Current Issues in Tourism

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rcit20

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CURRENT ISSUES IN TOURISM
2023, VOL. 26, NO. 18, 3004–3022
https://doi.org/10.1080/13683500.2022.2106826

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Space–time tourist flow patterns in community-based tourism: an application of the empirical orthogonal function to Wi-Fi data

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ABSTRACT
Community-based tourism is a sustainable form of tourism development where tourists visit residential communities to interact with local lives and cultures for an enhanced travel experience. Identifying and tracking tourist activities in community-based tourism is particularly challenging, as tourists have shared activity spaces with residents. The paper proposes a new method to study the space–time patterns of the tourist flow using Wi-Fi data. Specifically, we have tracked Wi-Fi probe requests over six months in the *Shichahai* scenic area, a famous community-based tourist attraction in Beijing, China. After deriving the tourist flow from the Wi-Fi data, we have applied the empirical orthogonal function (EOF) method to the identification of the spatial aggregation pattern and the temporality of the tourist flow. A follow-up explanatory analysis examines the environmental impacts, such as weather conditions, air quality, and travel days, on the space–time patterns. The study is among the first to employ Wi-Fi data to study travel behaviours in community-based tourism. The proposed method can shed insights into a better understanding of tourist behaviours in open-space, tourism-oriented urban communities.

ARTICLE HISTORY
Received 17 January 2022
Accepted 23 July 2022

KEYWORDS
Community-based tourism; Wi-Fi data; space–time; empirical orthogonal function (EOF); open-space

1. Introduction

Community-based tourism (CBT) has become an emerging trend in cities with rich cultural and historical heritage (Lee & Jan, 2019; Pawson et al., 2017). Unlike traditional mass tourism, where tourists are involved in sightseeing at a fully managed site, CBT features the participation of tourists in highly customized trips by bridging both cultural exploration and experiencing local residential lives (Li et al., 2020). Thus, CBT is recognized as a sustainable form of tourism development to promote urban gentrification, raise public awareness of cultural conservation, and boost local economies (Dodds et al., 2018; Lepp, 2007).

Tracking and monitoring tourist activities is a critical and challenging issue in CBT. The importance can be elaborated in two aspects. First, tracking tourist activities can make a positive influence on tourism development on the community scale. Tourist activities and daily contacts with residents can significantly affect residents' livelihoods and how they perceive and respond to outsiders, which dictates the sustainability of CBT development (Del Chiappa et al., 2018; Dodds et al., 2018). Second, monitoring tourist activities provides evidence for effective tourism planning and management. Specifically, as tourists' visits to the community may induce social and environmental

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issues, such as crimes and environmental pollution, tracking tourist activities can help identify areas with high-density activities and minimize disruptions to residents' daily lives (Lee & Jan, 2019).

To date, tracking tourist activities in CBT remains relatively challenging because of technical difficulties and behavioural uncertainties in identifying visiting patterns in a relatively small-scale, open-space area (Connelly & Sam, 2018). One emerging data source to study small-scale tourist activities refers to Wi-Fi data. This type of data can be passively collected by a Wi-Fi probe when users initiate a connection to a preset wireless network. Most importantly, the Wi-Fi data are characterized by high space–time granularities and are relatively cost-efficient in equipment installation and data collection. The mobility data derived from Wi-Fi probes have been used to study crowd behaviours and activity patterns in both indoor and outdoor environments, such as corridors (Poucin et al., 2018; Wang et al., 2020), shopping centres (Kaur et al., 2018), pedestrian commercial districts (Soundararaj et al., 2019), urban streets (Kontokosta & Johnson, 2017; Kulshrestha et al., 2020), schools (Wang et al., 2017), and tourist attractions (Li et al., 2021; Wang et al., 2019; Zhou et al., 2020).

In this study, we have identified the space–time patterns of the tourist flow in a community-based tourist attraction using Wi-Fi data. Specifically, we have tracked Wi-Fi probe requests over six months in the *Shichahai* scenic area, a famous cultural tourism community in Beijing, China. The empirical orthogonal function (EOF) method has been employed to derive the spatial aggregation pattern as well as the temporality of the tourist flow. We have further examined the environmental impacts on the tourist flow in a follow-up explanatory analysis. Using Wi-Fi as a new mobility data source, the study can contribute to a better understanding of travel behaviours in open-space, tourism-oriented urban communities.

2. Literature review

2.1. CBT: an evolving concept

The concept of CBT is rooted historically in the definition of tourism. As early as 1978, tourism was defined as a travel activity where people visit communities beyond their residence (McIntosh & Goeldner, 1985; Richards & Hall, 2000). Later on, De Kadt (1979) advocated that indigenous communities and their exotic cultures, especially those in a developing country, could become potential tourist attractions for outsiders to explore and experience, which can in turn bolster the tourism-oriented economy. Since then, CBT has been leveraged in many countries as an economic development strategy (Pawson et al., 2017). With CBT being commercialized around the globe, it allows more international tourists to closely interact with indigenous communities (Del Chiappa et al., 2018; Dodds et al., 2018; Li et al., 2020). Not only does CBT benefit the local economy by offering job opportunities and fostering new businesses (Lee, 2013a; Lee et al., 2013b; Lepp, 2007; Wearing et al., 2010; World Tourism Organization, 2002), it also benefits local residents by improving transportation infrastructure and public services, such as highways, water supply, and cellular coverage (Brunt & Courtney, 1999). Besides, involving residents in CBT development also increases their awareness of environmental protection, cultural conservation, and sustainable development (Lee, 2011; Lee, 2013a; Lepp, 2007). In past tourism research, different aspects of CBT were studied, including community participation (Okazaki, 2008), residents' perceptions (Joo et al., 2018; Lee & Jan, 2019; Lepp, 2007), influencing factors (Dodds et al., 2018; Li et al., 2020), and community growth (Castela, 2018; Zaei & Zaei, 2013).

However, the lack of planning and management in CBT could induce social and environmental issues (Dodds et al., 2018). For instance, high-density tourist activities in a CBT community can deplete natural and cultural resources (Bowers, 2016), raise the cost of living (Lee & Back, 2006), and even increase crimes (Ap, 1992; Lee & Jan, 2019). To this end, it is necessary to understand the spatial patterns of tourist activities in a CBT community as evidence to alleviate these negative impacts (McKercher & Lew, 2004).

2.2. Spatial analytics in tourism research

Generally, two kinds of spatial data analytics can be used to extract the spatial patterns of the geospatial data—exploratory analysis and explanatory analysis (Yang, 2020). The exploratory analysis reveals the general spatial characteristics and patterns of the data. For example, exploratory spatial data analysis (ESDA) represents a set of tools and techniques to measure the spatial heterogeneity of the data. The most known examples are the global Moran's *I* (Cliff & Ord, 1981) and the local indicator of spatial association (LISA) (Anselin, 1995). For example, García-Palomares et al. (2015) measured the concentration and dispersion of geo-tagged photos posted by residents and tourists in eight major European cities and identified tourist hot spots using the Getis-Ord General G statistic and the global Moran's I statistic. Salas-Olmedo et al. (2018) used the global Moran's I statistics and LISA statistics to examine the specialization of tourism in urban census tracts. Besides, some methods which do not explicitly consider spatial information, namely a-spatial exploratory methods (Yang, 2020), can also be used to measure the concentration of spatial data, such as the location quotient.

Based on the derived spatial patterns through exploratory analysis, explanatory methods further identify key factors that shape the spatial patterns. The widely used explanatory method is the regression analysis, which explains local influencing factors in areal data (Yang et al., 2017) or discrete destination choice in origin-destination or trajectory data (Nicolau, 2017). Besides, explanatory analysis can be used for both spatial pattern detection and explanatory analysis, including geodetector (Wang, 2016) and geographically weighted regression (Shabrina et al., 2021).

Though a variety of spatial data analytics and tools are employed to study tourist activities, research on revealing the space–time patterns of the tourist flow in CBT is still scant. An emerging location-aware technology, the Wi-Fi probe, can be employed for this purpose (Li et al., 2018). Specifically, Wi-Fi data or probe requests can be passively collected by Wi-Fi probes when nearby smartphones attempt to establish wireless connections (Figure 1). The collected probe requests contain the media access control (MAC) address, which is a unique identifier of the smart device. Then, the geocoded probe requests can be used to track tourists' locations and movement trajectories. This technology has been used for CBT research in limited case studies (Li et al., 2021; Nunes et al., 2017), which are all focused on relatively large-scale and short-term observations. Based on Wi-Fi data, we employ the EOF method, which has yet to be used for spatial data analytics in tourism research, to characterize a long-term tourist flow observation in a small-scale, open-space CBT community.

3. Method

The EOF method, proposed by Pearson (1901) and Hotelling (1933), is a multivariate statistical technique decomposing a space–time dataset into several orthogonal modes (Nezlin et al., 2005). The modes are ranked by the explained variance, where the first few modes contain most of the total variance of the multivariate dataset. As a geographically weighted principal component analysis

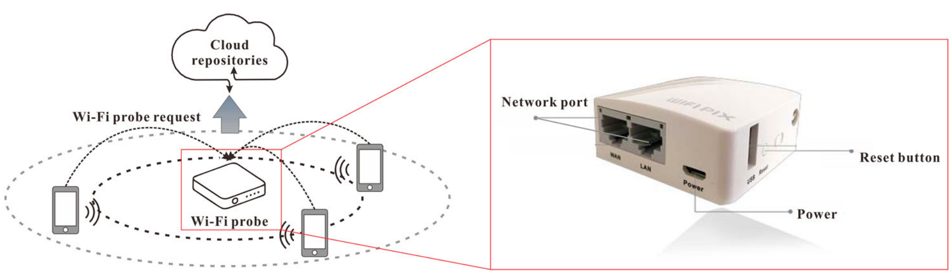

Figure 1. An example of Wi-Fi data collection by the Wi-Fi probe. The figure is adapted from Li et al. (2021).

method, the EOF method has been used primarily in earth science to analyze the spatial and temporal patterns of environmental and climatic variation (Aubrey, 1979; Chen & Wallace, 2015; Fiore, 2003; Oliver et al., 2018; Shen et al., 2015; Winant et al., 1975). Recently, the EOF method was employed to study environmental and public health issues, such as biomass burning (Liew, 2016) and infectious diseases (Xu et al., 2019). In these studies, the method was used to derive the primary space–time modes, which were associated with one or several mechanisms of variation and were interpreted by dominant driving factors.

Mathematically, the EOF method is a linear algebra methodology based on matrix transformation. This transformation can be completed in three steps. In the first step, the space–time dataset is converted into an m by n matrix F, where m is the number of locations, and n is the number of observations at a location, denoted as:

$$F = \begin{bmatrix} x_{11} & \cdots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

where $(x_{11} \ \cdots \ x_{m1})$ is the spatial vector representing the spatial data at time t_1, and $(x_{11} \ \cdots \ x_{1n})^{\mathrm{T}}$ is a time series at location x_1.

In the second step, the covariance matrix C of matrix F is derived. It first calculates the anomalous matrix A, which is the deviation from the average of each column, indicating the difference of each observation from the average of the location. Then, the covariance matrix C is calculated, as shown in Equation (2), where A^T is the transpose of A.

$$C = A^T \cdot A \tag{2}$$

In the third step, the method calculates the eigenvalue and eigenvectors of matrix C to identify the spatial modes and the temporality of the space–time dataset. In Equation (3), Λ is a diagonal matrix of the eigenvalues; P is the matrix of the eigenvectors. Eigenvectors are the EOF modes of spatial patterns, while eigenvalues indicate the relative importance of the EOF modes.

$$C = P \cdot \Lambda \cdot P^{-1} \tag{3}$$

Then, it calculates the principal component (PC) of the temporality, as shown in Equation (4).

$$\mathrm{PC} = P^T \times A \tag{4}$$

In general, the EOF modes are ranked by the eigenvalues in ascending order, such that $\lambda_1 > \lambda_2 > \lambda_3 > \ldots > \lambda_n$. Modes with $\lambda > 1$ mean statistical significance. The explained variance of matrix F by the ith EOF mode is estimated by dividing λ_i by $\sum \lambda_i$. To this end, the first few EOF modes contain most of the total variance of the space–time dataset.

After the matrix transformation, the matrix F is decomposed into three matrices, as shown in Equation (5). EOF and PC represent the derived spatial and temporal patterns of the space–time dataset, while the mean is the location-based averages of observations.

$$\mathrm{F} = \mathrm{EOF} \times \mathrm{PC} + \mathrm{Mean} \tag{5}$$

where EOF is a matrix of all EOF modes, such as $(EOF_1,\ EOF_2, EOF_3,\ \cdots)$, and PC is the time coefficients of the EOF modes, such as $(PC_1,\ PC_2,\ PC_3,\ \cdots)$.

By decomposing the space–time dataset into a linear combination of several EOF modes, the EOF method captures the dominant patterns which can explain the most variance. The modes are unaffected by the interference of random noises because they retain the primary space–time information of the original dataset (Dommenget & Latif, 2002; Obled & Creutin, 1986).

4. Materials

4.1. Study area

Our study area is the *Shichahai* scenic area in Beijing, China (Figure 2). This area is well-known for its unique *hutong* culture, where grassroots residents live in small alleys with a historical origin traced back to the Yuan Dynasty (1267–1368 AD). As the manifestation of the *hutong* culture in old Beijing city, the *Shichahai* has gradually developed into a typical example of CBT (Johnston, 2014; Li et al., 2020). Every year, this area attracts a large number of domestic and international tourists to experience the *hutong* culture through various activities, such as riding a rickshaw along narrow alleys to live the traditional Beijingers' way of life. Except for tourism, other urban functions are observed in this area, including residential housing and cultural preservation (Wang et al., 2018). Specifically, this area is home to over 16.3 thousand permanent residents and also hosts a well-preserved historical

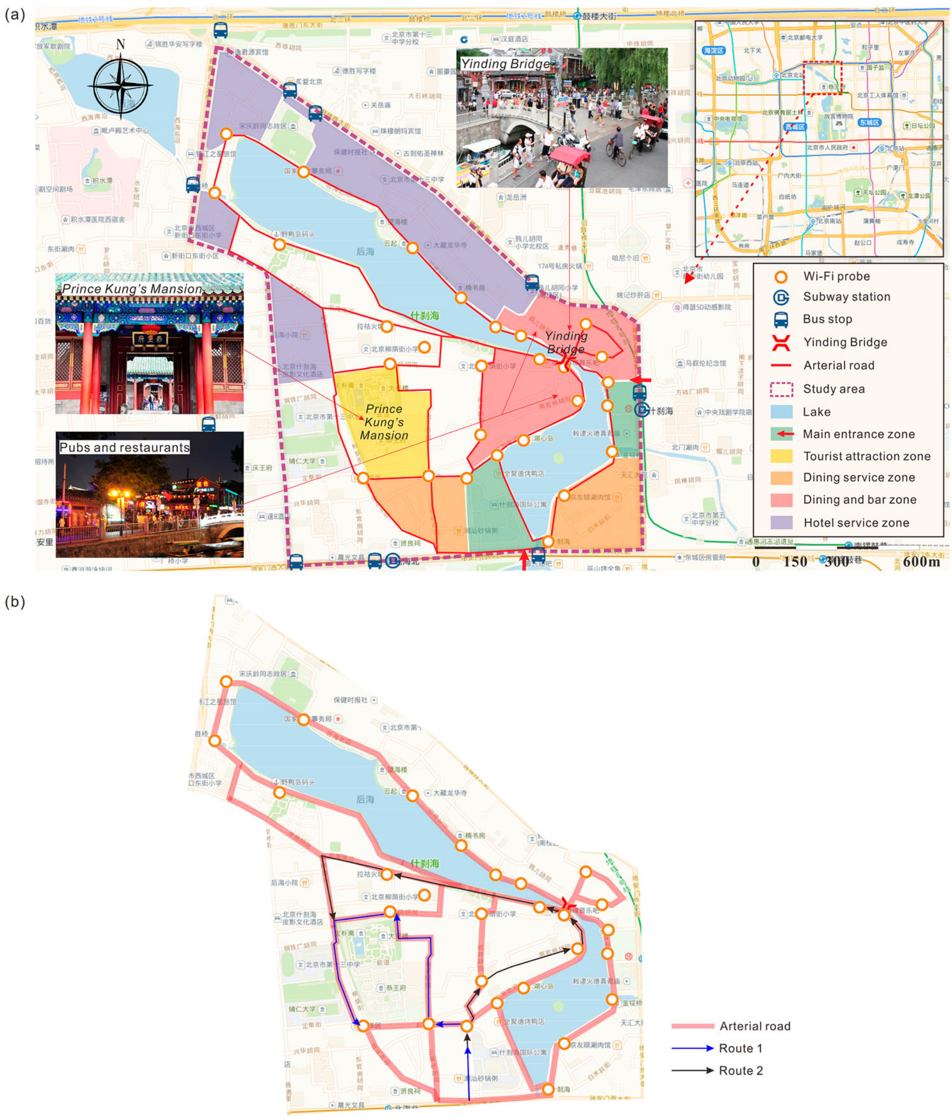

Figure 2. (a) Placement of Wi-Fi probes and identified functional zones and (b) the typical *hutong* tour route (referred to Liu et al., 2015).

relic, the *Prince Kung's Mansion*. While the *Shichahai* is a cultural and historical attraction during the daytime, the nightlife becomes untraditional with both tourists and residents flocking into modern pubs and fine-dining restaurants. For a long time, this area is faced with a contradiction between tourism development and residential use, which is not atypical in CBT (Wang et al., 2018). Because of the mixed urban functions in a relatively small area (about 146.7 hectares), travelers' types and behaviours are extremely complex. A thorough understanding of the space–time patterns of the tourist flow will provide evidence for better tourism planning and management in this area.

As an open-space community, the *Shichahai* is well-equipped with tourist reception facilities and convenient public transport services. We first identified tourist reception facilities in the study area, such as restaurants, bars, tourist attractions, and hotels from the point-of-interest (POI) data (www.amap.com). Specifically, we derived 139 restaurants, 60 bars, 80 tourist attractions, and 12 hotels. Based on the major POI types through a kernel density analysis (Figure 3), we further categorized each sub-region as one of the four functional zones: tourist attraction zone, dining service zone, dining and bar zone, and hotel service zone (Figure 2a). Considering the spatial distribution of surrounding subway stations and bus stops, we further identified two main entrance zones on the east and south edges. The *Yinding Bridge* is the major channel connecting the north and south parts of the area.

4.2. Data collection

We installed 28 Wi-Fi probes in the *Shichahai* scenic area for data collection (Figure 2a). The detection range of each Wi-Fi probe was 25 meters. To achieve optimal signal coverage, these Wi-Fi probes

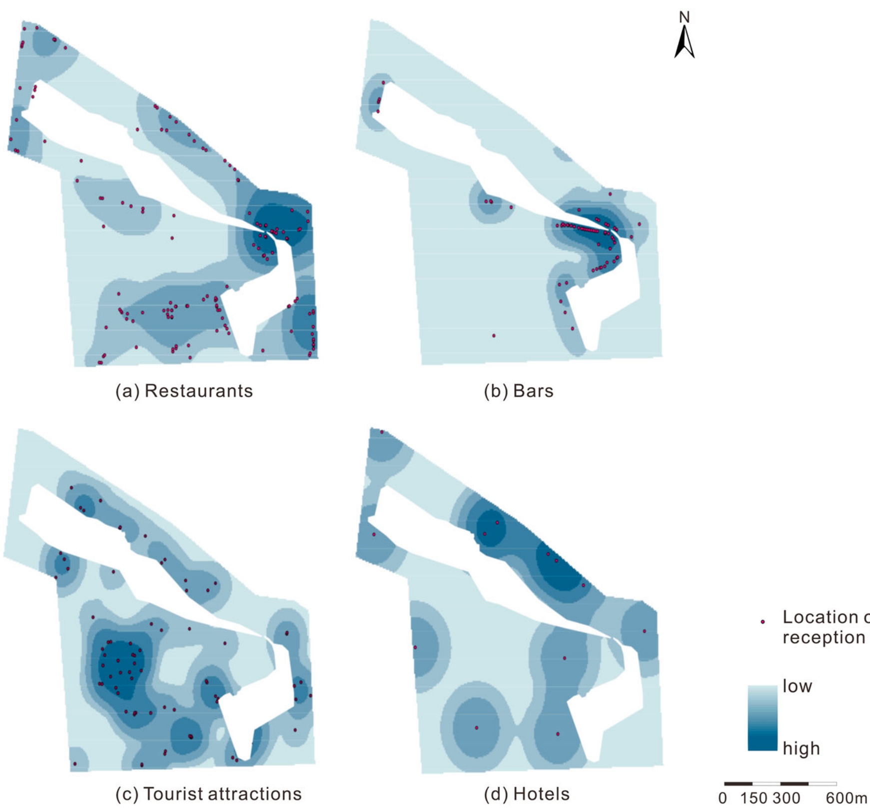

Figure 3. Kernel density surfaces of the tourist reception facilities by POI type: (a) restaurants, (b) bars, (c) tourist attractions, and (d) hotels.

were purposely installed near arterial roads, which overlap with the typical *hutong* tour route (Figure 2b). The identification of arterial roads and the placement of Wi-Fi probes were assisted by experts working in the local tourism management department. This placement strategy allowed for the sufficient coverage of Wi-Fi signals and the comprehensive tracking of tourist activities. The data collection lasted for six months (October 1, 2018, through March 31, 2019). This study period overlapped with China's National Day Holiday (October 1–7), New Year's Day Holiday (December 30 through January 1), and the Spring Festival (February 4–10). More than 21.8 million Wi-Fi probe requests from over 2.9 million unique users were collected.

Because of the complex traveler composition in the study area, we set two criteria to screen out non-tourists. First, we retained MAC addresses that only appeared one day during the study period. This criterion excluded fixed devices (e.g. network-enabled printers) and multi-day travelers (e.g. residents and staff working at a nearby facility). Second, we retained MAC addresses that appeared more than twice in the records. This criterion excluded passersby who did not stay for a visit. After the data cleaning, we obtained 7.7 million Wi-Fi probe requests representing over 1.3 million unique tourists. The 1.3 million unique tourist records were converted into a space–time matrix representing hourly tourist volumes based on the Wi-Fi probe location (Table 1).

Figure 4 illustrates the daily tourist volume in the study area (Figure 4a) and hourly tourist flow averaged to one day on the weekday, weekend, and holiday, respectively (Figure 4b). To further specify the space–time patterns, we generated the hourly tourist flow of the entire day (0:00–23:59). Also, we segmented the time of day into daytime (7:00-16:59) and evening (17:00-23:59) according to the opening hours of major tourist attractions in the area. These three space–time datasets (i.e. daily, daytime, and evening) were loaded into the EOF model to explore the space–time patterns of the tourist flow during different time periods.

5. Exploratory analysis of tourist flow

5.1. Daily space–time patterns

We first explored the space–time patterns of the daily tourist flow. The EOF values were first derived at the locations of the Wi-Fi probes. Then, they were interpolated on the road network using the inverse distance weighted (IDW) method (Wang et al., 2019). The map of EOF mode reveals the spatial pattern of the tourist flow. Locations with high EOF values mean high tourist volumes, representing the hot spots of tourist activities. The PC value is the time coefficient of the EOF mode. The absolute value of PC represents the magnitude of the tourist volume. The positive value indicates the spatial pattern of tourist flow at that time point is consistent with the EOF mode, and vice versa. The results of the primary EOF mode (EOF_1), the secondary EOF mode (EOF_2), and their PCs are shown in Figures 5 and 6, respectively.

Figure 5 shows that EOF_1, as the predominant spatial pattern, accounts for the majority (91.5%) of the total variance of the daily tourist flow. First, EOF_1 can be further discussed in terms of hot spots and cold spots. The hot spots are observed mainly around the *Yinding Bridge*, the dining and bar zones, and the east entrance zone. Besides, the dining service zones and the main entrance zone in the south are hot spots (Figure 5a). An isolated hot spot is observed in the southeastern corner

Table 1. The space-time matrix representing hourly tourist flows.

Wi-Fi probe ID \ Time (MM-DD-HH)	10-1-0	10-1-1	10-1-2	10-1-3	…
1	16	13	1	2	…
2	0	2	1	1	
3	0	4	0	1	
4	5	12	3	0	
…	…				

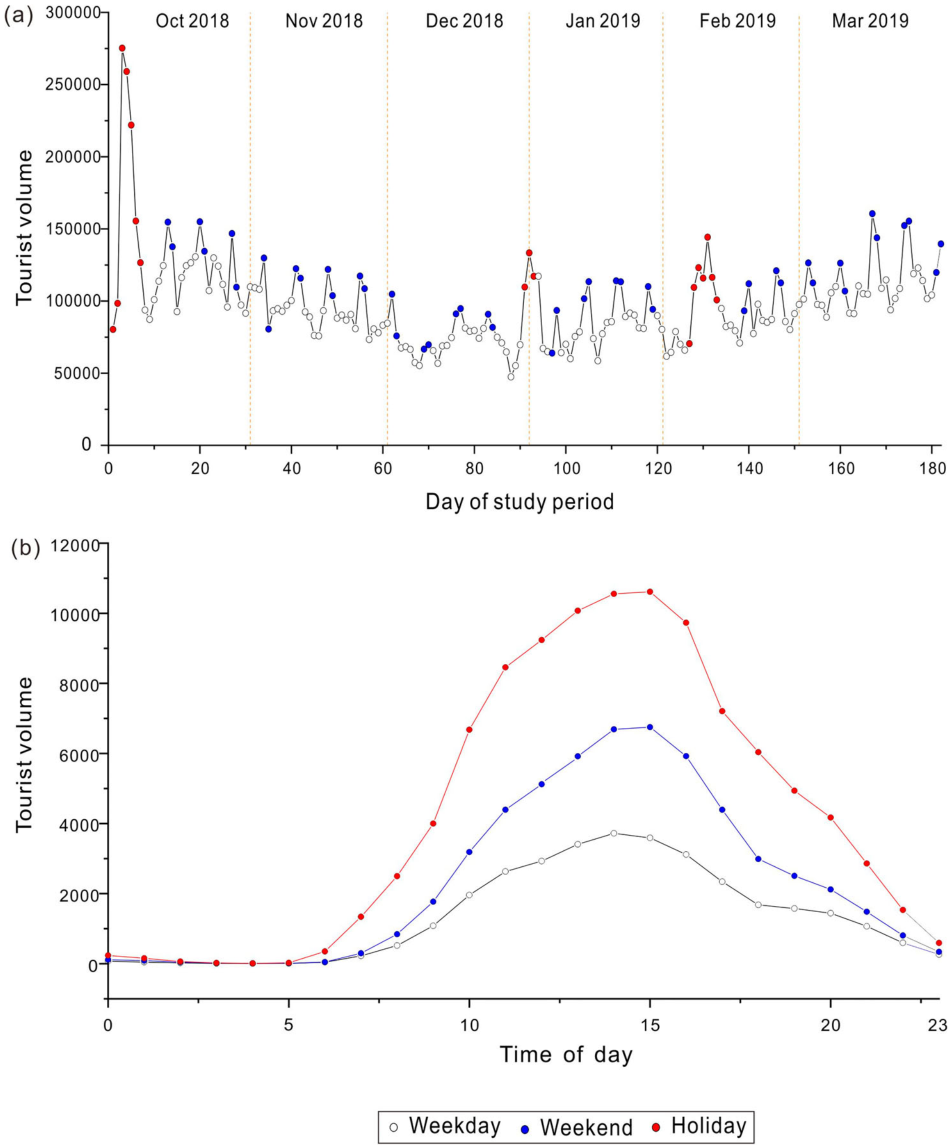

Figure 4. Tourist volume during the study period: (a) daily tourist volume, and (b) hourly tourist volume on weekday, weekend, and holiday, respectively.

of the tourist attraction zone, which includes the ticket office of *Prince Kung's Mansion*. The cold spots of the tourist volume are observed in the northwestern quadrant of the area. Second, PC_1 reveals the time coefficient of EOF_1 (Figure 5b). The tourist flows during the three holiday seasons are characterized by extremely high PC values. The high and positive PC value indicates a significant increase in the tourist volume, which has a consistent spatial pattern with EOF_1. Except for holidays, PC values on weekdays and weekends are also positive, with higher values on weekends than on weekdays. Therefore, the EOF_1 is the dominant spatial pattern during the study period and reveals the general characteristics of tourist flow on different travel days. A closer examination was conducted for the daily averaged PC_1 (Figure 5c). The daily averaged PC_1 is in the shape of a one-peak curve, with positive values from 10:00–20:00 and negative values from 21:00–9:00. This trend is similar to the hourly tourist volumes (Figure 4b). During the daytime when the tourist volume is high,

Figure 5. The primary EOF mode: (a) spatial pattern, (b) temporal variation, and (c) average variation of the daily tourist flow.

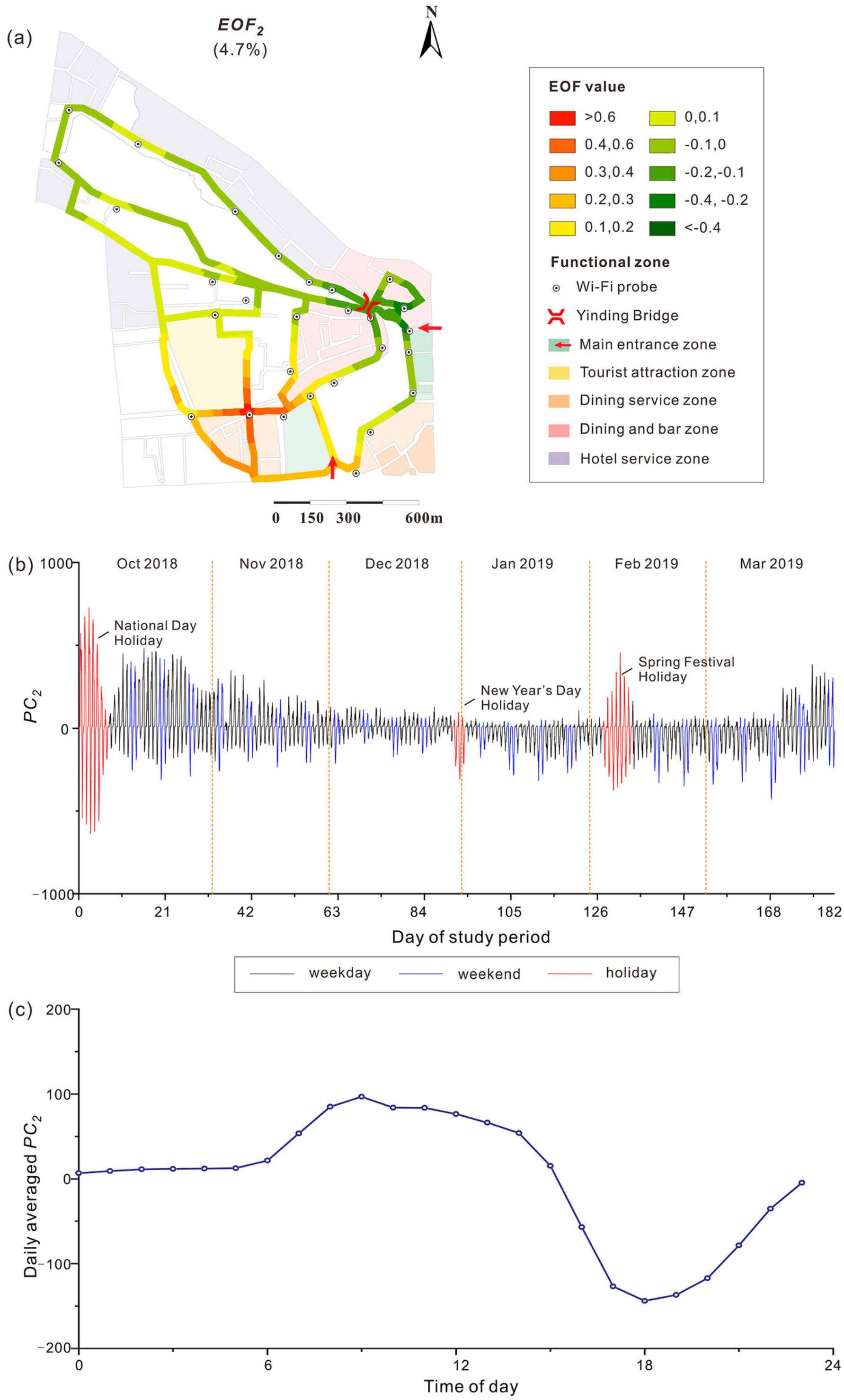

Figure 6. The secondary EOF mode: (a) spatial pattern, (b) temporal variation, and (c) average variation of the daily tourist flow.

the spatial pattern is consistent with EOF_1. While in the nighttime, the tourist volume is low and the spatial distribution is not consistent with EOF_1, and thus the PC values become negative.

The secondary EOF mode (EOF_2) accounts for 4.7% of the total variance of the daily tourist flow (Figure 6), suggesting that it is less prevalent than the primary mode. The spatial variation in the tourist volume between hot spots and cold spots is greater in EOF_2 than that in EOF_1. The hot spots of tourist activities are concentrated in the tourist attraction zone (Figure 6a).

PC_2 reveals a different temporal pattern. First, more negative values are observed in PC_2, indicating that EOF_2 is not temporally stable. At time points with negative PC values, the spatial patterns of tourist flow are opposite to EOF_2. Second, the two holiday seasons (i.e. the National Day Holiday and the Spring Festival) are characterized with extremely high variation of PC values, while that of the New Year's Day Holiday is not significant. This result can be explained by the smaller variation of daily tourist flow on the New Year's Day Holiday than that on the National Day Holiday and the Spring Festival (Figure 4a). While EOF_1 captures the majority of the total variance of the daily tourist flow, PC_2 reveals the remaining variance. Thus, the PC_2 value is smaller for the New Year's Day Holiday than that for other holiday seasons. Third, the daily averaged PC_2 indicates the daily variance of tourist volume and is directly impacted by the operating hours of *Prince Kung's Mansion*, the major tourist attraction in the study area.

5.2. Temporal variation

To explore the temporal component, we further analyzed the EOF modes of the daytime (7:00-16:59) and the evening (17:00-23:59). The EOF_1 (Figure 7a) and EOF_2 (Figure 7c) share similar spatial patterns with those of the daily tourist flow (Figures 5a and Figure 6a). Besides, the temporal variations of PC_1

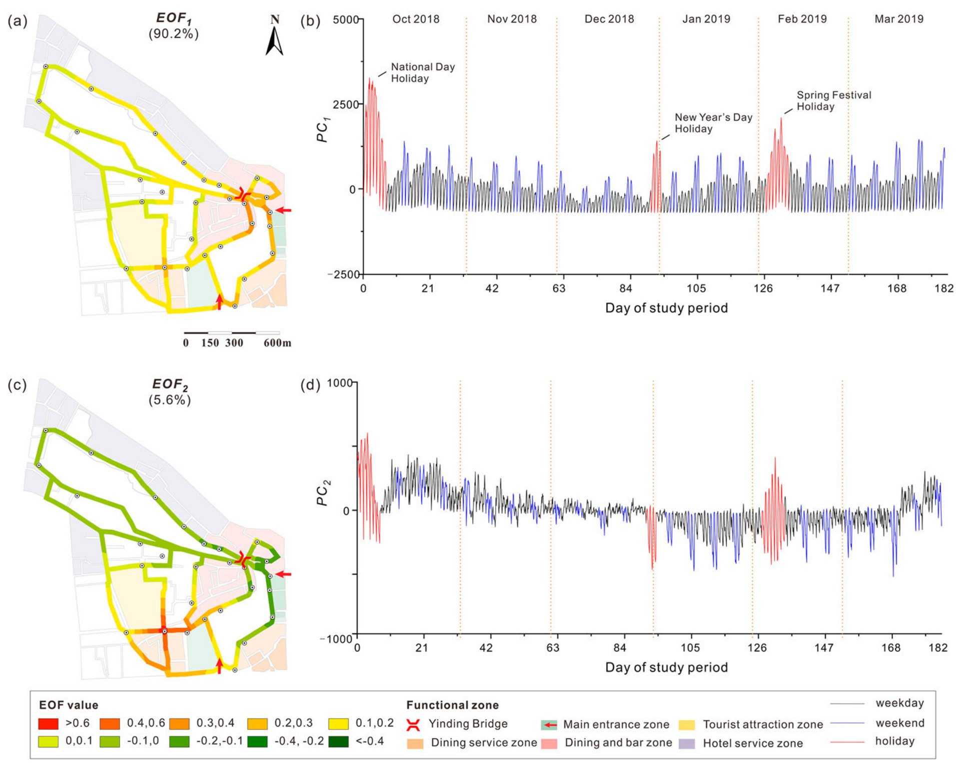

Figure 7. The primary EOF mode: (a) spatial pattern and (b) temporal variation; and the secondary EOF mode: (c) spatial pattern and (d) temporal variation in the daytime (7:00-16:59).

(Figure 7b) and PC_2 (Figure 7d) are similar to those of the daily tourist flow (Figure 5b and Figure 6b). Only the minimum PC_1 values of the daytime are higher than those of the daily tourist flow, especially on holidays. This is because the lowest values of tourist flow during the nighttime (0:00-6:00) are excluded (Figure 5c). While for PC_2, the differences are not observed, since the trough of the PC value happened around 18:00 (Figure 6c). Besides, PC_2 decreases at the end of November, with a significant drop into negative values during the New Year's Day holiday (Figure 7d). This result can be explained as the spatial pattern of the tourist flow is opposite to EOF_2 during the time period. Specifically, this period falls in the off-season (November through March) of the main tourist attraction, the *Prince Kung's Mansion*, in the study area. Therefore, the hot spot of tourist flow is inconsistent with EOF_2, resulting in a significant drop of PC_2 during the New Year's Day holiday. Even in the Spring Festival, there is a great variation in PC_2, indicating an unstable hot spot near the tourist attraction zone.

However, the space–time patterns of the tourist flow in the evening are different from the daytime (Figure 8). First, in EOF_1, the hot spots of tourist activities near the tourist attraction disappear after the closure of *Prince Kung's Mansion* (the red circle in Figure 8a). Tourists are more concentrated in the dining and bar zones near the *Yinding Bridge* (Figure 8c). Second, the EOF_1 in the evening has a greater explained variance (94.8%) than that in the daytime (90.2%), meaning that the spatial patterns of the tourist activities are less complex in the evening. It is worth noting that, during the first days of the National Day holiday, PC_1 is characterized by highly positive values, while PC_2 is negative. This difference can be explained by the fact that although most tourist activities concentrate in the dining and bar zones near the *Yinding Bridge*, these activities happen in other parts of the study area. The spatial pattern of the tourist flow is not consistent with EOF_2 during the time period, and thus PC_2 is negative.

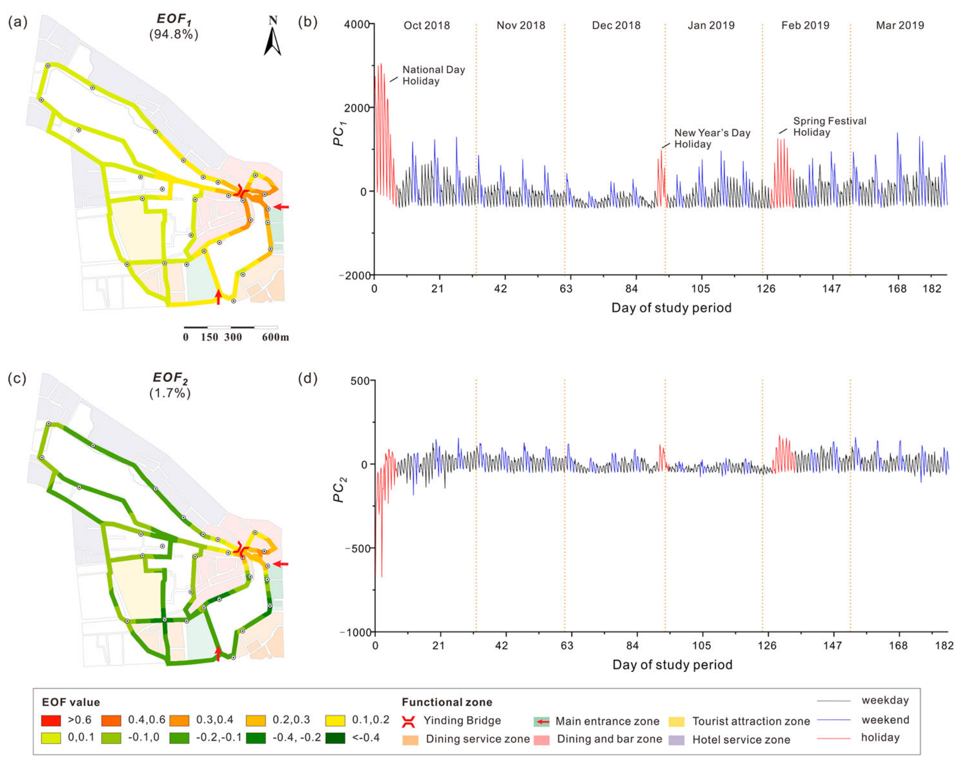

Figure 8. The primary EOF mode: (a) spatial pattern and (b) temporal variation; and the secondary EOF mode: (c) spatial pattern and (d) temporal variation in the evening (17:00-23:59).

For validation, we compared the results with previous findings by Hu et al. (2015). Specifically, Hu et al. (2015) surveyed over a thousand tourists in the *Shichahai* scenic area during the National Day Holiday and plotted their visiting pattern on the road network, which shares similarities with EOF_1 in the daytime (Figure 5a). Therefore, we conclude that the identified EOF modes are representative of the tourist flow in the study area.

6. Explanatory analysis of tourist flow

6.1. Determinants of tourist flow

Past studies have discussed the impact of weather conditions on tourist visits. While favourable weather increases tourists' willingness to travel, inclement or extreme weather (e.g. heavy rains, heatwaves) can deter out-of-home activities because of poor visibility and likely exposure to hazardous elements (Becken & Wilson, 2013; Scott & Lemieux, 2010). In addition to weather conditions, poor air quality also reduces visits, especially for outdoor attractions (Anaman & Looi, 2000; Chen et al., 2017). These two factors become more critical when the destination is an unshaded, open-space area (Becken & Wilson, 2013; Chen et al., 2017).

Based on the identified space–time patterns, we further explore the environmental determinants of the tourist flow by explanatory analysis. Since our study period spanned from middle autumn to late spring with a strong seasonality (Figure 9), the major environmental determinants are chosen as weather conditions (Becken & Wilson, 2013; Scott & Lemieux, 2010) and air quality (Anaman & Looi, 2000; Chen et al., 2017).

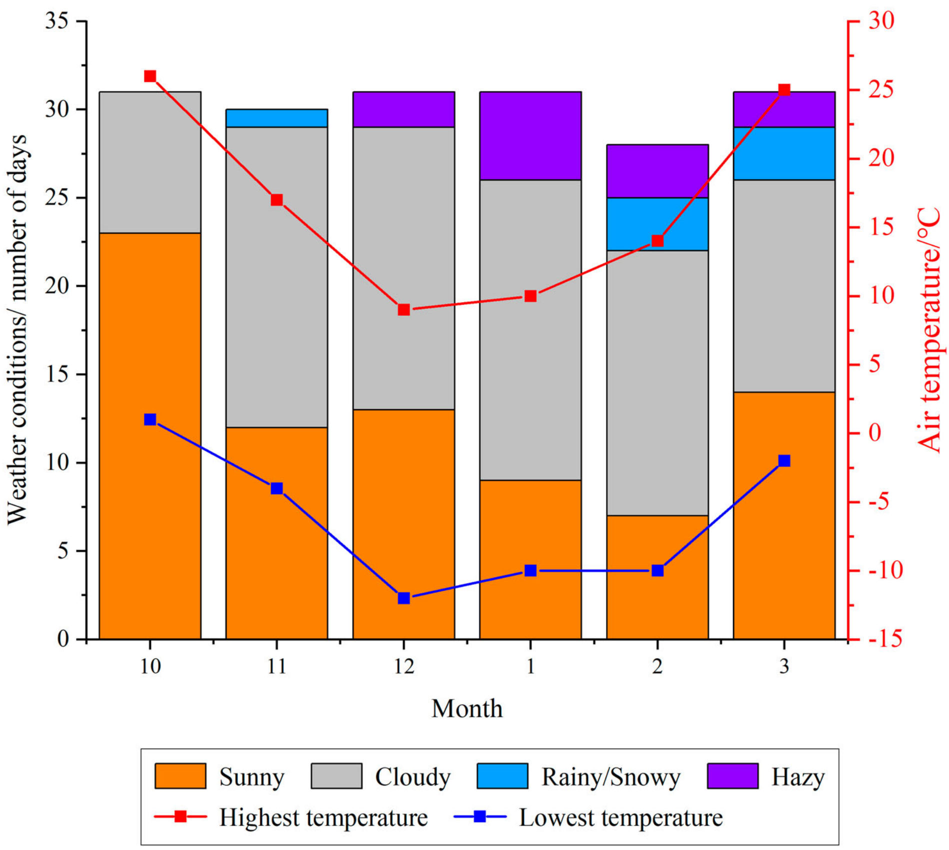

Figure 9. Monthly weather composition during the study period.

Table 2. Descriptive analysis of influencing factors.

Category	Variable	Min	Max	Mean	Std.
Weather conditions	Temperature-humidity index (THI)[1]	10	71	45.00	9.79
	Wind effect index (K)[1,2]	−1185.39	180.91	−514.26	180.91
	Precipitation (Pre)/cm[1]	0.00	0.70	0.001	0.02
Air quality	Air quality index (AQI)[3]	2	500	84.64	71.08
Date dummy	If holiday (0,1)	0	1	0.09	0.29
	If weekend (0,1)	0	1	0.24	0.43

[1]The weather data were collected from China Meteorological Data Service Centre (http://data.cma.cn/en).
[2]The sunshine duration data constituting the wind effect index were collected from the National Bureau of Statistics (http://www.stats.gov.cn/ztjc/ztsj/hjtjzl/1999/200312/t20031230_57844.html).
[3]The AQI data were collected from Beijing Municipal Ecological and Environmental Monitoring Center (http://www.bjmemc.com.cn/).

First, to quantify weather conditions, we employed the temperature-humidity index (THI), wind effect index (K), and precipitation (Pre), as shown in Table 2. The THI, as the sensation of the air temperature (in adjusted °F), was used to better represent the temperature felt by the human body, as shown in Equation 6.

$$\mathrm{THI} = \mathrm{T} - 0.55(1 - \mathrm{f})(\mathrm{T} - 58) \quad \mathrm{T} = 1.8\mathrm{t} + 32 \tag{6}$$

where T is the Fahrenheit temperature (°F), t is the Celsius temperature (°C), and f is the relative humidity (%). The THI has an inverted U-shape relation with the body comfort with a favourable THI around 65°F (Cao et al., 2019).

The wind effect index (K) was used to indicate the exchange of heat between body temperature and air temperature, as shown in Equation 7.

$$\mathrm{K} = -\left(10\sqrt{V} + 10.45 - V\right)(33 - t) + 8.55s \tag{7}$$

where t is the Celsius temperature (°C), V is the wind speed (m/s), and s is the sunshine duration (h/d). A negative K value means that the human body is losing heat, while a positive value means the human body is gaining heat. K value also has an inverted U-shape relation with the body comfort with a favourable value ranging from −200 through −300 (Cao et al., 2019).

Second, we used the air quality index (AQI) to measure daily air quality. The AQI is a composite index representing the daily concentration of air pollutants, including SO_2, NO_2, CO, O_3, particulate matter (PM) 2.5, and PM 10. Besides, two binary dummy variables (holiday/non-holiday and weekend/weekday) were added to indicate the influence of day types on travel behaviours.

6.2. Results of explanatory analysis

We employed the partial least squares (PLS) regression method in *Simca 14.1.0.2047* to analyze the impacts of the selected influencing factors on the time series of daily PC_1 (Figure 5b), daily PC_2 (Figure 6b), daytime PC_1 (Figure 7b), daytime PC_2 (Figure 7d), evening PC_1 (Figure 8b), and evening PC_2 (Figure 8d). The regression analysis results are shown in Table 3. First, the most influencing factor of PC_1 is the holiday, with a significantly positive impact, and the impact is more obvious

Table 3. Regression analysis results of influencing factors.

EOF variable	AQI	THI	K	Pre	Holiday	Weekend	R^2
Daily PC_1	−0.085	0.024	0.231*	−0.028	0.309*	0.109	0.173
Daytime PC_1	−0.040	−0.015	0.249*	−0.028	0.509*	0.189	0.331
Evening PC_1	−0.041	0.290*	0.298*	0.019	0.305*	0.096	0.324
Daily PC_2	−0.033	0.222*	0.155*	−0.001	−0.003	−0.059	0.117
Daytime PC_2	0.016	0.277*	0.268*	0.001	0.036	−0.080	0.247
Evening PC_2	0.075	0.000	0.029	0.061	−0.066	0.131	0.002

*The variable importance in projection (VIP) is greater than 1, indicating a significant influence on PC_1 and PC_2.

in the daytime than in the evening. Second, the wind effect index (K) also contributes significantly to the increase of the tourist flow, and the contribution is more obvious in the evening. The THI has a significantly positive impact in the evening. Third, though not statistically significant, the AQI has a negative impact on PC_1, meaning that a high AQI as a result of air pollution potentially decreases travel demand (Anaman & Looi, 2000; Chen et al., 2017). Forth, for daily and daytime PC_2, the most influencing factors are THI and K, where both factors have significant positive impacts.

Based on the regression analysis results, we conclude that for the *Shichahai* scenic area, the most influencing factors on the tourist flow variation are the day type (holiday/non-holiday) and the wind effect index (K). This finding can be further explained – holidays increase the travel demand, while the felt heat exchange decreases the likelihood of outdoor activities. The positive influence of the THI is only significant in the evening, indicating that tourists' outdoor activities in the study area are more sensitive to air temperature in the evening.

7. Discussion

The contribution of this work can be articulated in two aspects. First, using Wi-Fi data can overcome the methodological limitations in other geospatial data used for tourism research. For example, although mobile roaming data provide a large sample of tourist tracks, the data have relatively coarse spatial granularities and can also raise privacy issues (Ahas et al., 2008); while geotagged social media data can entail contextual information, they are subject to sampling bias, whereas young adults and minorities are overrepresented (Chua et al., 2016); GPS-based tracking data, although having high spatiotemporal granularities, are characterized by an active and invasive data collection nature – participants usually need to download a specific app and upload the travel log manually after the experiment (Hardy et al., 2017). To this end, the Wi-Fi data with a passive and non-invasive data collection mode can become a feasible and practical way for tourist tracking in small-scale tourism research and is of particular relevance to CBT research.

Second, this study is among the first to apply the EOF method to the analysis of the tourist flow. As an emerging statistical approach, the EOF method can identify successive modes by decomposing the space–time dataset into two orthogonal modes, including spatial and temporal patterns (Nezlin et al., 2005). Compared with other spatial data analytics in tourism research, the EOF method has advantages: (1) while non-spatial exploratory methods can also extract key factors of tourist flows, they cannot exaggerate the tourist spatial patterns on the ground (Yang, 2020); (2) while describing the spatial heterogeneity of the tourist distribution, the ESDA method cannot capture temporalities of the spatial patterns. For example, the tourist hot spots detected by García-Palomares et al. (2015) and Salas-Olmedo et al. (2018) were based on observations over years – the temporal variation (e.g. daily, weekly, and seasonal changes) of tourist hot spots were missing. Since the spatial and temporal patterns are closely intertwined in tourism research, the EOF method provides a promising way to segment tourist hot spots over time. Deriving the two EOF modes in the exploratory analysis and performing the follow-up explanatory analysis are critical for understanding tourist behaviours in CBT. The two tiers of information provide vital knowledge for tourism planning and management in a CBT community, such as identifying areas and time periods characterized by high-density tourist activities.

Nevertheless, the study has limitations. First, the identified space–time tourist flow is based on the Wi-Fi data collected from middle autumn to late spring, while the all-year-round patterns are not explored. Future studies should elongate the study period to identify the annual space–time patterns and variations of the tourist flow. Second, using Wi-Fi data is subject to sampling biases owing to the existence of the digital divide, meaning that the data collection does not cover certain population groups, such as people not owning a smart device (Driskell & Wang, 2009; Kontokosta & Johnson, 2017). Future research should complement the Wi-Fi data collection with structured surveys to verify the representativeness of the sample.

8. Conclusions

In this paper, we have employed Wi-Fi probes to perform long-term observations of tourist activities in a community-based tourist attraction. We have performed two levels of spatial data analytics. For exploratory analysis, we have employed the EOF method to derive the space–time patterns of the tourist flow. Then, for explanatory analysis, we have identified key environmental factors affecting the space–time patterns. In sum, we demonstrate how Wi-Fi data as a new mobility data source can contribute to tourist behavioural research through long-term observations of tourist activities. The paper will shed insights into future tourism management, such as optimizing the locations of tourist reception facilities and developing tourist flow control strategies, to enhance the sustainable development of CBT.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study is supported by National Natural Science Foundation of China (No.41977408)

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