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The Spatial Association between Residents' Leisure Activities and Tourism Activities Using Colocation Pattern Measures: A Case Study of Nanjing, China

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Abstract: With the increasing trend of residents and tourists sharing urban spaces, the boundary between leisure spaces and tourism spaces is gradually being blurred. However, few studies have quantified the spatiotemporal correlation patterns of residents' leisure activities and tourists' activities. To fill this gap, this paper takes Nanjing as an example to study the temporal and spatial correlation between residents' leisure activities and tourists' activities based on mobile phone signal data. First, through kernel density analysis, it is found that there is a spatial overlap between residents' leisure activities and tourists' activities. Then, the spatial and temporal correlation patterns of residents' leisure activities and tourists' activities are analyzed through the colocation quotient. According to our findings, (1) residents' leisure activities and tourists' activities are not spatially correlated, indicating that they are relatively independent in space both during the week and on weekends. (2) On weekday afternoons, the spatial correlation between residents' and tourists' leisure activities is strongest. On weekends, the night is when residents' leisure activities and tourists' activities are most closely related. (3) The correlation area is mainly distributed in areas near famous scenic spots, as well as public spaces such as parks and squares. Based on the above analysis, this paper aims to study the resident-tourist interaction in the spatial context to provide directions for improving the attractiveness of cities, urban transportation, services, and marketing strategies.

Keywords: spatial correlation; urban tourism; colocation quotient; mobile phone signaling data

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1. Introduction

Today, tourism is one of the key drivers of urban development [1]. The rapid development of urban tourism brings a large number of tourists into a city. Relevant empirical studies show that in some famous tourist cities, the proportion of tourists relative to residents is large. For example, in the central historic city of Venice, the number of tourists is 89.4% of the local resident population [2]. As the number of tourists continues to increase, residents and tourists interact more frequently. Existing studies on the interactions between residents and tourists have focused more on the subjective attitudes of residents and tourists and the impact of tourism on local communities [3–8]. However, tourist-resident interaction is not limited to face-to-face communication. The spatial relationship of tourist-resident interaction is also important [9,10]. Few studies have explored tourist-resident interactions in their spatial–temporal activity distributions [11]. Studies on the spatial context between residents and tourists are needed to manage the relationship between tourists and residents. In addition, tourists and residents share an increasing amount of public space and service facilities, such as transportation, accommodations, and restaurants [12,13]. Under the growing tourist and resident aggregation phenomenon within limited destinations, research on the aggregation area of tourist-resident interactions is important to improve the built environment and enhance the quality of life in these geographic fields.

In order to understand the tourist-resident interactions in the spatial context, it is necessary to examine the spatiotemporal correlation between tourists and residents and recognize the concentrated spaces of tourist-resident interactions. Therefore, based on mobile phone signaling data, this paper conducts a quantitative analysis of the spatiotemporal correlation between residents' leisure activities and tourists' activities through the global colocation quotient (GCLQ) and identifies the aggregation areas of residents' leisure activities and tourists' activities through the local colocation quotient (LCLQ). Based on this analysis, this paper aims to provide improvement directions for city attractiveness, urban transportation, services, and marketing strategies.

The structure of this paper is as follows. The next section reviews the relevant research, which provides a theoretical background for this study. The third section introduces the methods. The fourth section explains the study area and data sources for this study. Then, the fifth section presents the results of the GCLQ and LCLQ analyses. Finally, the last section summarizes and discusses the main research results as well as relevant suggestions and strategies.

2. Literature Review

As 'new urban tourism' rises, more tourists search for the true identity of cities. As a result, mundane places like cafes, markets, and streets become popular among tourists [14]. In addition, because of social media, an increasing number of residents tend to visit the city they live in again as "tourists" in recent years [15]. Under this trend, tourist-resident interactions become more frequent. Furthermore, their aggregation area is no longer limited to scenic areas. Recently, there are growing efforts to investigate the quality of the interaction between residents and tourists. For example, Su, Spierings, and Hooimeijer (2022) studied interactions between Mainland Chinese tourists and Hong Kong residents in different urban settings. In addition, it is found that the tourist and resident co-existence is lower in suburban areas, which may result in a higher quality of interactions [14].

Existing studies that investigate the spatial context of tourist-resident interaction are limited. These studies mainly focus on the temporal patterns and spatial patterns of residents and tourists, such as activity time, spatial distribution, and destination recognition [10,16,17]. The results show that the spatial and temporal characteristics of residents and tourists are different. Specifically, since the activities of tourists are greatly influenced by their time budget and monetary budget, the spatial concentration of tourists' activities is higher than that of residents [18,19]. The areas of interest to tourists are mostly concentrated in the downtown area of a city, such as the central city with city landmarks (such as Times Square in New York), while residents tend to concentrate in social spaces (such as parks, squares, or sports facilities), which are more dispersed [20–22]. In addition, although both residents and tourists visit representative urban attractions, residents tend to visit attractions rarely visited by tourists and spend time in areas outside the central areas where tourists gather [19,23]. Leisure activities are an important part of residents' lives, and the spatial scope of residents' leisure activities coincides with that of tourists' activities. For example, many scenic spots are also important spaces for leisure activities, such as Xuanwu Lake Park in Nanjing. In addition, shopping malls, coffee shops, and other places are not only part of residents' leisure spaces but also an important part of the tourism space [24].

Big data analytics are increasingly being used to examine the spatial relationships of tourist-resident interactions. For example, Su et al. (2020) analyzed the spatiotemporal behavior patterns of mainland Chinese tourists and residents in Hong Kong based on Weibo data. It was found that tourists are more concentrated in the central urban areas, while the residents are more dispersed [17]. Chen et al. (2022) analyzed the mapping and structures of tourist and resident activity spaces, and interpreted tourist-resident interactions through their spatial-temporal behaviors based on Wi-Fi log data [10]. However, existing studies on the movement patterns of residents and tourists mainly focus on their behavior at tourism attractions. Their activities in other areas are neglected. In addition, few studies investigate the spatiotemporal correlation patterns of residents' leisure activities and tourist activities based on big data, which can provide important insights to create services and attractions, the transport system, and the marketing strategy of tourism cities. In addition, residents' leisure activities are greatly influenced by the tourists' activities since mundane places become popular among tourists. However, few studies focus on analyzing the temporal and spatial relationship between residents' leisure activities and tourism activities. To fill these gaps, this paper studies the spatiotemporal correlation patterns of residents' leisure activities and tourists' activities to enrich the content of research on the spatial relationship of tourist-resident interactions.

The quantitative analysis methods used in current studies include kernel density analysis [17], density-based spatial clustering of applications with noise (DBSCAN) [16], regression analyses [25], etc. However, these methods cannot accurately obtain the spatiotemporal correlation space of residents and tourists, nor do they allow an overall measurement of the sharing of urban space. Recently, the analysis methods of spatial correlation patterns have been developing rapidly, including Ripley's K function [26] and the cross-K function [27]. These analytical methods are widely used in urban planning, urban traffic, crime, and other fields. Leslie and Kronenfeld (2011) et al. [28] proposed the colocation quotient (CLQ) on the basis of the cross-K function. However, the CLQ can reflect only the global spatial correlation and cannot reflect the spatial variation in the degree of spatial correlation. To solve this problem, Cromley et al. (2014) proposed the LCLQ by combining the GCLQ with geographical weighting parameters in a spatial regression model [29]. Wang et al. (2017) added a significance test to the analysis results to identify whether the results of the GCLQ and LCLQ are statistically significant [30]. At present, the CLQ is mainly used in urban research to analyze the spatial correlation pattern between fire incidents and land use facilities [31], the relationship between crime and facilities [30], and the racial and occupational segregation of residential areas [32]. Research on the application of spatial and temporal correlation patterns in different people's activities is lacking. This paper uses the GCLQ and LCLQ to study residents' leisure activities and tourists' activities, which expands the application of the CLQ in urban research.

In conclusion, some progress has been made in research on the spatiotemporal patterns of residents and tourists. However, currently, few studies investigate the spatiotemporal correlation patterns of residents' leisure activities and tourist activities based on big data. To fill this gap, we analyze the spatial correlation between residents' leisure activities and tourists' activities through the CLQ based on mobile signaling data. Through an empirical study of Nanjing, two questions are to be investigated. The first is whether there is a certain spatial correlation between residents' leisure activities and tourists' activities in the tourism city. The second is in which areas of the city do residents' leisure activities and tourists' activities mainly share?

3. Methodology

3.1. Global Colocation Quotient (GCLQ)

Methodologically, the Location Quotient (LQ) is used to measure the density of local economic activities in different industries and sectors [33,34]. The GCLQ was proposed by Leslie and Kronenfeld (2011) [28] based on the LQ and can examine the overall degree of attraction between points A and B. In this paper, the GCLQ is used to detect the association between residents' leisure activities and tourists' activities. The GCLQ is defined as follows:

$$\mathrm{GCLQ}_{\mathrm{A}\to\mathrm{B}} = \frac{\mathrm{N}_{\mathrm{A}\to\mathrm{B}}/\mathrm{N}_{\mathrm{A}}}{\mathrm{N}_{\mathrm{B}}/(\mathrm{N}-1)} \tag{1}$$

where N_{A} represents the number of points A (residents' leisure activities), N_{B} represents the number of points B (tourists' activities), and N represents the total number of points A and B. $\mathrm{N}_{\mathrm{A}\to\mathrm{B}}$ denotes the number of points A closest to points B. $\mathrm{N}-1$ represents the total number of elements outside of that point since no point can be its own neighbor. When the

$GCLQ_{A\to B}$ value is greater than 1, points A and B have spatial correlation; that is, points A are easily attracted to points B. In contrast, if $GCLQ_{A\to B}$ is less than 1, points A and B tend to disperse. If $GCLQ_{A\to B}$ is equal to 1, points A and B tend to be randomly distributed.

3.2. Local Colocation Quotient (LCLQ)

GCLQ assumes that associations remain spatially stationary. Therefore, the changes in spatial association strength cannot be detected. To address this limitation, the LCLQ was proposed by Cromley et al. (2014) [29], which can be used to reveal the spatial difference in the correlation between two point sets. In this paper, the LCLQ is used to reveal the spatial variability in the association between residents' leisure activities and tourists' activities. Then, based on the LCLQ analysis results, the spatiotemporal correlation regions of residents and tourists can be identified. The LCLQ is formulated as follows:

$$LCLQ_{A_i\to B} = \frac{N_{A_i\to B}}{N_B/(N-1)} \tag{2}$$

where N_B is the total number of points B and N is the total number of points A and B. $N-1$ represents the total number of elements outside of that point. $N_{A_i\to B}$ is the weighted average of the number of points B in the neighborhood of point A_i, and its calculation formula is as follows:

$$N_{A_i\to B} = \sum_{j=1}^{N}\left(\frac{w_{ij}f_{ij}}{\sum\limits_{j=1(j\neq i)}^{N} w_{ij}}\right), (j \neq i) \tag{3}$$

where f_{ij} is a binary variable that indicates whether point j is a point in the point B set. If it is, it is equal to 1 and 0 otherwise. w_{ij} is the geographical weight, indicating the importance of point j to point i. In this paper, the Gaussian kernel density function is used to calculate the geographical weight (w_{ij}), and the formula is as follows:

$$w_{ij} = \exp\left(-0.5 \times \frac{d_{ij}^2}{d_{ib}^2}\right) \tag{4}$$

where d_{ij} represents the distance between the ith point A and point j and d_{ib} represents the bandwidth distance around the ith point A.

There are two methods to obtain the bandwidth $d_{ib.}$ One is the actual distance metric and the other is adaptive bandwidth (distance ranks; e.g., first nearest neighbor, second nearest neighbor, or third nearest neighbor, etc.) [35]. In this paper, the GCLQ and LCLQ are used to investigate the resident-tourist interaction in a spatial context. It is found that 1 km travel distances can promote and support short walking trips in different groups and trip purposes, indicating that resident-tourist interaction is more likely to occur within a 1 km distance [36–38]. Therefore, we selected the former approach to determine the bandwidth $d_{ib.}$ The bandwidth distance for GCLQ and LCLQ is set to 1 km.

4. Study Area and Data Sources

Nanjing, the capital of Jiangsu Province, is located in the middle and lower reaches of the Yangtze River in Eastern China. It has a total area of 6587.02 square kilometers. As one of the four ancient capitals of China, Nanjing has rich cultural relics and a unique natural landscape, and it is a key scenic tourist city in China. In 2019, Nanjing received 146.82 million domestic and international tourists, and its total tourism economic income was 278.495 billion yuan, ranking among the top tourist cities in China. The main urban area of Nanjing is the core area of the overall development of Nanjing, and it has a total area of approximately 259 square kilometers. The main urban area of Nanjing includes Xuanwu Lake, Mochou Lake, Confucius Temple, and other famous scenic spots in Nanjing. As an area with a high residential population density, the main urban area of Nanjing is a highly active area for urban tourism and residents' leisure activities. Therefore, the main urban area of Nanjing is chosen as the study area (Figure 1).

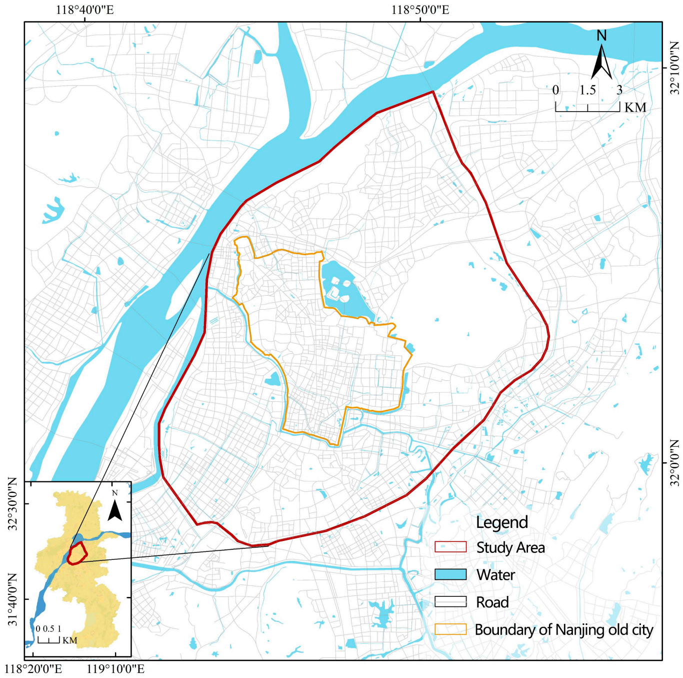


Figure 1. Study Area.

With the widespread use of mobile phones, mobile phone signaling data have become an ideal data source [39]. They have the advantages of wide coverage, wide spatiotemporal coverage, and continuous tracking of an individual's behavior. At present, mobile phone signaling data have rich applications in research on urban traffic, the urban spatial structure, and residents' activities. In this paper, mobile phone signaling data are used to study the spatiotemporal correlation pattern of residents' leisure activities and tourists' activities. In 2015, the number of users of China Mobile reached 826 million, accounting for 64.7% of the three major operators in the domestic market, meaning that China Mobile can provide a reliable data source. Thus, this paper uses the mobile phone signaling data provided by China Mobile.

In the selection of the study period, public holidays are avoided and the difference in leisure activities between weekdays and weekends is also taken into account. Therefore, mobile signaling data from 17 November 2015 (weekday) to 21 November 2015 (weekend) were selected for this research. The collected data include base station data and mobile phone signaling data. The base station data record the location information of each base station (Table 1), including the code (Location), longitude (LON), and latitude (LAT). The mobile phone signaling data are recorded by mobile phone users. They contain an encrypted unique user identification number (ID, anonymous number, no personal information), timestamp (Walktime), base station code (Location), and mobile phone number attribution code (City) (Table 2).

Table 1. Base station data content.

Location	LON	LAT
2098710641	118.91625	32.05497
2098613450	119.06581	32.02686
2062518602	118.87331	31.73291

Table 2. Mobile signaling data content.

ID	Walktime	Location	City
0072fcd5c7b63666 3460f44d3eed6178	20151117061526	2098710641	25
0643494c89960c2f 569a6b6ce4c45e97	20151117024335	2062518602	25
075d5c10d5a4dbbe 982677b27e40ae9c	20151117185144	2098613450	591

The original mobile phone signaling data used in this paper are CSV text files. Due to the enormous amount of data, the data in the CSV file are transferred to PostgreSQL database software, and the attribute data table of mobile phone signaling data is established in the database. SQL statements are constructed in the PostgreSQL database to clean, filter, and screen the signaling data of mobile phones. The data preprocessing process is as follows: (1) The PostGIS extension module of the PostgreSQL database is used to spatialize the attribute data table in terms of latitude and longitude in the database and save it as a new spatial element table. (2) The necessary map projection transformation is performed to convert the coordinate system used by the GIS base map and the mobile phone signaling data to the UTM50N plane projection. It offers a database for spatiotemporal correlation research on residents' leisure activities and tourists' activities by merging multi-source spatiotemporal data into a consistent geographical coordinate system.

The tourists referred to in this paper are non-native tourists who carry out tourism activities in the main urban area of Nanjing. The process of the tourism activity data extraction is shown in Figure 2. To identify tourists, first, the PostgreSQL database of mobile phone signaling data is associated with the data table of the mobile phone identification number. Then, the province and city information of the mobile phone users is obtained to identify people from places other than Nanjing and local people. Subsequently, given that the activities of users who use out-of-town numbers in Nanjing include not only tourism but also business travel and medical treatment, we overlay the point surface space on the polygonal surface element layer of the city's main scenic areas. Non-local-number users who visited scenic areas more than twice in one day are recognized as tourists. Then, the tourist activity data set is extracted through the ID code of tourists [40].

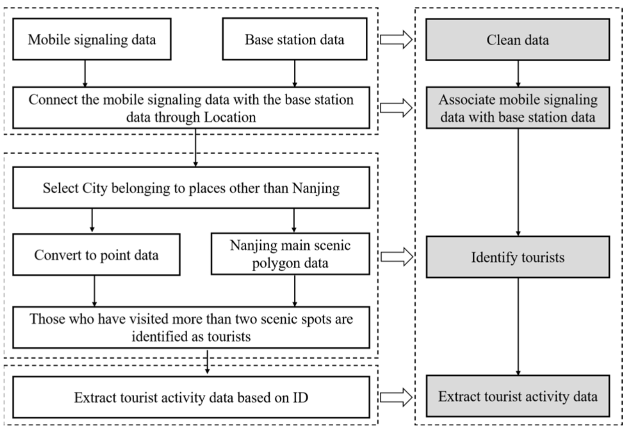


Figure 2. The process of the tourism activity data extraction.

The process of the resident leisure activity data extraction is shown in Figure 3. To complete the extraction of the leisure activity data of residents, it is necessary to identify residents. Firstly, the mobile phone numbers which belonged to Nanjing are extracted using the City value. Secondly, the users who stay in a Nanjing community for more than 4 h during 0:00–6:00 every day for a week are regarded as residents [41]. Then the resident activity data are extracted based on the ID code of residents. Subsequently, depending on the community and the office space in the main urban area of Nanjing, the residents' leisure activities which are outside of these two areas are extracted. Then, GCLQ and LCLQ analyses were performed on the acquired data sets using ArcGIS Pro software.

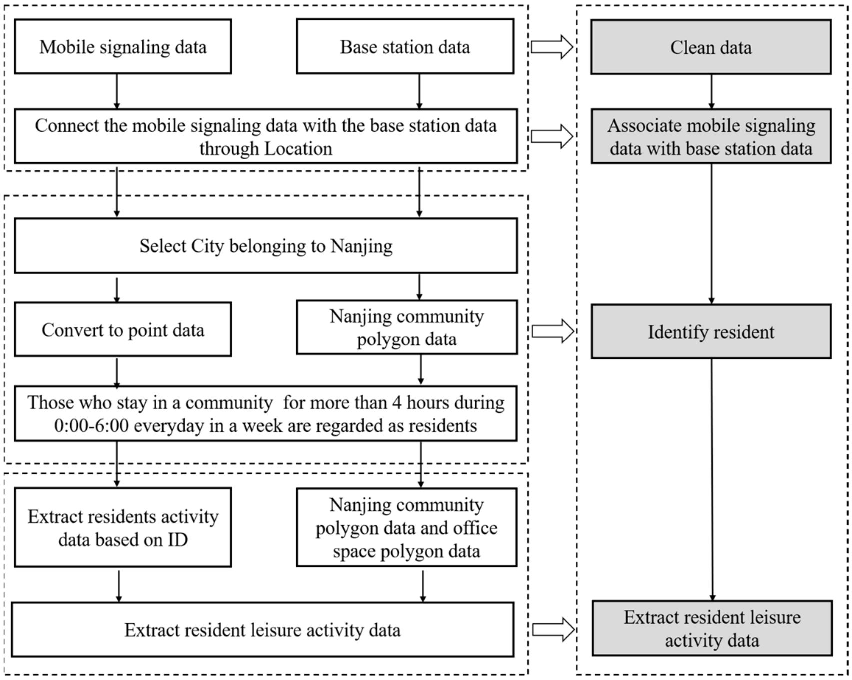


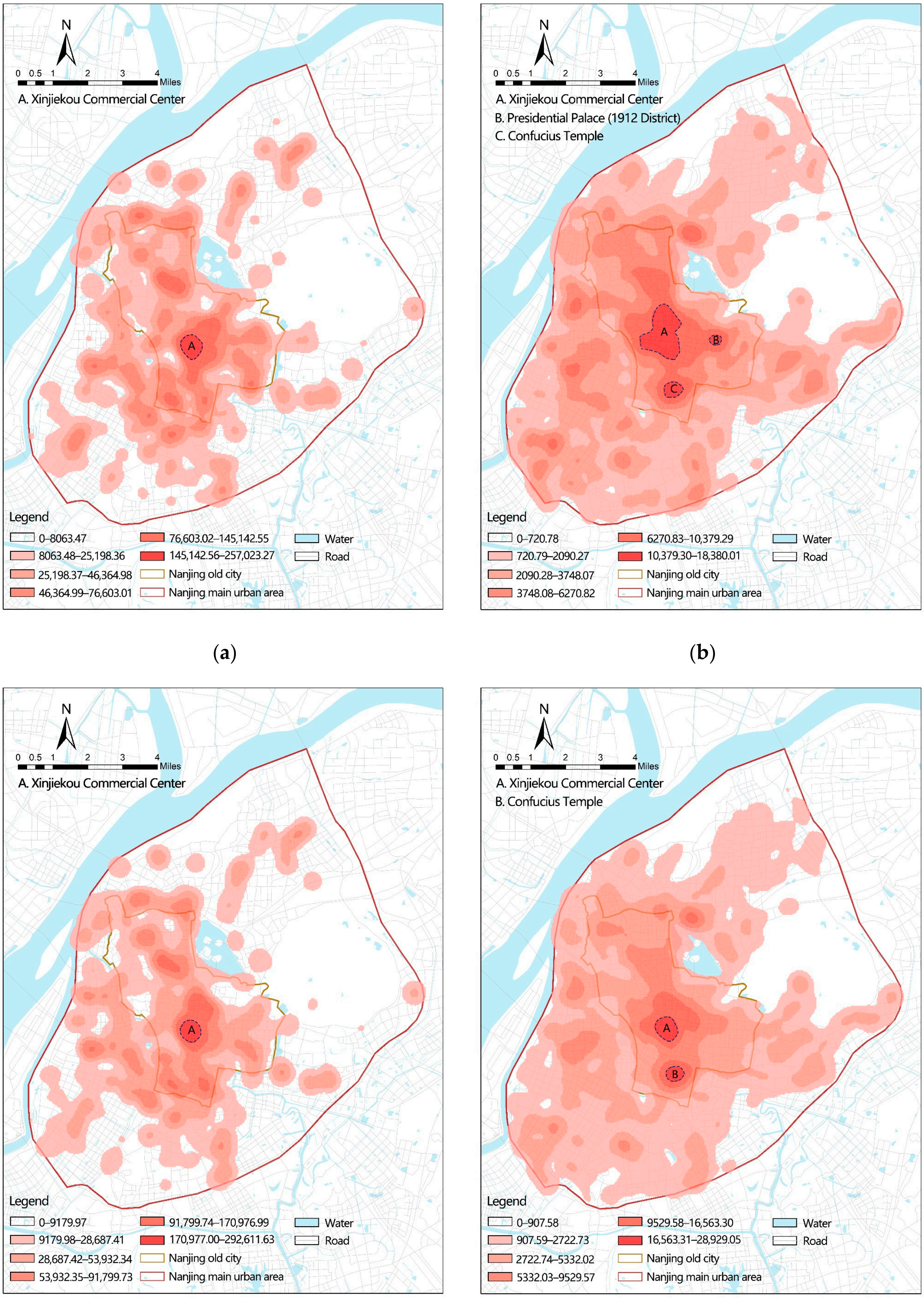
Figure 3. The process of the resident leisure activity data extraction.

5. Results

5.1. Exploratory Spatial Data Analysis Based on Kernel Density Estimation

Firstly, this paper conducts kernel density analysis on the extracted leisure activity data of residents and the tourism activity data of tourists in the main urban area of Nanjing. The results of kernel density analysis are shown in Figure 4. On a weekday, residents' leisure activities are mainly distributed in the Xinjiekou commercial center and commercial centers around residential areas. The presidential palace, Confucius Temple, and other famous scenic spots in Nanjing are where most tourists congregate. In addition to these tourist attractions, the Xinjiekou commercial center is a key area for tourist activities. On the weekend, the quantity of leisure activities rises and the spatial scope of leisure activities also expands. The Xinjiekou commercial center and the surrounding commercial centers continue to be important gathering areas for residents' leisure activities. The amount of tourism activities also increases, with hot spots concentrated in Confucius Temple and Xinjiekou commercial center.

In general, residents' leisure activities and tourists' activities show obvious differences in spatial distribution due to the distinct purposes of these activities. However, the area around the Xinjiekou commercial center attracts both residents and tourists on the weekend and weekdays. There is a spatial overlap between residents' leisure activities and tourists' activities in the main urban area of Nanjing, as shown in Figure 4. Therefore, the GLCQ and LCLQ are used to conduct a quantitative study on their spatiotemporal correlation. In addition, to study the spatial correlation patterns of residents' leisure activities and tourists' activities in different periods, this paper further divides the research time range from 0900 to 2200 into four different periods (Table 3).



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

(**c**) (**d**)

Figure 4. Kernel density estimation heatmaps of tourists' activities and residents' leisure activities in the main urban area of Nanjing. (**a**) Residents' leisure activities on 17 November 2015 (weekend); (**b**) tourists' activities on 17 November 2015 (weekday); (**c**) residents' leisure activities on 21 November 2015 (weekend); (**d**) tourists' activities on 21 November 2015 (weekend).

Table 3. Mobile phone signaling data in different time periods.

Time Slot	Number of Mobile Phone Signaling Data (Ten Thousand)					
	17 November 2015 (Weekday)		Sum	21 November 2015 (Weekend)		Sum
	Resident	Tourist		Resident	Tourist	
Morning (9:00–10:59)	55.53	6.83	62.36	54.19	9.13	63.32
Noon (11:00–13:59)	88.18	14.50	102.68	91.00	13.24	104.24
Afternoon (14:00–17:59)	119.51	17.98	137.49	123.41	18.02	141.43
Night (18:00–22:59)	124.91	16.85	141.76	131.52	19.71	151.23
Sum	388.13	56.16	444.29	400.12	60.10	460.22

5.2. Global Colocation Analysis

This paper conducts a random sampling of residents' leisure activity data and tourists' activity data in each time period, sampling seventy thousand respectively. Doing so improves computational efficiency and reduces the issue of large differences in the amount of residents' leisure activities and tourists' activities. Then, residents' leisure activities and tourists' activities on 17 November 2015 (weekday) and 21 November 2015 (weekend) are analyzed based on the GCLQ (Table 4).

Table 4. GCLQ results.

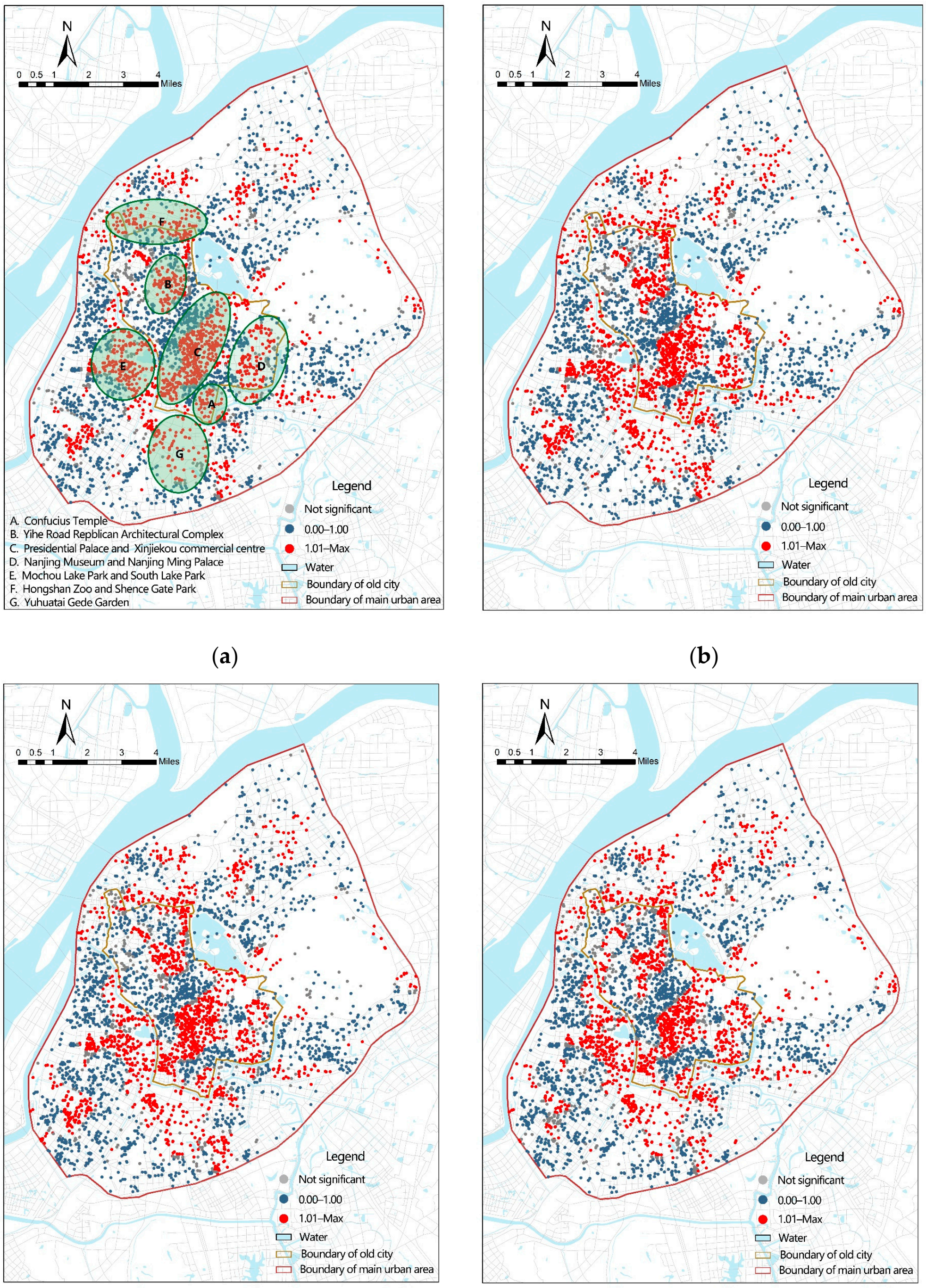
	17 November (Weekday) Residents	21 November (Weekend) Residents
Tourists (morning)	0.916 *	0.921 *
Tourists (noon)	0.914 *	0.921 *
Tourists (afternoon)	0.918 *	0.925 *
Tourists (night)	0.917 *	0.933 *

GCLQ values with * are significant at the 0.05 level.

The analysis results show that residents' leisure activities are not correlated with tourists' activities spatially, and the GCLQ value is less than 1 for both the weekend and weekdays. This finding indicates that tourism activities overlap with the leisure activities of residents in some local areas. However, in general, the two are independent in space, and their mutual influence is limited. In different time periods, the GCLQ value of residents' leisure activities and tourists' activities shows the following changes: (1) On weekdays, from morning to night, the GCLQ value of leisure activities of residents and tourists' activities shows a slight increase, which indicates that the aggregation trend of the leisure activities of residents and tourists' activities continues to strengthen as time progresses overall. On weekdays, residents spend most of their free time in the afternoon and at night. As a result, the leisure activity intensity is higher in the afternoon and at night and there is a stronger spatial and temporal correlation with tourists' activities. (2) On the weekend, the night is the time period when residents' leisure activities and tourists' activities are most closely correlated in time and space. As most scenic spots are closed at night, residents and tourists have a limited choice of destinations during the night, increasing their spatial correlation. (3) On the weekend, the spatial correlation of residents' leisure activities and tourists' activities at different time periods is greater than on weekdays. This is because more tourists visit Nanjing on weekends and residents have more free time on weekends. As a result, they have more opportunities to gather in the same space.

5.3. Local Colocation Quotient Analysis

The LCLQ is used to analyze the clustering areas of residents' leisure activities and tourists' activities on a weekday (17 November 2015) and the weekend (21 November 2015). As shown in Figure 5, on weekdays, the number of spatial correlation points for residents' leisure activities and tourists' activities accounts for 36.17%. The number of spatial correlation points increased slightly from morning to noon and decreased in the afternoon and at night on weekdays. The correlation areas are relatively stable in different periods, mainly concentrated in famous scenic spots and the commercial center within the old city of Nanjing, such as the Presidential Palace, Confucius Temple, and Xinjiekou commercial center, and other areas in the main city, such as Nanhu Park and Yuhuatai Gede Garden. Furthermore, some spatial correlation points are dispersed throughout the neighborhood hotels, supermarkets, etc.



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

(**c**) (**d**)

Figure 5. Results of the LCLQ of tourists' activities and residents' leisure activities on 17 November 2015 (weekday). (**a**) Results of the LCLQ in the morning (9:00–10:59); (**b**) results of the LCLQ at noon (11:00–13:59); (**c**) results of the LCLQ in the afternoon (14:00–17:59); (**d**) results of the LCLQ at night (18:00–22:59).

As shown in Figure 6, on weekends, the number of spatial correlation points in each time period increases, accounting for 37.11%. In terms of spatial distribution, the correlation areas are still mainly distributed in the city's famous scenic spots, parks, and other open spaces. The gathering area has expanded further outside the old city of Nanjing due to the increasing intensity of residents' leisure activities on weekends, forming more small gathering centers around the communities.

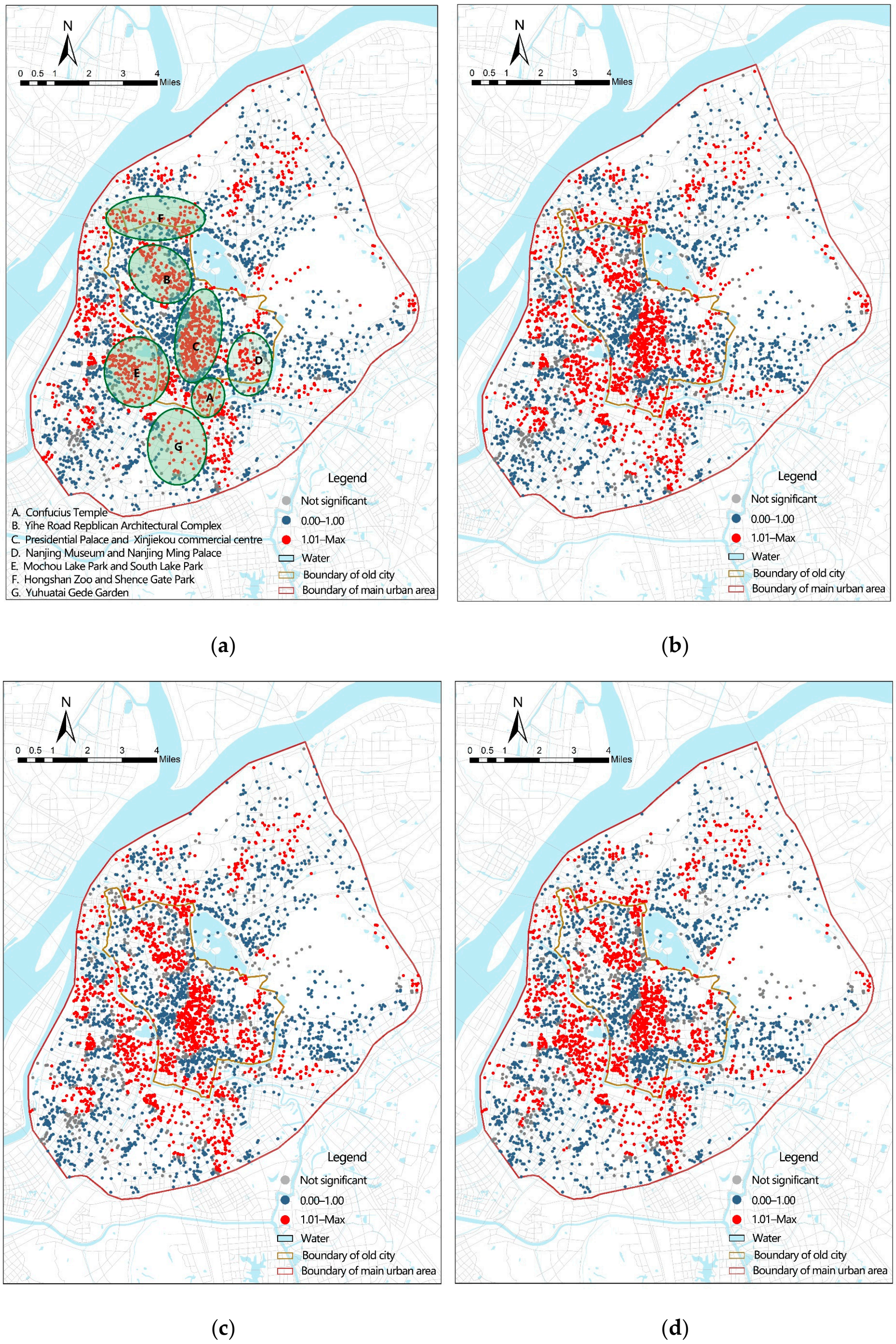


Figure 6. Results of the LCLQ of tourists' activities and residents' leisure activities on 21 November 2015 (weekend). (**a**) results of the LCLQ in the morning (9:00–10:59); (**b**) results of the LCLQ at noon (11:00–13:59); (**c**) results of the LCLQ in the afternoon (14:00–17:59); (**d**) results of the LCLQ at night (18:00–22:59).

6. Conclusions and Discussion

6.1. Conclusions

Firstly, this study conducts kernel density analysis on residents' leisure activities and tourists' activities. The study's findings demonstrate that residents' leisure activities and tourists' activities show obvious differences in spatial distribution. However, in the Xinjiekou commercial center and surrounding areas, an obvious spatial overlap is found. To study the sharing of urban space for residents' leisure activities and tourists' activities, we analyzed the spatial correlation patterns of residents' leisure activities and tourists' activities through CLQ analysis. The following are the primary conclusions:

(1) Overall, residents' leisure activities and tourists' activities are not correlated in time and space, indicating that the residents' leisure activities and tourists' activities are relatively independent in space both during the week and on weekends. On weekdays, from morning to night, the GCLQ value of leisure activities of residents and tourists' activities shows a slight increase, with the afternoon being the time when the spatial correlation between residents' and tourists' leisure activities is strongest. On weekends, the GCLQ value rises as time passes. The spatial correlation is strongest at night, with a GCLQ value of 0.933. Weekends have a higher spatial correlation between residents' leisure activities and tourism activities than weekdays.

(2) In terms of spatial distribution, whether on weekends or weekdays, the clustering area of residents' leisure activities and tourists' activities mainly distributes in the areas near famous scenic spots and commercial centers in the old city of Nanjing, as well as urban parks, squares, and other open spaces in the main city. On weekends, when residents have more free time for leisure activities, the aggregation area is expanded outside the old city further and more small gathering centers are formed around the communities.

(3) On weekdays, the proportion of spatial correlation points with LCLQ values greater than 1 for residents' leisure activities and tourists' activities is 36.17%, while on weekends, it rises to 37.11%. Noon is the time period with the largest number of spatial correlation points on the weekdays, while on the weekends, the spatial correlation points with LCLQ values greater than 1 at night is 40.46%, which is the highest in the four periods.

6.2. Discussion

Existing studies that examine the spatial relationships of tourist-resident interactions are limited [10,16,17]. By using kernel density analysis and other methods, most studies primarily identify the places where residents and tourists congregate and conduct qualitative comparison assessments. In addition, these studies pay more attention to the spatial distribution of tourists and residents. Few studies focus on whether there is a spatial correlation between the activities of residents and tourists. The spatial correlation of residents' and tourists' activities can be used to quantitatively analyze the aggregation of residents and tourists in tourist cities, which could provide important insights for improving services and attractions, the transport system, and the marketing strategy of cities. In addition, existing research identifies hotspots area primarily through the congregation of residents and tourists. Residents' leisure activities have the greatest interaction with tourism activities. As a result, the aggregation areas identified by the spatial correlation pattern of residents' leisure activities and tourism activities will be more accurate. With the rapid development of urban tourism, it is inevitable that residents and tourists will share urban spaces. Quantitative analysis of the spatiotemporal correlation patterns of residents' leisure activities and tourists' activities holds great significance for guiding the future development of urban tourism. Therefore, this study conducts a quantitative analysis of the spatiotemporal correlation between residents' leisure activities and tourists' activities based on the GCLQ and LCLQ.

The results show that residents' leisure activities and tourists' activities have two trends in urban space sharing. One trend is that residents tend to go to well-known scenic spots for leisure activities, which makes it easy for them to meet tourists in these famous urban tourism spaces. The results of Song's (2020) study are consistent with this trend.

He noticed that residents frequently select well-known scenic spots [42] because these spots provide them with higher-quality services and serve as a reminder of their city's past. Another trend is that tourists are no longer satisfied with just staying in the tourist space; they will also go into communities or commercial centers for the experience [43]. This trend is reflected in the spatial distribution of aggregation areas of residents' leisure activities and tourists' activities. In addition to many famous scenic spots, some correlated areas are near communities. In addition, the shared space of residents' leisure activities and tourists' activities includes the Xinjiekou commercial center, district commercial centers, and commercial areas around scenic spots. Based on analyzing mobile signaling data, this paper validates the sharing of the city's commercial facilities by residents and tourists [44–46]. According to the results, the degree of sharing of commercial facilities is deepening and commercial facilities from urban commercial centres to residential areas are becoming the shared commercial space of residents and tourists. Tourists' desire to experience daily life in the city is an important reason for this trend. This is supported by an empirical study in Paris, which showed that non-first-time tourists are more likely to go to the same places as residents, and this tendency to homogenize increases with the number of times that tourists visit the city [47].

For a long time, urban planning has taken residents as the main body of research. However, with the increasing number of urban tourists, the frequency of tourists in commercial facilities and urban public spaces other than tourism spaces is gradually increasing. As tourists perceive the destination city image in more diversified ways, the optimization of the city image should be promoted based on the construction of not only tourism spaces but also surrounding commercial facilities, commercial centers, and urban public squares. Furthermore, despite accounting for a small proportion of total residents' leisure activity data, the total number of residents' leisure activities distributed in urban scenic spots and urban parks reached approximately 866 thousand on 17 November 2015 and 1137 thousand on 21 November 2015, which was higher than the total number of tourists carrying out tourism activities in the city on the same day. Therefore, the design of urban scenic spots needs to not only consider the needs of tourists but also take into account the needs of residents' leisure activities.

This study quantitatively analyses the spatiotemporal correlation patterns of residents' leisure activities and tourists' activities through the CLQ, which contributes to understanding the resident-tourist interaction from a time-spatial perspective. In the future, we can further explore the spatial and temporal interaction patterns of residents and tourists in tourism cities through GCLQ and LCLQ analysis. However, this paper also has some limitations. First, in GCLQ and LCLQ, the edge effect is not taken into account [35]. The spatial association patterns of point datasets near the boundary are biased as a result. In future research, the boundary effect correction methods of Ripley's K function, such as the buffer and correction coefficients, can be used to solve the problem [48]. Second, it is difficult to obtain individual mobile phone signaling data, so we used mobile phone signaling data from November 2015 for research. As a result, there is a problem of data timeliness. In the future, we can try to obtain individual activity data from mobile apps for up-to-date data. Third, based on mobile phone signaling data, this paper studies the spatiotemporal correlation patterns of leisure activities and tourist activities. The subjective feelings of residents and tourists are not studied. In future research, this aspect will be supplemented by questionnaire surveys to realize the combination of big data and small data for relevant research.

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