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Fine-Grained Spatiotemporal Dynamics of Inbound Tourists Based on Geotagged Photos: A Case Study in Beijing, China

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ABSTRACT The aim of this study was to provide scientific support for the creation of policy on inbound tourism. A comprehensive and thorough understanding of fine-grained spatiotemporal dynamic patterns is crucial for tourism management, planning and policymaking. In spite of spatiotemporal pattern analysis on tourism movements, environment- and society-related topics have been developed to stimulate tourism. However, few studies have focused on the fine-grained spatiotemporal analysis of tourist behavior. Depending on a fine-grained Flickr data source, we investigated the spatiotemporal dynamic patterns of inbound tourism in the context of fine granularity in the spatial and temporal dimensions. The proposed approach based on fine-grained Flickr data and the emerging spatiotemporal analysis method was to first conduct a refined temporal variation analysis based on the annual, monthly, and daily variation; second, a thorough analysis of the seasonality of tourism was conducted with the kernel density estimation (KDE) method; third, the correlation between the attraction grade and popularity was complementarily exploited with both qualitative and quantitative methods; and finally, the patterns were identified and visualized with the space-time cube in the context of fine granularity. The results from the analysis revealed that the downtown region of Beijing was the most popular place throughout the year due to the many famous Chinese cultural heritage attractions. In contrast, the landscape sites and thematic parks were nearly cold spots because of their strong seasonality. Our approach can also be applied to other crowdsourced data, such as that from Twitter and Instagram. Spatiotemporal analysis and empirical research have interesting implications for other cities in China or other developing countries.

INDEX TERMS Inbound tourism, fine-grained pattern, spatiotemporal analysis, geotagged photo, Beijing.

I. INTRODUCTION

The tourism industry is a crucial sector for improving economic and social development in many countries and regions [1], [2]. In particular, the recent growth in inbound tourism has played a major role in the openness of the country. Tourism stimulates economic development but has unique behavioral patterns in different areas. As a result, the tourism behavior. patterns in tourism management are receiving increasing attention from both academia and industry [3], [4], which is very useful for tourism policy decisions, tourism planning and management, and destination recommendation systems for the international tourism market.

Fine-grained spatiotemporal dynamics are vital for providing comprehensive and thorough information and insights into travel behavior [3], [5]. Inbound tourism research can provide important significance for the development of international tourism market and planning. However, the visualization of the spatiotemporal dynamics of tourist behavior and quantification of the factors at a more fine-grained scale have much room for improvement. In this study, we focused on developing an approach to unfold the fine-grained spatiotemporal dynamics of tourism and a visualization method to represent the multiple dimensions of tourist behavior.

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In terms of data sources, the traditional data sources include yearbooks [6], tourism survey [7], and questionnaires [8]. However, these data have low spatial resolutions in the aggregated data and coarse temporal properties. Therefore, it is impossible to calibrate the behavioral patterns of inbound tourists [9]. Due to the popularity of digital devices and social media, large amounts of volunteered geographic information (VGI) data, such as Flickr (flicker.com) and Booking.com (booking.com), have demonstrated the potential for use in investigations of human behavior [10].

Tourism has an important spatial dimension and distinctive seasonal feature, which results in heterogeneous localized impacts in the spatial and temporal dimensions [11]. Flickr, a type of VGI data, is a widely used photosharing service that provides a vast number of geotagged photos that support spatial pattern analysis at the city level [12]. Based on Flickr data, travel accommodation behavior [10], tourist movement behavior [5], and spatial interactions between tourists and residents [13] have been conducted. To predict the more precise locations of tourists, a context-aware recommendation method was developed in which the similarity of the POI and weather were used to determine the precise location [14]. A maximum entropy model was proposed to estimate the geographic distribution of tourists to facilitate disaster and crisis management in tourism management [15].

In general, most of the existing research on spatiotemporal dynamics suffers from drawbacks in several aspects. First, the granularity of analysis is not considered on multiple scales with fine granularity. More studies focus on country-wide or city-wide seasonal or monthly analysis [11], without considering the daily tendency and attraction-oriented analysis. Second, it has been widely recognized that the type or grade of attractions is the main determining factor of its popularity with tourists [5]. However, the extent to which the variation in tourists can be explained by the attraction grade had not been empirically examined until now. Third, density maps [16] or tag word-cloud maps [13], [17] have been used to visualize tourists or destinations. However, these methods lack clear visualization with multiple views of the spatiotemporal pattern of tourists, such as the 3D mapping approach for spatiotemporal patterns.

Despite the surge of interest in using geotagged photos in tourism research, only a few studies have examined the fine-grained spatiotemporal dynamics of tourists. In this paper, taking the aspects described above into consideration, we discussed how geospatial analytical methods should be applied to examine inbound tourist spatiotemporal dynamics via a Flickr dataset from Beijing, China. The Flickr data covered fine-grained spatiotemporal dimensions over the last ten years in Beijing. As a VGI data source, Flickr data are a bottom-up approach. In contrast, conventional tourism data collected and maintained in a top-down manner by authorities were usually sampled and aggregated. Therefore, fine-grained spatiotemporal dynamics could be portrayed by the Flickr data. The variation in tourist presence at popular attractions at the micro level was another issue of concern in our study. A quantitative analysis of the popularity and the relationship with factors will be examined in the follow sections. Finally, the space-time cube was used to visualize the spatiotemporal pattern, which simplified data visualization by 3D mapping. As other crowdsourcing platforms allow geotagging that reveals real-time locations, e.g., Twitter, Instagram, and Facebook, our methods can also be applied to these data. Furthermore, the spatiotemporal analysis and empirical results proposed in this paper have interesting implications for other cities in China. To a large extent, these methods can also be applied to cities in other developing countries.

The contributions of this paper can be summarized as follows:

(1) A fine-grained spatiotemporal dynamic pattern analysis approach was developed. Fine-grained data (Flickr data) were used to ensure a refined analysis. Furthermore, novel and thorough methods were employed to ensure fine-grained pattern analysis. For example, for the daily temporal variations, quantitative analysis was used to measure the correlation magnitude and to detect and visualize the fine-grained pattern. This approach was validated with Beijing inbound tourist data in this paper.

(2) A 3D mapping visualization based on a space-time cube was proposed to detect and visualize fine-grained patterns. In this paper, the month step was set to detect monthly patterns. That is, finer granularity can be achieved if the time step and spatial step are set more precisely. Moreover, with the powerful 3D mapping of the space-time cube, we were able to clearly identify the pattern with the interactive visualization method.

The remainder of this paper is structured as follows. In Section 2, the background and studies relating to spatiotemporal analysis on tourism are reviewed. Section 3 presents a definition of the case study area and data, the studies that were consulted, and the methods in this paper. Section 4 covers the experiments and results of our approach. A discussion on our fine-grained analysis approach is presented in Section 5. Finally, Section 6 provides some concluding remarks and proposes some future directions.

II. RELATED WORK

The focus of our paper was spatiotemporal pattern analysis of Flickr data. Therefore, the investigation of the literature background of tourism studies based on Flickr data and spatiotemporal methods for studying tourism can provide clues for our research. The literature review of existing applications and methods indicated the granularity of pattern analysis and the involved methods. In this section, these two aspects of tourism were examined.

A. TOURISM STUDIES WITH FLICKR DATASETS

In terms of the data sources for tourism studies, traditional data and new emerging data are used. Traditional data, such as statistical yearbooks [6], surveys [7], and questionnaires [8], can support tourism research. However, these data are nearly all static statistical data or data aggregated by administrative officials [11], [18]. They have limited sample numbers and spatial and temporal resolutions, hindering the abstraction of tourists' profiles or characteristics at fine spatial and temporal scales. Another drawback of conventional data sources is the cost and time consumption [3], [19]. With the growth of Web 2.0 technology, nonconventional data sources are emerging, such as mobile call records [5], [20], location-based check-in data from Ctrip.com or Booking.com [11], and the Flickr dataset [3]. Among these, the Flickr dataset is uploaded and generated by volunteers around the world, which supports low-cost data collection and makes the data freely available. Furthermore, this dataset has a sufficient sample size and fine-grained spatial and temporal variations. Some prior studies have specifically evaluated the possibility of using Flickr for tourism research [10], [21]. Therefore, the Flickr dataset has been widely used [12], [21].

This review of the existing applications of Flickr data can be classified into three categories: spatial scale, research topics and research methods. Owing to the global data coverage, Flickr data supports research at all kinds of spatial scales, such as county-, region- or city-wide. To investigate the spatiotemporal pattern in Europe, Flickr data have been utilized as a data source in combination with other data sources [11]. Hong Kong was selected as the study area for an investigation of travel behavior with Flickr data [3]. Flickr data from six cities in six countries were used to extract and analyze the urban areas of interest [19]. For city-wide research, the accommodations in Vienna [10] and tourist movement in Xi'an and Shanghai in China [5], [18] were investigated. For the research topic, the social, economic, and environmental aspects were all involved. The tourist groups or party sizes were determined by their trajectory [5]. Another example in social research is the destination preference by the cultural backgrounds of the tourists [3]. Economic research on tourism management or behavior is mainstream, ranging from the destinations [22] and patterns [5], [10], [11] to the markets [23]. Environmental research has focused on the analysis of urban areas of interest [19], [24] and on environmental analysis [17], [25]. In terms of research on methods, the AOI extraction, spatial interaction analysis, and spatiotemporal pattern methods were all developed by integrating common methods such as spatial analysis [5], Markov chains [26], and complex network theory [18].

In reviewing the literature and applications of Flickr data, many studies are working on tourism management. However, to the best of our knowledge, few studies have focused on fine-grained inbound tourism analysis. Flickr data have accurate spatial and temporal dimensions, which allows them to represent fine-grained spatiotemporal dynamics.

B. SPATIOTEMPORAL ANALYSIS OF TOURISM

Tourism managers pursue thorough insight into travel behavior to support planning, management, and attraction marketing. This requires managers and planners to know about tourism patterns, tourist preferences and their interactions. Spatiotemporal analysis can help to identify patterns and refine knowledge from data to support tourism management and planning [7].

Spatiotemporal analysis is used to obtain insight into dynamics, events, tendencies, or patterns, incorporating both the spatial and temporal dimensions [27]. Spatiotemporal analysis was originally proposed in the early 1970s [28] and has become widely used since its birth. Incorporating spatial and temporal concepts ensures a powerful and comprehensive understanding of event occurrence, which has been widely used in tourism research, such as to study tourist behavior [3], tourist movement [5], spatial interactions [13], event detection [29] and recommendation systems [30].

A more general analysis procedure can be drawn from these studies: information extraction and pattern analysis. Information extraction may entail geographical information extraction [3] or thematic information extraction. For example, to analyze tourist behavior or movements, hot spots of areas of interest (AOIs) have been identified [3], [18], [31]. Many spatial analysis methods, such as spatial clustering and density estimation, have been used for AOI identification. In regard to pattern analysis, mathematical methods or visualization methods have been developed. To reveal the movement pattern of tourists, Markov Chains have been used [3], [31]. Complex network theory has been used to mine tourism flow patterns [18]. Different attempts have been devoted to developing visual analytics methods for pattern analysis. Visual analysis is the science of analytical reasoning with the aid of interactive visual interfaces [32]. To understand the spatial interaction between tourists and residents, a visualization method was used to examine it in ten US cities [13]. In another attempt, a density map was used to analyze the density of attractive areas and hot spot destinations [16].

Due to the demand for fine-grained information for tourism management and planning, several drawbacks and points of improvement need to be pointed out. First, the existing methods need to be developed. For example, kernel density estimation (KDE) is an effective spatial method that has not been widely utilized in tourism research [33]. Mapping events or phenomena in predefined time periods is probably the most common method for mining spatiotemporal patterns for spatiotemporal analysis. However, this may have the risk of obscuring important patterns. Therefore, the development of a comprehensive visualization method is necessary [34]. Second, the existing literature has paid more attention to qualitative analysis, but to what extent is quantitative analysis able to reveal fine-grained relationships? The variation in tourist presence could be explained by the attraction grade or other factors, but it had not been empirically examined until now.

III. MATERIALS AND METHODS

In this section, we describe the case study area, data, and methods employed in this paper. The data were carefully filtered and prepared. Traditional spatiotemporal analysis

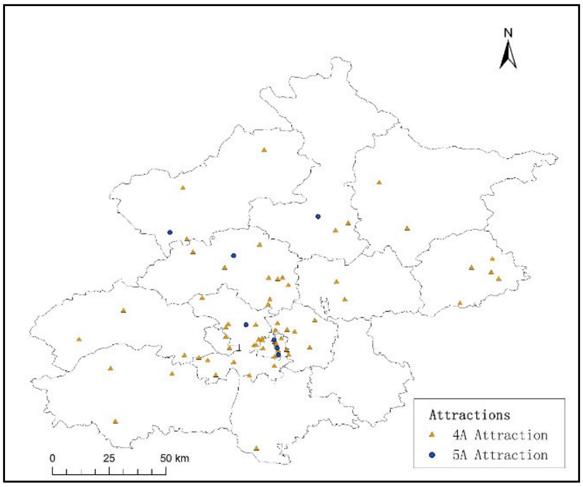

FIGURE 1. The overview of Beijing city and some of its attractions.

methods and emerging novel methods are described in this section.

A. DATA AND STUDY AREA

Since this paper focuses on Beijing, it was selected as the case study area. Beijing is the capital city with a history that extends at least 3000 years. Beijing has a rich variety of attractions, such as the Great Wall, which has been named a wonder of the world, Palace Museum and Summer Palace. There are eight "AAAAA" (5A) grade attractions and thirty-one "AAAA" (4A) grade attractions. These attractions cover three main categories: cultural heritage, landscapes, and theme parks. An overview of the study area and the studied attractions is shown in Fig. 1.

The dataset used in this paper was harvested from the Yahoo Flickr Creative Commons 100 Million dataset (YFCC100M) via its application programming interface (API) (https://www.flickr.com/services/api/). This dataset contains approximately 100 million Flickr photos uploaded by volunteers between 2004 and 2014, and approximately half of the photos were geotagged [35]. This dataset has many photo attributes with spatial, temporal and semantic coverage in many cities across the world, such as IDs and URLs, which provide access to the photo, shot time, latitude, longitude, and tags, which provide fine-grained metadata for spatiotemporal analysis.

B. PREPROCESSING OF DATA

The data preprocessing included discriminating between residents and tourists, extracting spatiotemporal information from the data and cleaning the data. After preprocessing, the dataset contained 48,685 records.

The photos in the Flickr dataset were taken and uploaded by residents or tourists. To differentiate the photos taken by tourists, two approaches were developed. The indicators involving the number of pictures and duration of visits were used to determine whether the users were residents or tourists [36]. Another method was to examine the user profile extracted by the Flickr API [3], [13]. In our research, the second method was employed.

The next preprocessing step was the reconstruction of the geographic information of the photos. The photos in the Flickr dataset had the latitudes and longitudes of the location. To carry out the spatial analysis conveniently, the location information was extracted and reconstructed in shapefile format for spatial analysis with ESRI software.

The third step in data preparation was the data cleaning. Therefore, we performed the following steps to clean the data. First, we refined the dataset within the study time period. We selected the pictures between 2007 and 2013 as the research data source since there were sufficient pictures in these years. Second, we removed imprecise records from the dataset. Owing to the device (such as GPS sensor) error, the locations were less accurate, which may have resulted in one tourist having multiple photos with different locations at the same time. This was not precise enough for our research, so we removed these records to allow accurate analysis. Third, we aggregated the records from the same owner at the same geographic place into one record. Our research focused on tourists rather than on photos, but the records in the dataset were photo metadata. To avoid the side effects of duplicate records at the same place from the same tourists, we aggregated these records.

C. SPATIAL ANALYSIS ON SPATIOTEMPORAL PATTERN

This study employed a variety of spatial, temporal and spatiotemporal analytical methods for the fine-grained spatiotemporal dynamics of inbound tourism, including basic statistical methods and advanced spatial analysis. First, the temporal patterns of tourists were examined using statistical methods. Second, the kernel density estimation (KDE) method was utilized to detect the spatial density and hot spots. Furthermore, spatial correlation analysis was used to quantitatively analyze the relationship between the attraction grade and popularity. Finally, the space-time cube method was employed to identify and visualize the spatiotemporal dynamic patterns of tourists. In this section, we place more emphasis on the KDE and space-time cube methods.

1) KDE FOR THE SPATIAL PATTERN

KDE was used to estimate a smooth empirical probability function from the point sample data [37]; KDE is a powerful spatial analysis method that converts a geographically distributed set of points into a smooth surface and estimates the density [34]. For example, hot spots have been identified for Twitter activity [38] and other social media big data [39]. Compared to clustering methods such as DBSCAN and k-means clustering, the visualization results are the same; however, they have completely different analyses. KDE focuses on the spatial patterns of the data; in contrast, clustering methods place more emphasis on the classification and on deepening the understanding of the spatial clusters of geospatial phenomena [40]. Therefore, to analyze the geographical

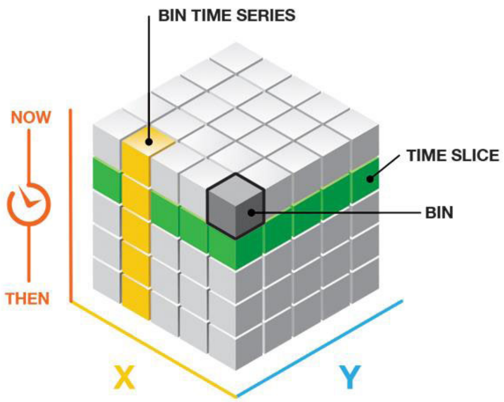

FIGURE 2. The conceptual structure of the space-time cube (ESRI, 2016).

distribution of tourists and identify tourist hot spots, KDE was employed in our study.

The key parameters of KDE are the bandwidth and kernel weight functions. However, more important than the weight function is the bandwidth, which certainly impacts the density estimation result and controls the degree of smoothing of the surface [10], [41]. If the parameter is large enough to cover the whole study area, the density in all areas will be the same, which means that patterns will be ignored; otherwise, if the value is very small, the result will be coarse and fragmented. Although many theoretical methods, such as average distance-based methods, have been developed [42], the interactive selection of an appropriate bandwidth is fairly useful due to the uneven distribution of the data.

In our study, we chose the default weight functions in the ArcGIS software. For the bandwidth parameters, we tried different values in 500 m intervals, including 500 m, 1000 m, 1500 m and 2000 m, to find the optimal bandwidth. Finally, we chose the 2000 m bandwidth because it was able to maintain the heterogeneity of the hot spots in our study.

2) SPACE-TIME CUBE FOR 3D VISUALIZATION OF SPATIOTEMPORAL PATTERNS

The space-time cube is a spatiotemporal information visualization method that represents a spatiotemporal pattern inside a cube. The space-time cube was originally proposed by Hagerstrand and has been developed to visualize vehicle stopping behavior [43] and crime patterns [34], [44]. The distinctive advantage compared to 2D map visualization is its ability to efficiently transfer or represent complex spatiotemporal patterns to users from a 3D perspective [45]. In addition, the space-time cube can support the exploration of spatiotemporal patterns, clusters and changes, which are not available in many space-time methods [46]. Research has demonstrated the efficacy of the space-time cube method, especially in focused analysis of small geographic areas [34], [44]. Therefore, the space-time cube method has been employed to visualize the spatiotemporal properties of tourist behavior.

The space-time cube employs bins of space and time to display spatiotemporal information (Fig. 2). A set of points

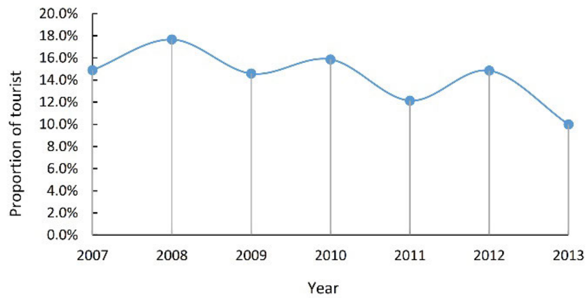

FIGURE 3. Annual variation in the proportion of tourists (2007-2013).

is aggregated into a netCDF data structure according to specified attributes. Each bin represents the location and time by counting these aggregated points. Emerging hot spot analysis (Getis-Ord Gi*) was employed to identify the statistical significance of each bin, which resulted in a z-score and p-score for each bin. Mann-Kendall trend tests were applied to measure the temporal trends at each individual location [47]. The Mann-Kendall method, which was proposed by Mann and Kendall, is used for statistical column counts or hierarchical correlation analysis of geographic phenomena and time series. It is a nonparametric statistical test method that is applied to time series of runoff, temperature, precipitation and water quality [48].

IV. FINE-GRAINED ANALYSIS OF SPATIOTEMPORAL DYNAMICS

In this section, we show the fine-grained analysis results. These results include the temporal variation, seasonal analysis, qualitative and quantitative correlation analysis, and spatiotemporal pattern analysis.

A. TEMPORAL VARIATIONS

For the fine-grained spatiotemporal dynamic analysis, we examined multiple scales of temporal variation across the annual, monthly and daily scales. Differentiating between the macro-scale view of tourist movements with only annual and monthly data and the micro-scale view of tourist behavior. with daily data was also investigated in this paper. This is useful for tourism planning and management since daily temporal variation can provide detailed hourly information.

The annual variation in tourist presence is shown in Fig. 3. It can be seen that in general, the numbers showed a downtrend, which was especially large in 2013. In contrast, the trend increased in 2008 and 2010. The uptrend was also suggested by the government statistical data (http://www.china.org.cn/travel/news/2008-08/27/content_16339382.htm), which argued that large events such as the Olympic Games in 2008 may stimulate inbound tourism. This trend was also demonstrated by academic research. The main findings in the literature showed the close linkage of the Olympic Games mega-event with inbound tourism [49]. This was the same conditions as those of the uptrend in 2010.

The monthly and daily temporal variations in inbound tourism were further examined using a line chart and rose

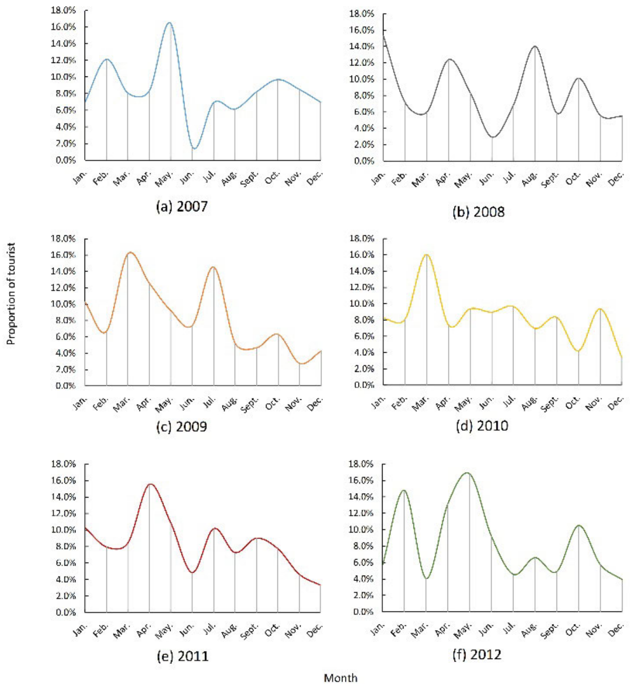

FIGURE 4. Monthly variations in tourist proportions (2007-2012).

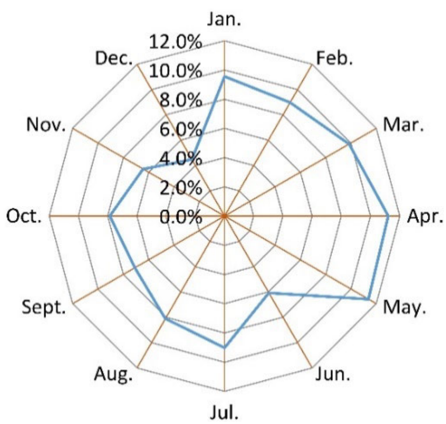

FIGURE 5. Monthly variations in the proportions of all tourists.

diagram, as shown in Fig. 4, Fig. 5 and Fig. 6. Fig. 4(a) to Fig. 4(f) show the tendency of tourists across all months of the year. It can be seen that the peak is often from March to May of each year; on the contrary, the low point is often from November to December. This change is more dependent on the climate, which has been validated by other research [50]. Beijing has four distinct seasons that are delineated by the temperate and continental monsoon climate: spring, summer, autumn, and winter. The spring is warmer from March to May, while it is cold and dry in winter from December to February. Therefore, the number of tourists is largely influenced by the climate. There are two exceptions shown in Fig. 4, which were in 2008 and 2010. In 2008, there were two peak tourism seasons in April and August. One of the possible reasons was the Beijing Summer Olympic Games that were held in August 2008, which had a strong attraction for

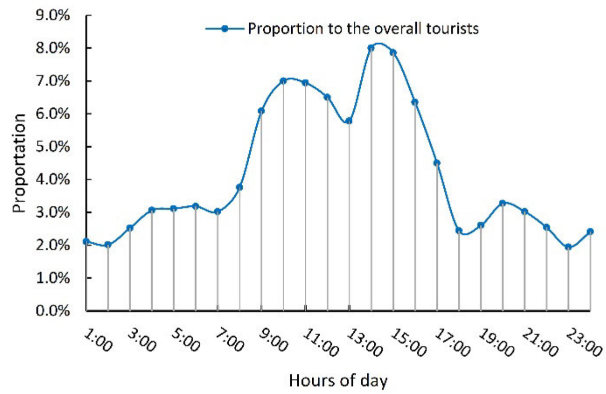

FIGURE 6. Hourly variations within one day of the proportions of all tourists.

foreign travelers. Expo 2010 Shanghai was open from May to October 2010, which may have influenced inbound tourism in Beijing and maintained high levels in these months. Although the site of Expo 2010 is in Shanghai, inbound tourism was probably influenced by the convenient transportation and Beijing's urban charm.

Fig. 5 shows the monthly rose diagram of the study period. The line in the diagram is the proportion of monthly tourists to the overall amount of the study time period. It can be seen that the first half of the year is the major tourism season compared to the second half of the year. In terms of the monthly distribution, the top two highest ratios occurred in April and May. The tourist distribution by month was more even throughout the whole year, which had a standard variation of 0.021.

Compared to Fig. 4 and Fig. 5, Fig. 6 shows the tourist temporal variation at a finer granularity through a daily analysis. Daily analyses can reveal the travel habits of tourists, which are useful for planning public infrastructure, scheduling travel times, and extending related activities. Two peaks occurred from the hours of 10:00-11:00 and the hours from 14:00-15:00, which are the peak travel hours of the whole day. The two low points next to the peaks were at 13:00 hours and 18:00 hours, which was largely due to the lunch and dinner times. There was a small peak at 20:00 hours, which may indicate short distance travelling after dinner, such as nighttime sightseeing. From 23:00 hours to the next day at 7:00 hours, travel was more stable, which may imply that the tourists rested or slept in hotels. The more interesting finding was the sharp tendency in two intervals: an uptrend from 7:00-9:00 hours and a downtrend from 16:00-18:00 hours. From the hourly distributions of the tourists, we may infer that the two tendencies probably represented departures and returns, respectively.

In summary, temporal variation is a common avenue for analyzing spatiotemporal data. However, the review of the existing literature revealed that data with coarse temporal scales, such as annual or monthly data, are widely used rather than fine-grained data. Fine-grained data, such as hourly data, are useful for tourism management and planning. Two lessons can be learned from these experiments. The tourism

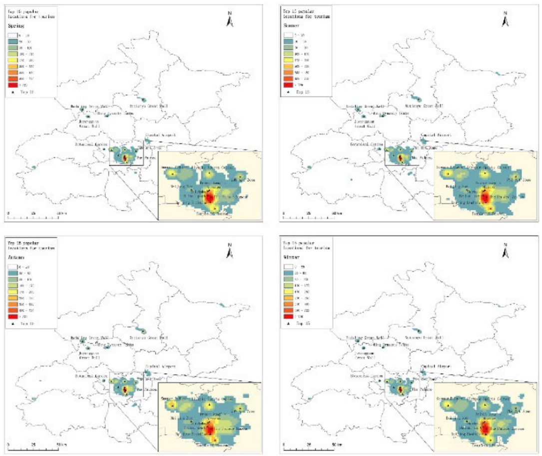

FIGURE 7. Top 15 attraction locations in the four seasons.

uptrend outliers in the annual and increased popularity in the second parts of 2008 and 2010 were closely related to special international events. Thus, the relationship between these events can be concluded. Another lesson was from the fine-grained temporal analysis at the hourly scale, which can describe tourist behavior patterns. This information is very helpful for decision making about tourism management and planning. It has been validated by the Beijing government with the ongoing nighttime economic policies.

B. SEASONAL ANALYSIS

As mentioned above, the population of tourists in spring is larger than that in winter, which is also demonstrated in Fig. 4. This result was consistent with the existing theory that seasonality is a distinctive feature of tourism [10], [11], [51].

The map in Fig. 7 highlights the top 15 attraction locations regarding the populations of tourists in the four seasons. It as noticeable that some attractions were persistently popular throughout the year, particularly the Palace Museum, Summer Palace and other cultural heritage locations. However, some of the attractions located in the mountains had few tourists in winter due to the cold weather. In addition, the ranking of the attractions in the four seasons is listed in Table 1. The order of the top 15 attractions as relatively stable across the various seasons. The top 2 and bottom 5 attractions did not change, which implies a fixed pattern. The famous and nonseasonal attractions were the most popular sites throughout the year, such as the Palace Museum and Beijing Dashilan. Some attractions, such as the Summer Palace and the Great Wall, have beautiful natural scenes in autumn; therefore, their rankings are higher in the order during autumn. Similarly, in the winter season, owing to the windy and cold weather in Beijing, theme parks such as the Temple of Heaven and Shichahai Park are the better choice for tourists.

Fig. 8 indicates the seasonal suitability of each attraction in regard to the number of tourists by season. As shown in Fig. 4, warming months such as March to May are more popular than cold months. However, with the fine-grained analysis, the suitability of each attraction needs to be examined. In terms of seasonality, the warm spring season was suitable for all locations, especially the attractions that were located downtown. Travelers can walk around the old downtown area or ride in cars to view the city, sightsee or conduct tourism activities in the suburbs. During the summer season, owing to the hot weather, only the lakes, mountains or caves (shown in Fig. 8) are better destinations. In the cool autumn, some landscapes and natural attractions, such as Xiangshan Park and Phoenix Mountain, are suitable for visits due to favorable natural conditions. However, few locations are good choices in the cold winters. Nevertheless, one exception in the winter is the hot spring leisure city shown in Fig. 8.

In summary, this experiment attempted to validate the seasonal attraction suitability with Flickr data. Although the experience of the attractions and seasonality were determined from prior studies, such as [10], [11], and [51], these studies covered larger spatial areas such as countries or regions. The fine-grained analysis of the attractions is helpful for seasonal itinerary planning.

TABLE 1. Order of attractions in the four seasons.

Attractions	Spring	Summer	Autumn	Winter
Palace Museum	1	1	1	1
Qianmen	2	2	2	2
Tiantan Park	3	3	4	5
Summer Palace	4	4	3	4
Beihai Park	5	5	6	3
Olympic Sports Center	6	6	7	6
Mutianyu Great Wall	7	7	5	7
798 Art District	8	9	8	9
Badaling Great Wall	9	8	10	10
Shichahai Park	10	10	9	8
Juyongguan Great Wall	11	11	11	11
Ming Tombs	12	12	12	12
Prince Kung's Mansion	13	13	13	13
Beijing Zoo	14	14	14	14
Beijing Botanical Garden	15	15	15	15

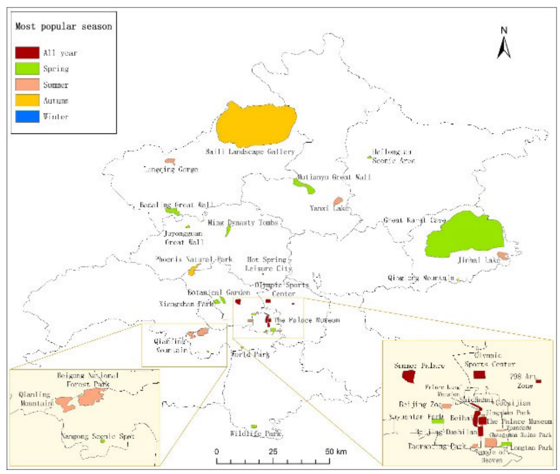

FIGURE 8. Most popular season for attractions (2007-2012).

TABLE 2. Pearson's correlation coefficients between the attraction and popularity (2007-2013).

Year	2007	2008	2009	2010	2011	2012	2013
Pearson coefficients	0.712	0.703	0.703	0.722	0.693	0.696	0.702

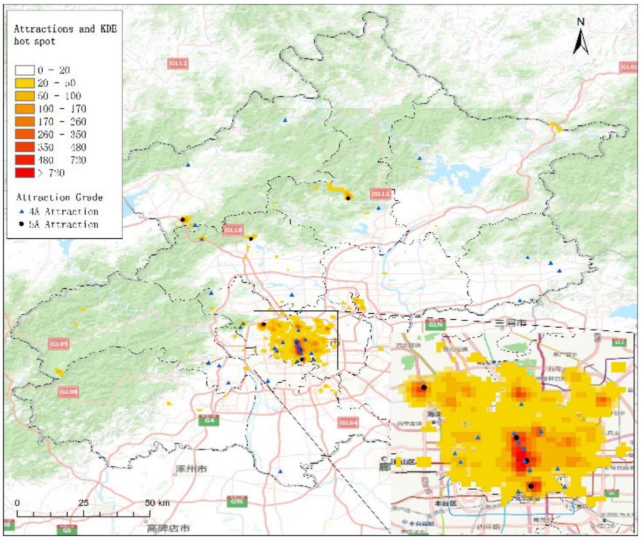

FIGURE 9. Overlay of attraction distribution and KDE hot spots.

C. QUANTITATIVE ANALYSIS OF CORRELATION BETWEEN ATTRACTIONS AND POPULARITY

To further illustrate the dynamic characteristics of the spatiotemporal pattern of inbound tourism, both qualitative and quantitative methods were employed to examine the correlation between attractions and tourists. Fig. 9 shows the spatial relationship by overlap analysis. Table 2 shows the quantitative evaluation using the Pearson's correlation coefficient method, which revealed a correlation variation between the attraction grade and popularity. Specifically, for tourism, common sense dictates that a higher attraction grade indicates greater interest from tourists. That is, the 5A attractions had a larger number of tourists than the 4A sites. Fig. 9 shows evidence that the attraction grade was closely correlated with the popularity. However, we have no idea of the strength of this linkage. To further comprehensively characterize the tourism patterns, we utilized quantitative analysis to investigate the magnitude of the correlation. The Pearson coefficients shown in Table 2 reveal the value behind the data. In the calculation, the attraction grade was normalized as a numerical value, that is, the 5A attractions are represented by the number 5, and the 4A attractions are 4. The mean value of the coefficients was 0.704, and the standard variation of the coefficients was 0.01. This implies that they have strong positive correlations and that this relation was stable over years.

In general, common sense dictates that the attraction grade is closely related to the attraction popularity. However, we have no idea of the strength of the correlation strength and the variation between popularity and attraction grade.

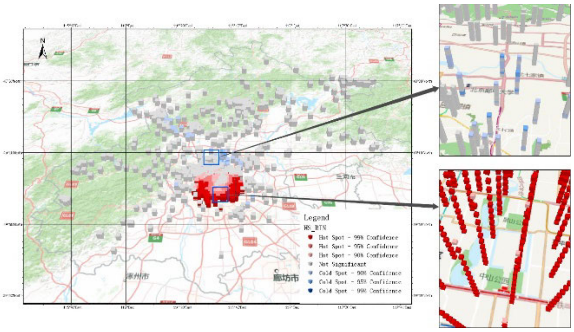

FIGURE 10. Space-time cube map of the hot spots and cold spots.

With traditional tourism data such as aggregation data, it is impossible to obtain this measurement due to the coarseness of the data. In contrast, fine-grained data provide the precise tourist number at each attraction or at every point. The results of the analysis provide useful information for refining attraction planning and management.

D. SPATIOTEMPORAL DYNAMICS

A space-time cube was used to demonstrate the spatiotemporal dynamics of inbound tourism. The space-time cube tool created 984 locations and 12 time steps that represented the 12 months. Then, it generated 11808 space-time bins, in which approximately 22 percent (2569) of the bins had at least one data point. Fig. 10 shows the space-time cube map. The colors indicate the hot spots and cold spots; the intensity of the color indicates the different confidence levels, that is, 0.99, 0.95 and 0.90. It can be seen from Fig. 10 that the downtown area was a hot spot, while the cold spots were concentrated in the suburbs to the north of downtown. The western part of the city is a mountainous area, so the difference was not statistically significant. One cube represents the number of tourists in one month; therefore, the monthly tendencies of tourist numbers are clearly demonstrated. The 3D map of the data provides detailed insight into the spatial and temporal variations in tourist numbers; meanwhile, the granularity of mapping depends on the space-step and time-step parameters. Thus, the space-time cube was able to support fine-grained spatiotemporal analysis.

Fig. 11 shows the tendency of the spatiotemporal dynamics for the hot spots and cold spots of tourism. The Emerging Hot Spot Analysis tool in the ESRI software was employed for this analysis. The results were classified into many categories according to the definitions in the referenced literature [47]; for each bin, a category had to be assigned. For the inbound tourists in Beijing, there were 292 persistent hot spots, 123 historical hot spots, 132 new cold spots and 111 sporadic cold spots. Upon further investigation of the attraction distribution, we were able to draw he concise conclusion that the type of attraction was closely related to the spatiotemporal dynamic pattern of the tourists.

There were more than 292 persistent hot spots identified in the downtown area of the city. This demonstrated that these areas were statistically significant hot spots for ninety percent

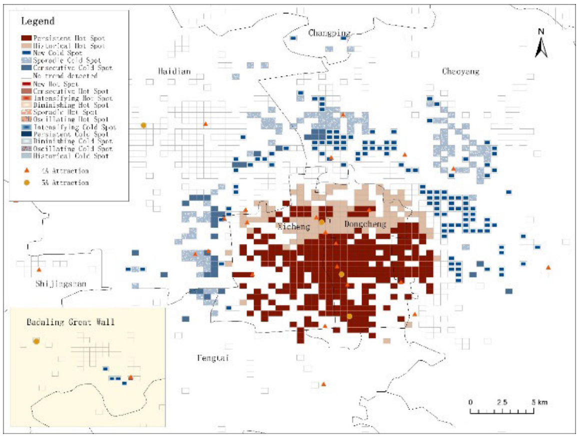

FIGURE 11. **Tendency of spatiotemporal hot spots and cold spots.**

of the time-step intervals. With the further investigation of these persistent hot spot areas, we can see that almost all of these areas have many cultural heritage attractions, such as the Palace Museum, Beijing Dashilan and the Temple of Heaven. This implies that Chinese cultural heritage is of strong interest to foreign tourists.

A large number of historical hot spots were detected in the northern downtown area, which means that these spots were not statistically significant within the final time step; however, at least ninety percent of the time-step intervals showed significant hot spots. These historical hot spot areas included thematic parks such as the Beijing Zoo and Shichahai. Therefore, the existence of these hot spots implies that tourists often visited these sites previously but not now, owing to the strong temporal variations in this type of attraction.

Approximately 132 new cold spots were also identified, which were located in the north and northeast of downtown. These spots were mainly distributed in Sun Park and Yuandadu Chengyuan Ruins Park. These areas were characterized by newly generated cold spots. These two parks have no added interest for foreign tourists because they are mainly leisure and nature parks and have no distinctive features.

There were 111 sporadic cold spots in the west, north and northeast of downtown, including attractions such as Yuyuantan Park, the Olympic Sports Center and the 798 Art Zone. These areas were categorized as sporadic cold spots, which means they are fluctuating on different days as cold spots. This trend may be caused by the sponsorship of some scattered and intermittent large events or activities that can attract many tourists.

In summary, the spatiotemporal dynamics were revealed and clearly visualized by the space-time cube method with fine granularity. The scalability of the spatial and temporal step parameters in this method supported the fine-grained analysis of dynamic patterns. Compared to the density maps [16] or tag word-cloud maps [13], [17], the results were more clear for visualizing tourism patterns.

V. DISCUSSION

This study was carried out at a fine-grained resolution due to the high-resolution Flickr data and the refined granularity spatiotemporal analysis methods. The emergence of new data sources such as Flickr has stimulated tourism research, urban studies and research in other domains. In the past, statistical yearbooks [6], surveys [7] and questionnaires [8] were the main data sources. However, these data sources cannot support fine-grained analysis. The high spatial resolution and rich temporal information of the Flickr data provided to the opportunity of fine-grained spatiotemporal analysis. Other studies based on Flickr have examined urban areas of interest [19], accommodations for tourists [10], tourist movements [5] and so on.

Some spatiotemporal pattern studies have also been proposed in recent years [3], [11]. However, these studies have almost all paid more attention to macrospatial zones or coarse-grained temporal variation. To differentiate this study from the existing research, we analyzed the monthly and daily temporal variations with fine-gained data for the purpose of gaining comprehensive insight. In particular, we followed prior studies and conducted novel work with fine-grained data for thorough seasonal analysis of the attraction suitability for tourists. Both qualitative and quantitative methods were also utilized to investigate the correlation strength between the attraction grade and the popularity. In terms of the spatiotemporal dynamic analysis, the space-time cube method was employed to create a 3D visualization of the spatiotemporal patterns and to provide a fine-grained visual analysis. Therefore, fine-grained spatiotemporal dynamic analysis was achieved with the aid of Flickr data and these spatiotemporal methods.

This study of fine-grained patterns has implications for tourism management and planning. The daily temporal variations provide the tourist daily schedule patterns, which may provide guidance for the management of attraction opening times or some public infrastructure planning. Some similar studies have reached similar conclusions that the Flickr data support urban functional area identification [19]. Furthermore, several categories of hot spots or cold spots were detected in the spatiotemporal analysis, which were mentioned in Section IV to provide comprehensive insight for tourism managers. For example, the areas identified as sporadic cold spots may indicate that more attention needs to be paid or additional infrastructure needs to be added. Our findings on seasonality were similar to those of existing studies [11], [51], but we employed KDE to detect the tourism hot spot that provided more precise data-driven tourism information than the static statistical data collected at attraction gates or from ticket numbers. Similar to the correlation analysis between the attractions and popularity, which were different from existing research, we used both qualitative and quantitative methods. This can guide planners in making specific plans for each attraction from the derived magnitude of the correlation.

Nonetheless, there were some limitations in this study. One was the data accuracy. Studies such as ours have also mentioned the data biases in location-based social media data [13], [52]. Specifically for Flickr data, picture contributors are almost all from Western countries and do not include most tourists or tourists at all times [53]. Another limitation was the parameter settings of the spatial analysis method. This is a common limitation in many spatiotemporal analyses since differing parameters may induce a greater variety of results. Some existing literature has argued that large space or time steps may ignore some patterns, while small parameters may not be sufficient for pattern detection [27]. Therefore, the use of many interactive experiential experiments may be a practical approach.

VI. CONCLUSION

Knowledge of the fine-grained spatiotemporal dynamic patterns of tourists is crucial for helping tourism departments or managers refine management and planning. Despite dedicated research efforts, fine-grained analyses still face challenges due to the lack of precise data sources and emerging methods. To address these challenges, we used an approached that employed emerging Flickr data and used novel spatiotemporal analysis methods to achieve fine-grained pattern analysis. The Flickr data contain rich and precise spatial and temporal information, which ensured a fine-grained data basis for our research. By exploiting the annual, monthly and daily temporal variations, a micro-scale perspective on tourists was identified. In particular, the KDE method was used to validate the distinctive seasonal features of inbound tourists. Furthermore, both qualitative and quantitative methods were employed to capture the correlation between the attraction grade and tourism popularity, which was not a focus of the existing research. Finally, the novel space-time cube method was employed to identify and visualize the spatiotemporal patterns. The results demonstrated that many patterns were found and clearly visualized by the space-time cube and that detailed fine-grained information can be obtained by setting the time step and spatial step.

However, our approach still has some room for improvement in future studies. Except for the limitations mentioned in Section 5, there were several points to be improved in our future research, including (1) validating the correlation between the popularity of a tourist destination and the built environment; (2) detecting tourist convergence and divergence patterns at attractions; and (3) extending the potential usage of Flickr data, such as textual and tourist profiles. Future work may reveal deeper insights into tourist patterns.

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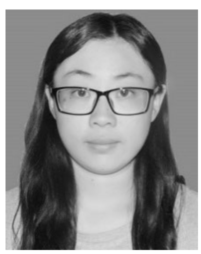

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