. (**a**) Land use map of Guangzhou and (**b**) kernel density of check-in in Guangzhou.

Gender-based (male and female) analysis on the LBSN data set is performed to investigate the check-in behavior in Guangzhou. Figure 4a,b represents the check-in trend during a weekend and illustrates that, from the dataset, the female users are observed to be more inclined towards the use of Weibo in comparison to the male users during a week in Guangzhou. Moreover, it is also observed that the check-in frequency of the male starts to increase during Friday and almost matches females during Saturday and Sunday. Furthermore, Figure 4 shows that female users are more likely to use Weibo than males. Figure 5 demonstrates that the pattern is similar in all districts.

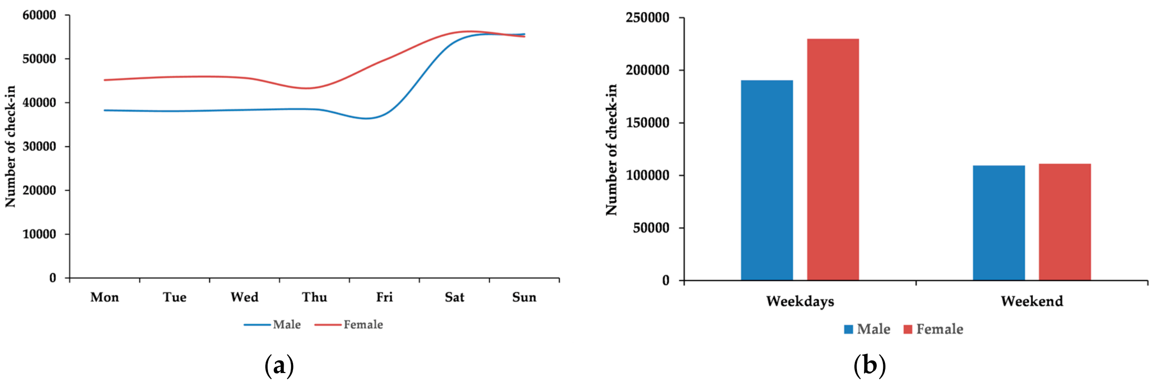


Figure 4. (**a**) Weekly check-in trend. (**b**) Weekdays and weekend check-in distributions.

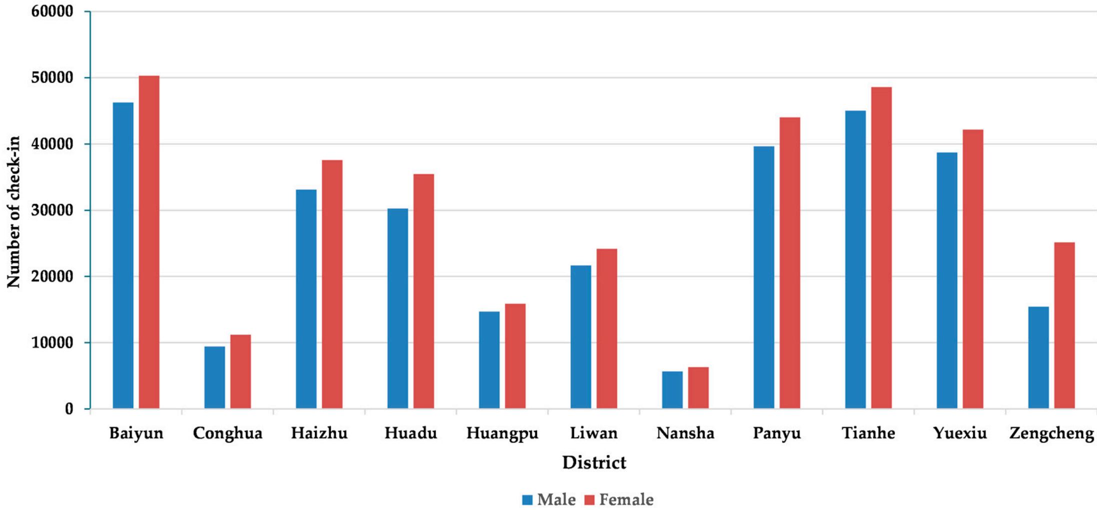
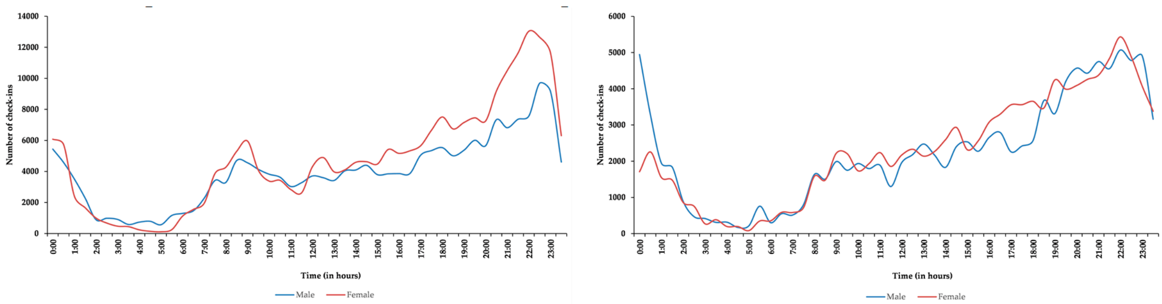


Figure 5. Gender wise check-in distribution in Guangzhou.

To study the check-in trend in Guangzhou, it is vital to observe the gender-based check-in trend through weekdays and weekend. In Figure 6a,b, the growing activity trend can be witnessed through the weekdays from 05:30–09:30 and 17:00–22:30. However, an increasing check-in trend was also observed throughout the weekend from 08:00–22:30. Furthermore, it can also be observed that the frequency of use from female users is a bit steady with a minor rise during the weekend in comparison to male users. Comparatively, the check-in frequency of male users differs a lot during weekdays and weekends. Furthermore, it is observed that, during the whole week, check-in frequency increases from 20:00–23:59. Additionally, during the weekend, the check-in frequency of male users peaks between 19:00–23:00 as compared to female users.



(**a**) (**b**)

Figure 6. Temporal trend of check-in during (**a**) weekdays and (**b**) weekend.

Figure 7 illustrates the check-in distribution in all districts of Guangzhou. In comparison, Baiyun, Panyu, Tianhe, and Yuexiu districts (which are considered the business center of Guangzhou) have denser check-in frequency. However, from Figure 8, we can observe more check-ins during Saturday as compared to Sunday in Huadu, Huangpu, and Zengcheng districts when compared to other districts.

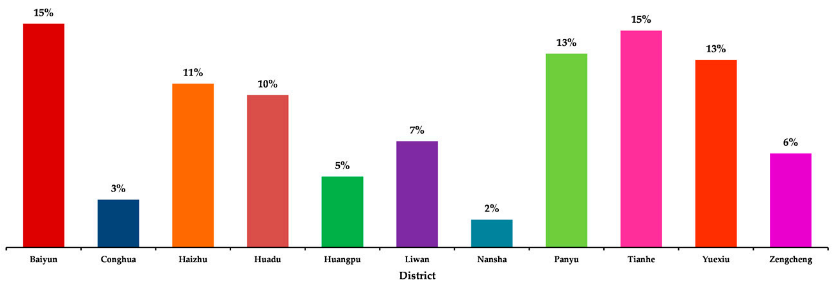


Figure 7. Check-in distribution in districts of Guangzhou.

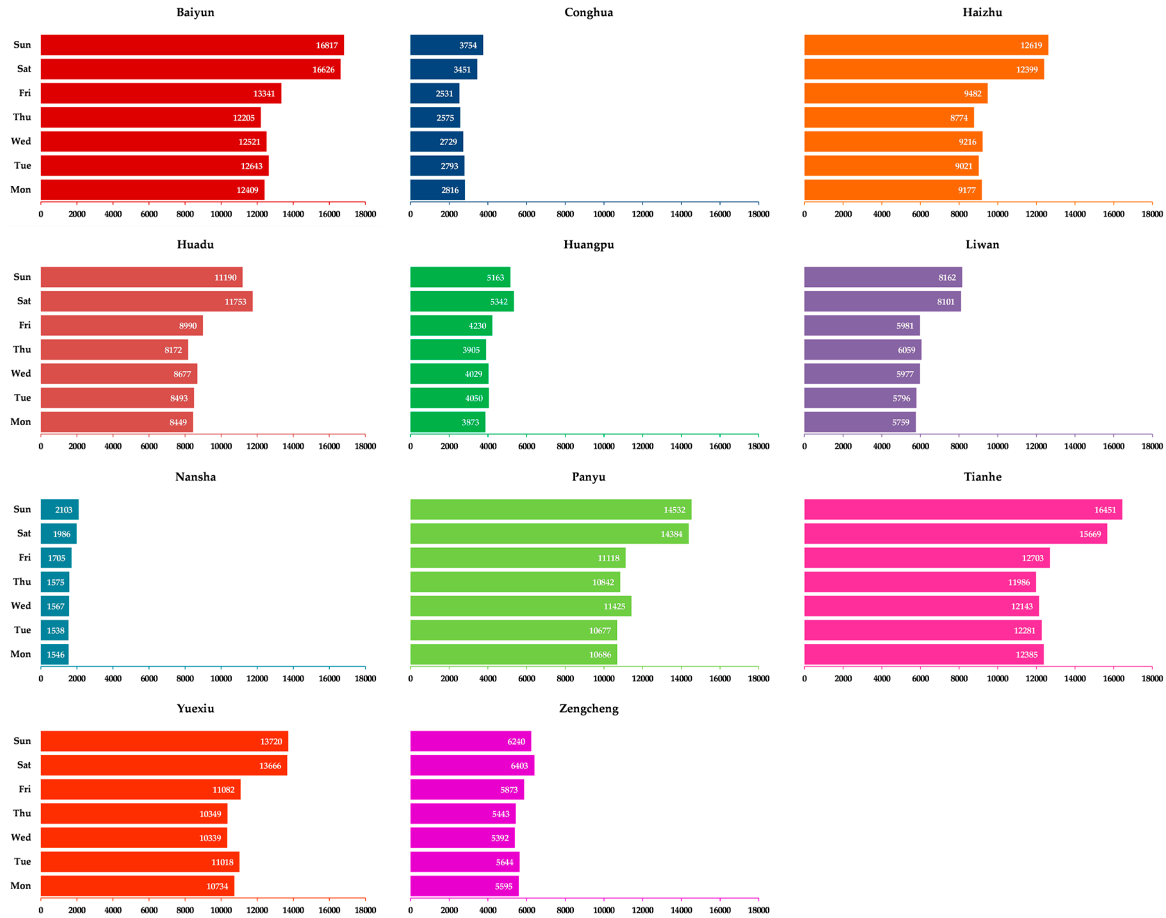
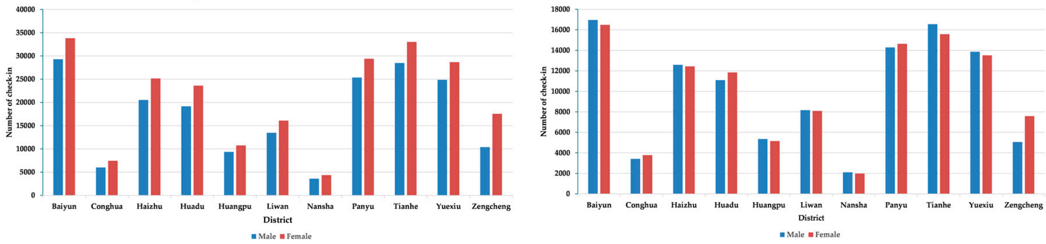


Figure 8. Weekly check-in distribution of check-ins in districts of Guangzhou.

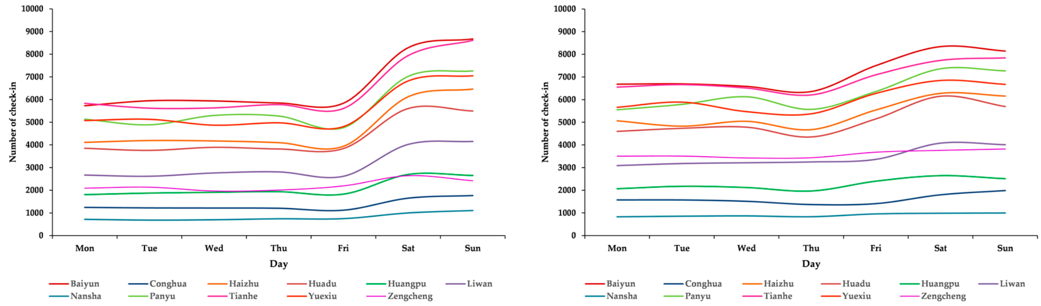
Figure 9a,b show the gender wise check-in distribution in Guangzhou during weekdays and weekend. Meanwhile, more check-ins are made by female users during the weekdays, as shown in Figure 9a. Surprisingly, more check-ins are made by male users in most of the districts (Baiyun, Haizhu, Huangpu, Liwan, Nansha, Tianhe, and Yuexiu) in Guangzhou as compared to female users during the weekend.

Figure 10a,b represent the gender-based weekly check-in trend in all districts of Guangzhou. The difference of check-in behavior by male and female users during Saturday and Sunday can be observed clearly and is mainly due to the change in check-in behavior by male users. Hence, the results of Figure 10a,b also justify the results of Figure 9a,b.



(**a**) (**b**)

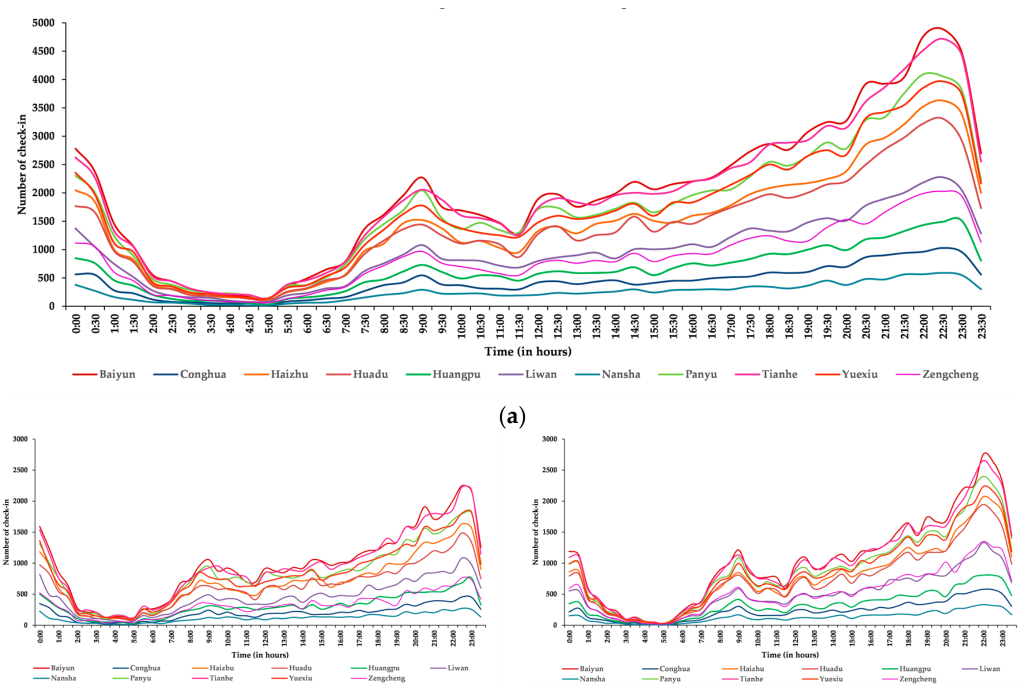
Figure 9. Gender wise check-in distribution in Guangzhou during (**a**) weekdays (**b**) and weekend.



(**a**) (**b**)

Figure 10. Gender wise weekly check-in distribution in Guangzhou (**a**) male and (**b**) female.

Furthermore, we analyzed the Weibo dataset to observe a gender-based check-in trend during 24 hours in all districts of Guangzhou and is presented in Figure 11a,b,c. Figure 11a presents the day-to-day check-in trend in Guangzhou. An increase in check-in trend is observed from 07:00 AM to 09:00 AM. However, a decrease in the check-in trend is observed from 09:00 to 11:30. Furthermore, It can also be observed that the check-in trend starts to rise again at 11:30 AM and continues to rise until 22:30, as shown in Figure 11b,c.



(**a**)

(**b**) (**c**)

Figure 11. Temporal trend of check-in in Guangzhou (**a**) average daily (**b**), average daily male (**c**), and average daily female.

Average density distribution of check-ins made in Guangzhou was calculated using the KDE method, and the density maps are visualized using ArcGIS in both space and time. Figure 12 reveals the spatiotemporal dynamics of Guangzhou, and it reveals that the center of the Guangzhou city has a higher density of check-ins. Besides higher density of check-ins, it can also be observed that most of the check-ins are made near the borders of the district that are mostly near highways and the subway.

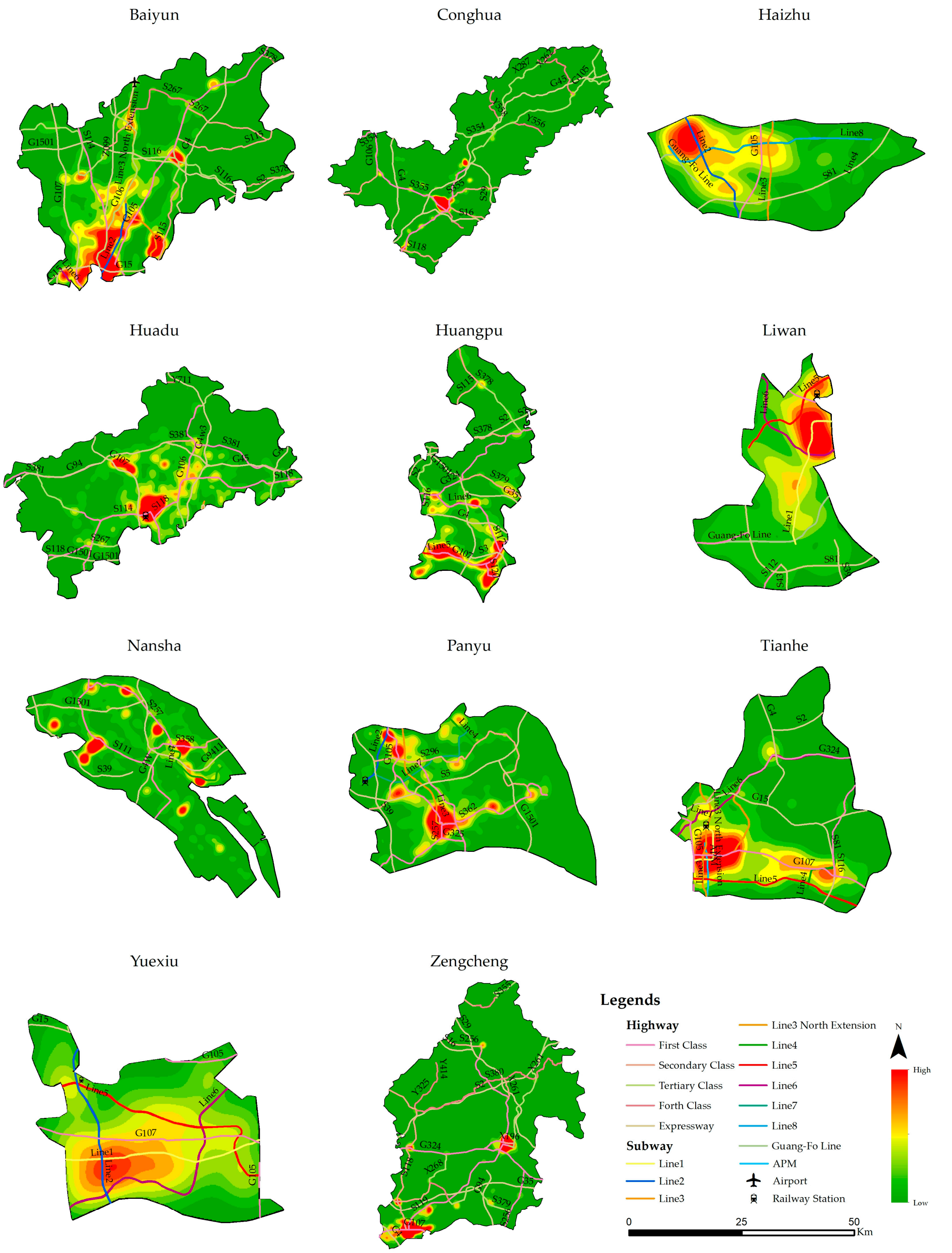


Figure 12. Kernel densities of check-in in the districts of Guangzhou.

In summary, the KDE results reveal that the check-in behavior patterns in Guangzhou are as follows: (1) in terms of the spatial distribution, main agglomeration areas with high frequencies and densities are evident in the center of the city (Baiyun, Haizhu, Liwan, Tianhe, and Yuexiu). (2) From a temporal perspective, people's activity frequencies are almost zero between midnight and early morning (00:00-05:00) and relatively low during working times (09:30-11:30) and relatively high during leisure times and at dinner time. The information from KDE can facilitate studying the dynamic evolution of check-in across both space and time. Additionally, the KDE results verify that the check-in behavior varies at fine temporal (i.e., a day) and spatial (i.e., a city) scales. The results also show that the check-in data can reflect more refined phenomena and results than traditional data with fine time and spatial granularity.

5.2. Geographically Weighted Regression (GWR)

The GWR results for male and female during weekdays and weekends are presented in Table 1. All selected variables are significant at the 1% level. The R^2 values are 0.9288 and 0.9157, which denote that the selected variables can explain 92.8% and 91.5% of the variation in the check-in on weekdays and weekend, with optimal spatiotemporal bandwidths of 0.300 and 0.301 for weekdays and weekend, respectively. The variation trends for male and female during weekdays vary due to the higher number of check-ins by a female as compared to males and can be observed in Figure 14. The variation trends for males and females during the weekend are roughly the same due to the increased number of check-ins by the male as compared to weekdays and can be observed in Figure 14.

Table 1. Estimated GWR parameters for weekdays and weekends by males and females.

	Weekdays					Weekend				
	Min	**Mean**	**Max**	**SD**	***p*-Value**	**Min**	**Mean**	**Max**	**SD**	***p*-Value**
Male	0	25.737	1266.668	92.991	0.000 ***	0	15.133	1206.001	58.904	0.000 ***
Female	0	31.078	1437.804	112.434	0.001 ***	0	15.117	670.302	54.261	0.000 ***
	Diagnostic information:					Diagnostic information:				
	Moran's I				0.2082	Moran's I				0.1999
	R^2				0.9288	R^2				0.9157
	AIC				10010.62	AIC				10002.32
	Bandwidth				0.3000	Bandwidth				0.3010

*** represents a significance level of 1%.

Table 2 presents the GWR results for weekdays and weekends in all districts of Guangzhou. All selected variables are significant at the 1% level. The R^2 values are 0.9203 and 0.9212, denoting that the selected variables can explain 92% and 92.1% of the variation in the check-in on weekdays and weekends in all districts of Guangzhou, with optimal spatiotemporal bandwidths of 0.331 and 0.320 for weekdays and weekends, respectively. The variation trends during weekdays and weekends are very different in most of the districts due to the higher number of check-ins in the city center during weekdays. There is a slight increase in activity in the suburban districts (i.e., Conghua, Nansha, and Zengcheng) during the weekend as compared to weekdays.

Table 3 presents the GWR results for males and females in all districts of Guangzhou during weekdays. All selected variables are significant at the 1% level. The R^2 values are 0.9024 and 0.9186, which denote that the selected variables can explain 90% and 92% of the variation in the check-in for male and female in all districts of Guangzhou during weekdays, with optimal spatiotemporal bandwidths of 0.3554 and 0.3138, respectively. The variation trends during weekdays by males and females are quite different in most of the districts due to the higher number of check-ins by females in all districts of Guangzhou.

Table 2. Estimated GWR parameters for weekdays and weekends in districts of Guangzhou.

	Weekdays					Weekend				
	Min	**Mean**	**Max**	**SD**	***p*-Value**	**Min**	**Mean**	**Max**	**SD**	***p*-Value**
Baiyun	0	68.688	1500.464	142.125	0.010 ***	0	74.817	1571.392	159.727	0.000 ***
Conghua	0	4.744	1372.073	35.885	0.000 ***	0	5.652	1727.263	45.294	0.000 ***
Haizhu	0	367.824	1799.977	380.681	0.001 ***	0	418.028	2112.234	440.147	0.010 ***
Huadu	0	31.090	1310.871	89.061	0.000 ***	0	36.435	1580.608	105.450	0.000 ***
Huangpu	0	31.306	703.263	67.124	0.000 ***	0	33.854	825.094	75.191	0.000 ***
Liwan	0	329.503	2092.561	413.853	0.010 ***	0	368.540	2470.301	478.330	0.001 ***
Nansha	0	15.854	712.007	42.482	0.000 ***	0	17.645	876.957	50.111	0.010 ***
Panyu	0	67.906	1363.761	130.817	0.001 ***	0	75.283	1593.028	150.951	0.001 ***
Tianhe	0	334.986	3318.354	477.392	0.001 ***	0	361.432	3778.293	519.751	0.000 ***
Yuexiu	0	1145.853	3011.301	664.719	0.001 ***	0	1246.494	3353.170	748.794	0.001 ***
Zengcheng	0	9.496	1089.747	51.324	0.000 ***	0	15.428	1734.161	83.137	0.000 ***
	Diagnostic information:					Diagnostic information:				
		Moran's I			0.0628		Moran's I			0.0600
		R^2			0.9203		R^2			0.9212
		AIC			10128.92		AIC			1010.515
		Bandwidth			0.3317		Bandwidth			0.3204

*** represents a significance level of 1%.

Table 3. Estimated GWR parameters for males and females in districts of Guangzhou during weekdays.

	Male					Female				
	Min	**Mean**	**Max**	**SD**	***p*-Value**	**Min**	**Mean**	**Max**	**SD**	***p*-Value**
Baiyun	0	43.528	937.598	88.674	0.001 ***	0	50.339	1076.319	107.096	0.000 ***
Conghua	0	3.024	902.968	23.323	0.000 ***	0	3.745	1121.849	29.513	0.000 ***
Haizhu	0	227.986	1108.790	236.494	0.001 ***	0	280.048	1416.303	295.593	0.001 ***
Huadu	0	19.686	793.073	54.664	0.000 ***	0	24.262	1046.881	69.608	0.000 ***
Huangpu	0	19.937	423.187	42.100	0.000 ***	0	22.920	534.047	50.288	0.000 ***
Liwan	0	206.122	1395.648	258.472	0.001 ***	0	245.638	1677.278	319.213	0.001 ***
Nansha	0	9.984	444.819	26.769	0.000 ***	0	11.908	575.094	32.835	0.010 ***
Panyu	0	43.531	824.870	81.660	0.000 ***	0	50.323	1030.004	99.977	0.010 ***
Tianhe	0	211.895	2112.353	304.614	0.010 ***	0	245.488	2567.303	353.042	0.000 ***
Yuexiu	0	734.656	1907.466	429.445	0.000 ***	0	845.272	2254.169	504.612	0.010 ***
Zengcheng	0	6.380	762.068	34.471	0.000 ***	0	10.765	1222.445	57.740	0.001 ***
	Diagnostic information:					Diagnostic information:				
		Moran's I			0.0665		Moran's I			0.0529
		R^2			0.9024		R^2			0.9186
		AIC			11334.555		AIC			11275.415
		Bandwidth			0.3554		Bandwidth			0.3138

*** represents a significance level of 1%.

Table 4 presents the GWR results for males and females in all districts of Guangzhou during the weekend. All selected variables are significant at the 1% level. The R^2 values are 0.9264 and 0.9020, which denote that the selected variables can explain 93% and 90% of the variation in the check-in for males and females in all districts of Guangzhou during weekdays, with optimal spatiotemporal bandwidths of 0.3315 and 0.3449, respectively. The variation trends during the weekend by males and females are roughly the same due to the higher number of check-ins by the males as compared to females.

Moreover, Figure 13 shows the average spatial change tendencies of the parameter estimates for check-ins, which are pivotal and focus factors in this article. This article also manually sets zero as a threshold to distinguish between the positive and negative effects. This shows the general tendencies and nuances of check-ins by male and female users. The effects of check-ins by the female users in the city center are greater than 0.5 StdResid as compared to male. The greater StdResid means that check-in frequency is high among the female users.

Table 4. Estimated GWR parameters for males and females in districts of Guangzhou during the weekend.

	Male					Female				
	Min	**Mean**	**Max**	**SD**	***p*-Value**	**Min**	**Mean**	**Max**	**SD**	***p*-Value**
Baiyun	0	25.160	562.867	53.821	0.010 ***	0	24.478	500.145	52.878	0.000 ***
Conghua	0	1.720	483.899	12.687	0.000 ***	0	1.908	605.415	15.849	0.000 ***
Haizhu	0	139.838	691.187	145.229	0.001 ***	0	137.981	695.931	145.194	0.001 ***
Huadu	0	11.405	517.797	34.904	0.000 ***	0	12.173	533.726	36.229	0.000 ***
Huangpu	0	11.369	290.520	25.540	0.000 ***	0	10.935	291.047	25.160	0.000 ***
Liwan	0	123.381	751.988	156.679	0.010 ***	0	122.901	806.843	159.533	0.010 ***
Nansha	0	5.871	267.188	16.019	0.010 ***	0	5.736	301.862	17.533	0.000 ***
Panyu	0	24.375	538.892	49.567	0.001 ***	0	24.960	563.024	51.292	0.000 ***
Tianhe	0	123.091	1206.001	173.388	0.000 ***	0	115.943	1210.991	167.107	0.001 ***
Yuexiu	0	411.197	1103.834	237.592	0.001 ***	0	401.222	1108.737	245.131	0.001 ***
Zengcheng	0	3.115	327.679	17.024	0.000 ***	0	4.663	511.716	25.604	0.000 ***
	Diagnostic information:					Diagnostic information:				
	Moran's I				0.0367	Moran's I				0.0580
	R^2				0.9264	R^2				0.9020
	AIC				10511.428	AIC				10050.409
	Bandwidth				0.3315	Bandwidth				0.3449

*** represents a significance level of 1%.

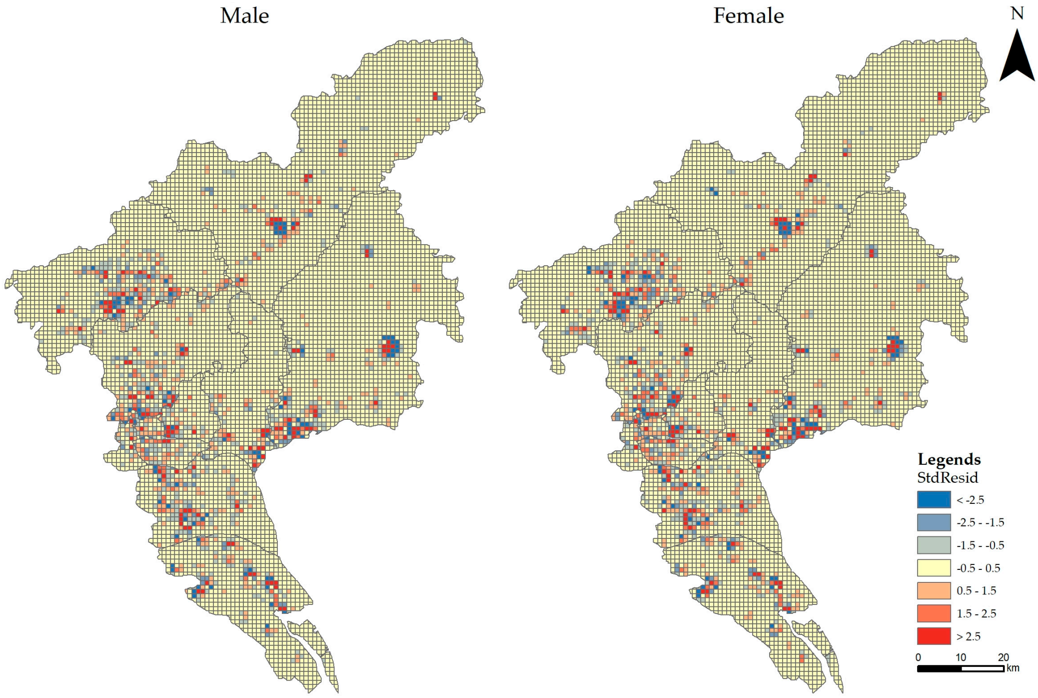


Figure 13. Spatial distribution of check-ins by males and females in Guangzhou.

Figure 14 shows the average spatial change tendencies of the parameter estimates for check-ins by males and females during weekdays and weekends. The effects of check-ins during weekdays in Guangzhou are mostly greater than 0.5 StdResid by females. However, the effects of check-ins during the weekend in Guangzhou are almost the same by male and female users. Lastly, urban areas that are also considered the city center, including Baiyun, Haizhu, Liwan, Tianhe, and Yuexiu, all have positive effects on check-in frequency. The other districts have mostly negative effects, which have few settlements.

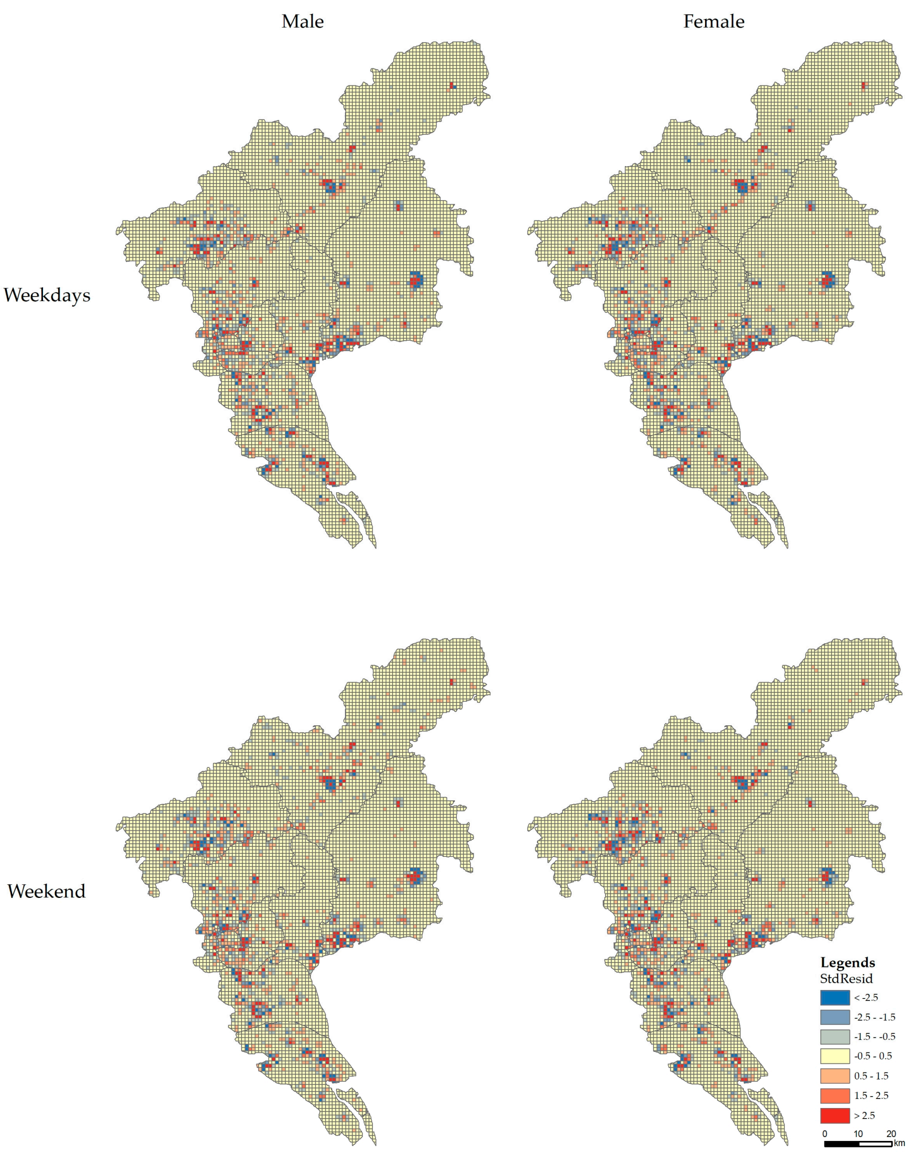


Figure 14. Spatial distribution of check-ins by males and females during weekdays and weekends in Guangzhou.

5.3. Standard Deviational Ellipse (SDE) Analysis

The overall spatial pattern changes of check-ins by males and females across Guangzhou were determined through a standard deviational ellipse analysis and is plotted in Figure 15, which shows the overall spatial pattern of check-in within the city by males and females. In this case, the major axis indicates the direction and the minor axis indicates the range of the data distribution.

The trajectory of the center in Figure 15 shows a linear movement by the female users in a clockwise direction toward the north-east by rotating azimuth 3°, and the movement of the male users is counterclockwise when rotating azimuth 179°. However, it can be observed from Table 5 that the value of the minor axis for the female users is 40.86 km with an area of 6343.12 km^2, which results in the larger eccentricity of the SDE. The larger eccentricity of the SDE represents that the check-ins for females are more scattered in the city as compared to males. It also represents that the check-in distribution is mostly close toward the city center by the male users.

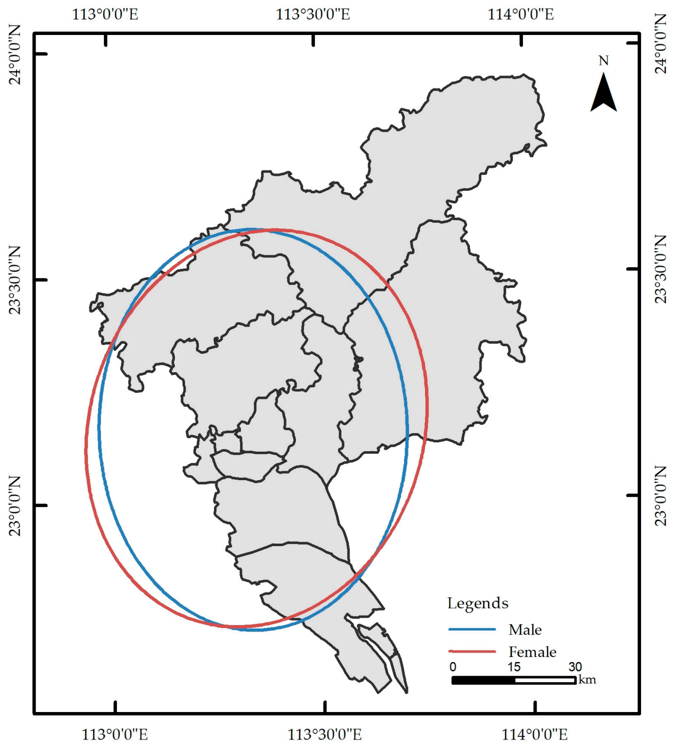


Figure 15. SDEs for check-in distribution by males and females in Guangzhou.

Table 5. SDE features on the major axis, minor axis, area, azimuth, and flattering in Guangzhou.

	Major Axis (km)	Minor Axis (km)	Area (km^2)	Azimuth°	Flattering
Male	49.11	37.75	5823.19	179	1.301
Female	49.41	40.86	6343.12	3	1.209

Figure 16 shows the SDEs for the overall spatial pattern of check-in within the city by males and females during weekdays and weekends in Guangzhou. During weekdays, a linear movement by the female users in a clockwise direction toward the north-east by rotating azimuth 5° and the movement of the male users is counterclockwise by rotating azimuth 179°. However, during the weekend, a linear movement is taken by the female users in a clockwise direction toward the north-east by 1° and the movement of the male users is counterclockwise when rotating azimuth 174°. Moreover, it can be observed from Table 6 that the value of the minor axis for females during weekdays is 38.14 km with an area of 6381.89 km^2, which results in the larger eccentricity of the SDE as compared to males. The larger eccentricity of the SDE represents that, during weekdays, the check-ins for females are more scattered in the city as compared to males. It also represents that, during the check-in, distribution is mostly close toward the city center by the male users as compared to the female users. However, during the weekend, a linear movement by the female users in a counterclockwise direction toward the north-west by rotating azimuth 1° as compared to rotating azimuth 5° during weekdays and the movement of the male users is also counterclockwise toward the north-west when rotating azimuth by 174° as compared to rotating azimuth 179° during weekdays. This change in a pattern during the weekend indicates that the check-in distribution by both males and females shifts to the city center.

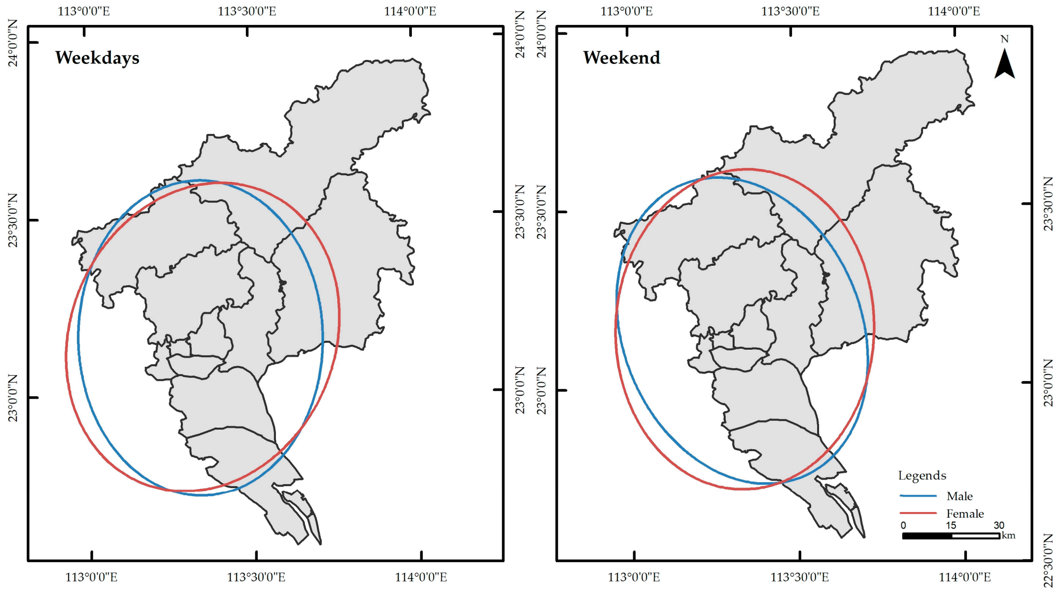


Figure 16. SDEs for check-in distribution by males and females during weekdays and weekends in Guangzhou.

Table 6. SDE features on the major axis, minor axis, area, azimuth, and flattering during weekdays and weekends in Guangzhou.

		Major Axis (km)	Minor Axis (km)	Area (km^2)	Azimuth°	Flattering
Weekdays	**Male**	49.15	41.20	5888.83	179	1.1931
	Female	49.30	38.14	6381.89	5	1.2927
Weekends	**Male**	49.03	40.13	5705.79	174	1.2218
	Female	49.64	37.04	6258.46	1	1.3403

Moreover, it can be observed from Table 6 that the value of the minor axis for females during weekdays is 37.04 km with an area of 6258.46 km^2, which results in the larger eccentricity of the SDE as compared to males. The larger eccentricity of the SDE represents that, during the weekend, the check-in distribution for females are also more scattered in the city as compared to males, but, during the weekend, the spatial pattern of check-ins is mostly scattered toward the city center.

Figure 17 shows the district-wise SDEs for the overall spatial pattern of check-ins within the city by males and females in all (eleven) districts of Guangzhou. It can be observed that the overall spatial pattern of check-ins is almost the same by males and females in Baiyun, Huadu, Liwan, and Yuexiu districts. However, in the Conghua district, a linear movement is taken by the female users in a clockwise direction toward the north-east by rotating azimuth 50° and the movement of the male users is taken as the clockwise direction toward the north-east by rotating azimuth 51°. It can be observed in Table 7 that the value of the minor axis for the female users is 16.94 km with an area of 430.80 km^2 and a minor axis for the male users is 18.50 km with an area of 487.26 km^2, which results in the larger eccentricity of the SDE as compared to females. The spatial pattern of check-ins by the male users is more scattered within the district as compared to females. In the Haizhu district, a linear movement by the female users is taken in a clockwise direction toward the south-east by rotating azimuth 98° and the movement of the male users is taken in the clockwise direction toward the south-east when rotating azimuth by 99°. The value of the minor axis for the female users is 5.58 km with an area of 35.30 km^2 and the minor axis for the male users is 4.62 km with an area of 29.54 km^2, which results in the larger eccentricity of the SDE by the female users as compared to males. The spatial pattern of check-in by the female users is more scattered within the district as compared to males.

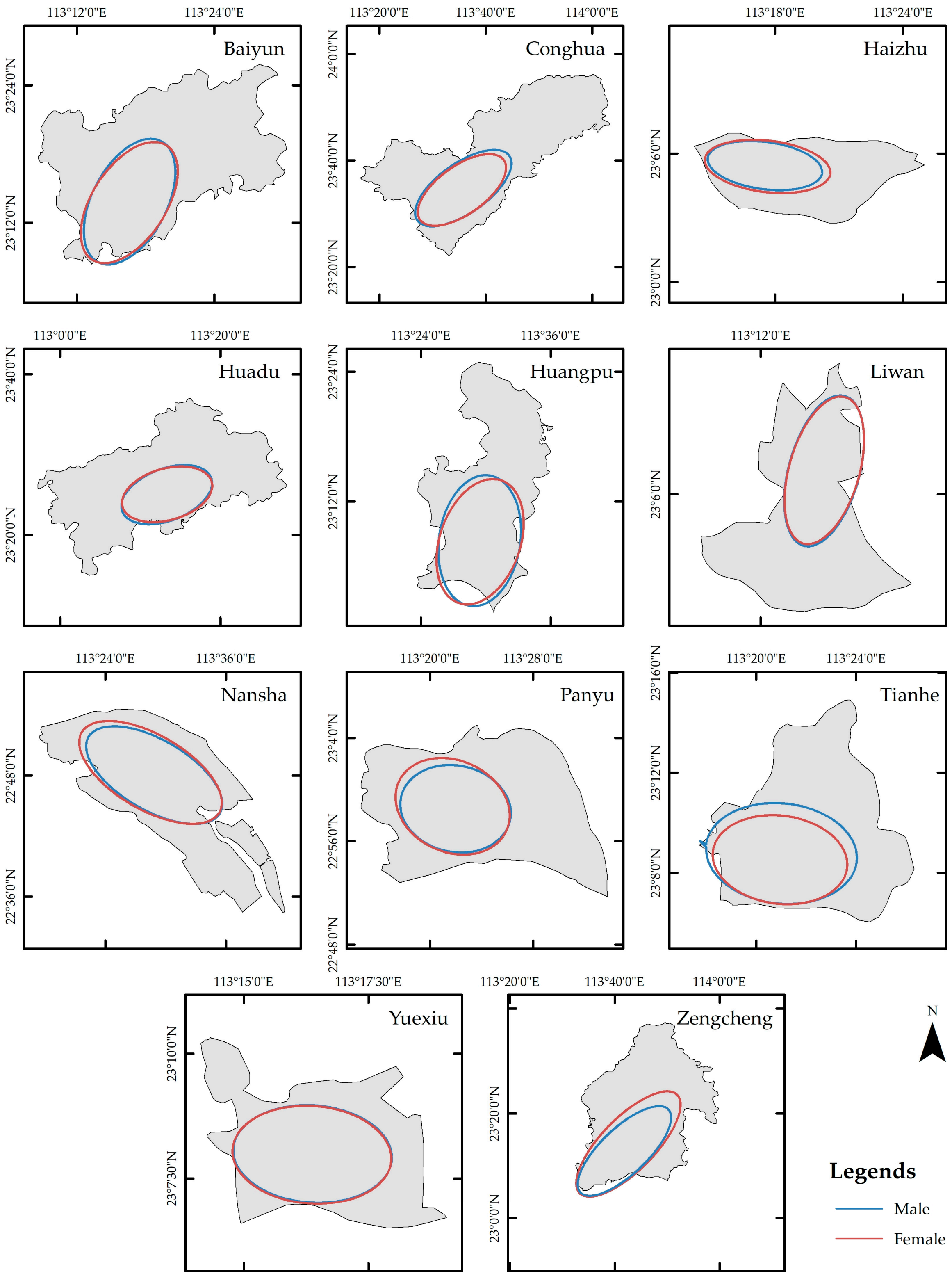


Figure 17. SDEs for check-in distribution by male and female users in districts of Guangzhou.

Table 7. SDE features on the major axis, minor axis, area, azimuth, and flattering in districts of Guangzhou.

		Major Axis (km)	Minor Axis (km)	Area (km^2)	Azimuth°	Flattering
Baiyun	**Male**	10.76	5.68	191.87	29	1.8951
	Female	10.75	5.62	189.80	31	1.9130
Conghua	**Male**	8.39	18.50	487.26	51	2.2056
	Female	8.09	16.94	430.80	50	2.0933
Haizhu	**Male**	2.04	4.62	29.54	99	2.2675
	Female	2.01	5.58	35.30	98	2.7727
Huadu	**Male**	5.96	10.15	190.00	72	1.7041
	Female	5.90	9.91	183.82	71	1.6793
Huangpu	**Male**	11.26	6.45	227.97	6	1.7464
	Female	11.06	6.38	221.64	9	1.7328
Liwan	**Male**	4.07	1.74	22.21	13	2.3412
	Female	3.99	1.72	21.53	14	2.3191
Nansha	**Male**	6.33	13.18	262.13	122	2.0810
	Female	6.30	12.98	290.50	122	2.0612
Panyu	**Male**	6.42	7.93	143.03	120	1.2347
	Female	6.43	7.96	160.78	121	1.2389
Tianhe	**Male**	3.26	5.58	59.99	97	1.7093
	Female	3.24	4.62	47.06	98	1.4253
Yuexiu	**Male**	1.79	2.72	15.32	94	1.5149
	Female	1.81	2.72	15.44	94	1.5073
Zengcheng	**Male**	20.49	7.85	505.09	42	2.6103
	Female	20.37	11.81	661.52	37	1.7252

In the Huangpu district, a linear movement by the female users is taken in a clockwise direction toward the north-east by rotating azimuth 9° and the movement of the male users is taken in the clockwise direction toward the north-east when rotating azimuth by 6°. The value of the minor axis for the female users is 6.38 km with an area of 221.64 km^2 and the minor axis for the male users is 6.45 km with an area of 227.97 km^2, which results in almost the same eccentricity of the SDE by both males and females. Moreover, the overall spatial pattern of check-in is almost the same by males and females in Nansha and Panyu districts, where the only difference of more scattered distribution of check-ins is conducted by females as compared to males. In the Tianhe district, a linear movement by the female users in a clockwise direction toward the north-east direction by rotating azimuth 98° and the movement of the male users is in the clockwise direction toward the north-east when rotating azimuth by 97°. The value of the minor axis for the female users is 4.62 km with an area of 47.06 km^2 and the minor axis for the male users is 5.58 km with an area of 59.99 km^2, which results in the larger eccentricity of the SDE by the male users. The spatial pattern of check-ins by the male users is more scattered within the district as compared to females. In the Zengcheng district, a linear movement by the female users in a clockwise direction is conducted toward the north-east by rotating azimuth 37° and the movement of the male users is conducted in the clockwise direction toward the north-east when rotating azimuth by 42°. The value of the minor axis for the female users is 11.81 km with an area of 661.52 km^2 and the minor axis for the male users is 7.85 km with an area of 505.09 km^2, which results in the larger eccentricity of the SDE by the female users. The spatial pattern of check-in by the female users is more scattered within the district as compared to the male users.

Furthermore, considering the eleven districts in the study area, we plotted the trajectory of SDEs center for each district, as shown in Figure 18. The geometry of trajectories indicate different spatial patterns of check-in behavior by males and females in each district. In general, the spatial aggregating degree of trajectories in the district indicates the check-in distribution in that district and a certain degree of temporal autocorrelation. The apparent features of change in trajectories for all check-ins are presented in Figure 18. It indicates that a larger difference in trajectories is observed in the Conghua, Haizhu, Huangpu, Panyu, Tianhe, and Zengcheng districts. That may be attributed to Conghua and Zengcheng having a larger area, which accounts for the larger extent of the trajectory and indicates more dispersing in check-ins as compared to the Baiyun, Huadu, Liwan, Nansha, and Yuexiu districts having a comparatively smaller area.

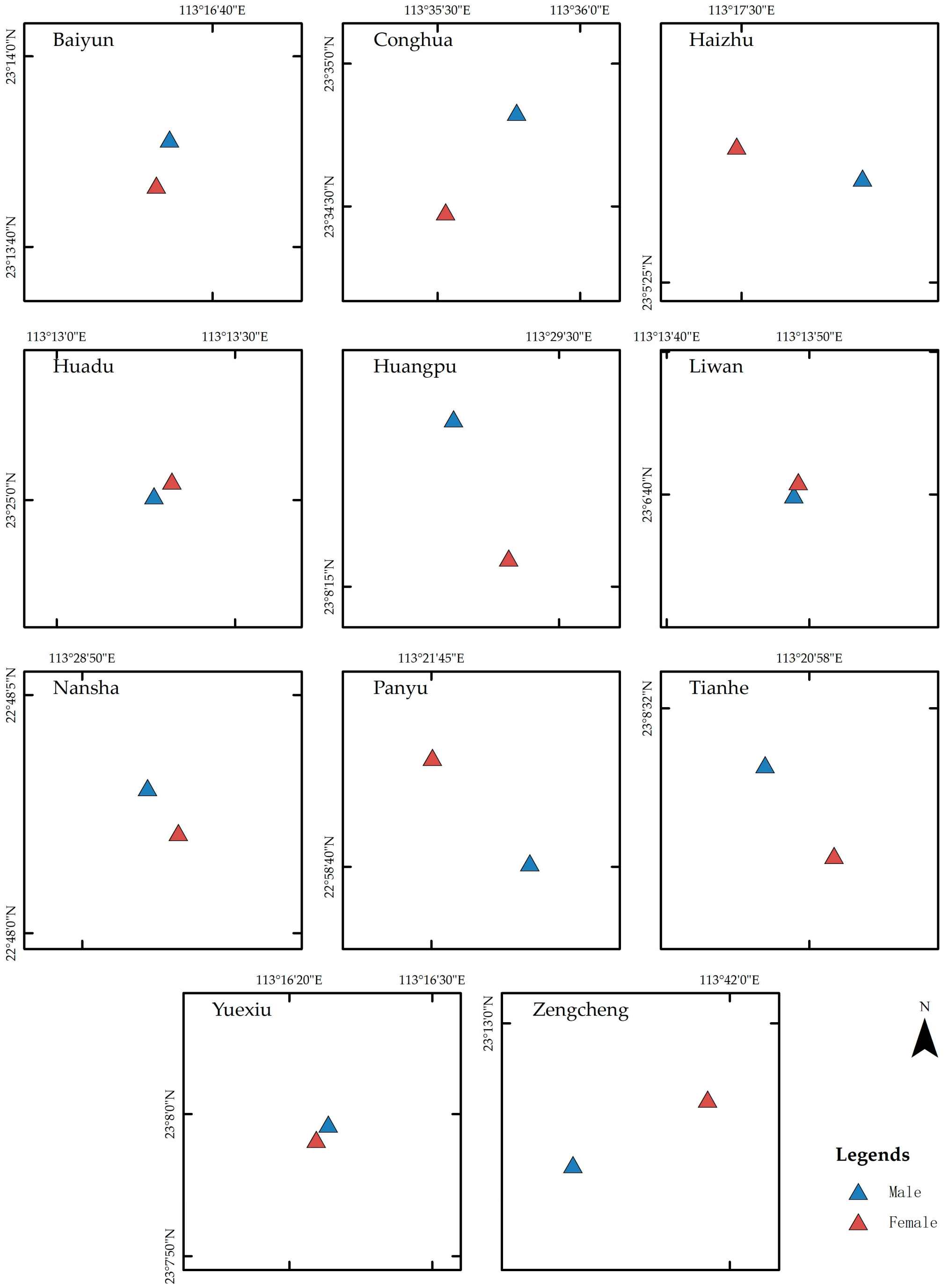


Figure 18. The trajectory of SDEs center by male users and female users in districts of Guangzhou.

Although check-in data are very raw and imprecise for movement of both males and females from one destination to another and, thus, check-in data cannot precisely indicate the nature of the movement of users among the districts, it can still be helpful to understand the check-in behavior.

6. Conclusions

The current study utilized density maps and trends to present the spatiotemporal investigation of gender-based human check-in behavior to explore hourly and daily check-in patterns, as well as patterns during weekdays and weekends. Results show that, in almost all districts of Guangzhou, females are more inclined toward using Weibo as compared to males during the weekdays. However, during the weekend, almost the same check-in trend is observed by both males and females. Furthermore, the center of the city has a comparatively high density of check-in near the subway and highways.

With a supplement to the prior research on check-in behavior, we also consider LBSN data as a supplement rather than a substitute for traditional data sources to observe (i.e., human mobility, activity analysis, and defining city boundary and social issues in a city). Additionally, compared to other traditional data sources, the LBSN dataset has some advantages (low cost and high spatial precision) and disadvantages (i.e., the gender prejudice, a low frequency in sampling, and location type prejudice).

Lastly, based on the results, we consider the LBSN dataset as a novel source of big data with the potential to offer a new viewpoint as an add-on to observe the gender-based check-in density in space and time. The information from KDE can facilitate studying the dynamic evolution of check-in across both space and time. Additionally, the KDE results verify that the check-in behavior varies at fine temporal (i.e., a day) and spatial (i.e., a city) scales. The results also show that the check-in data can reflect more refined phenomena and results other than traditional data with fine time and spatial granularity. Despite the difference of methodologies being used with different types of LBSN and datasets, both early studies [16,18] and the current study based on gender-based check-in behavior on LBSN, draw a similar conclusion that the female users are more likely to use LBSN than male users. Additionally, it can be helpful for policymakers to define policies regarding the supply of services (i.e., transport, health, and entertainment) by highlighting the check-in hotspots in the city. The SDEs indicate the difference of trajectories by males and females in the district of Guangzhou and the trajectory of the SDEs center by males and females in districts of Guangzhou represents the differences in check-in behavior patterns in those districts.

In the future, we will tend to study the use of LBSN data to explore the activities associated with the check-ins and study the motivation toward those activities. Moreover, we will also tend to examine the aspects that bring change in the check-in behavior toward those activities in space and time.

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