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Cycling in Tibet: An analysis of tourists' spatiotemporal behavior and infrastructure

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ABSTRACT

Cycling tourism has grown in popularity worldwide, motivating its inclusion in the development strategies of tourism organizations. This paper builds an analysis model based on spatial analysis and Empirical Mode Decomposition, providing a data-driven way to utilize GPS cycling trajectory data to analyze the spatiotemporal behavior of Chinese cycling tourists using a case study example of the Tibet Autonomous Region. The results show that: (1) The fluctuation of the number of cycling trajectories in Tibet presents multi-modal characteristics, corresponding to fluctuations in China's tourism industry and economy; (2) Cycling tourists in Tibet prefer to use national roads (arguably due to the safety of the road infrastructure and the availability of supporting tourism infrastructure); (3) Cycling tourism is highly concentrated in and around the popular attractions of Tibet. The presented data and methods help to understand the spatiotemporal behavior of cycling tourists, which is of great significance for tourism management.

1. Introduction

Cycling tourism is an emerging trend and, in tandem with technological enhancements such as electronic bicycles, its appeal is expected to continue growing (Han, Lho, Al-Ansi, & Yu, 2020). Cycling tourism is therefore of great interest with respect to tourism management as it also contributes to: 1) regional development via derived tourism expenditure, which is a source of additional local income (Weed et al., 2014) and 2) the transformation of the tourism industry towards increased sustainability (Lőrincz, Baná). However, as pointed out by (Ritchie & Hall, 1999) already two decades ago: "although bicycle tourists may prove useful in assisting with revitalisation and diversification in rural and regional areas, the planning and provision of infrastructure and information are key considerations in maximizing the economic development benefits of this form of tourism for regional areas." Traditionally, researchers and tourism planning officials have had to rely on official statistics and survey data to support these key management efforts in developing cycling tourism. Recently, new data sources (such as GPS trajectory data) have emerged that could potentially contribute to the analysis and management of cycling tourism. However, these data and methods for analyzing it have, thus far, remained underutilized and underdevelopment in the contemporary tourism management literature. This research and methodological gap is explored in this paper.

As a means of low-carbon and fashionable traveling, cycling is an important form of sustainable tourism (Hjalager, 2015; Lamont, 2009) that is becoming increasingly popular among tourists. In contrast to many other forms of tourism, cycling tourism is not only green and healthy (Han, Meng, & Kim, 2017), but also contributes to the flexibility and autonomy of travel. For attracting cycling tourists the journey itself is thus as important as the destination (Lumsdon, 2000; Speakman, 2005). With the increasingly prominent impact of cycling on urban and regional development (Deenihan & Caulfield, 2015), national governments have gradually increased their investments in developing cycling tourism (Kaplan, Manca, Nielsen, & Prato, 2015). The increased prominence of cycling tourism has therefore highlighted a profound need to understand the diverse spatiotemporal behavior characteristics of cycling tourists for improved local tourism route planning, related facilities placement, and tourism product development.

With the development of web-based technologies, many travel sharing platforms have recently emerged. With the help of these

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platforms, tourists can record, upload and share their travel diaries, geotagged photos, GPS trajectories and other information voluntarily (Mou & Zheng et al., 2020b). Girardin, Calabrese, Fiore, Ratti, and Blat (2008) called this kind of data "digital footprints," and pointed out that as electronic traces, digital footprints not only provide new ideas for the collection of tourist's behavior information, but also provide new perspectives for tourism research. Further, as a (generally) reliable data source, GPS trajectory data not only contains the geographical coordinates of the tourist's location, but also accurately records the tourist's speed, timestamp and other related information in real time, from which the characteristics of the tourist's spatiotemporal behavior can be effectively obtained (Xiao-Ting H, 2012; Zheng, Huang, & Li, 2017).

Our case study example, the Tibet Autonomous Region, is located in the southwest of China. With the recent construction of and improvements made in Tibet's road infrastructure, the accessibility of the road network in the region has greatly improved, significantly contributing to the promotion and development of local tourism (Su & Wall, 2009). Consequently, increasing numbers of tourists and cycling enthusiasts are traveling to Tibet, and "Cycling in Tibet" has become an important component of Tibetan tourism marketing.

Given the importance of cycling tourism, it has received surprisingly little scholarly attention (Deenihan & Caulfield, 2015). Moreover, scholars have focused more on the travel experiences of cycling tourists (see Hu, Li, & Luo, 2015 and Cui, Xu, & Yang, 2014 for recent case studies on Tibet), while generally ignoring their spatiotemporal behavior characteristics. In view of this, and based on the perspective of digital footprints, this paper focuses on the spatiotemporal behavior of cycling tourists in Tibet by using GPS trajectory data to address this obvious gap within the tourism management literature. The introduced data and methods for analyzing it offer implications for tourism management in Tibet, but are naturally applicable, in principle, to other regions (with similar data sources) interested in developing cycling tourism.

2. Literature review

2.1. GPS data in tourism research

With the rise of GPS technology, the location data generated by people during traveling, if effectively used, can directly show people's travel trajectories and also often reveal other specific behavior patterns and spatiotemporal information (Li et al., 2020). As such, compared with traditional survey methods, GPS data offers an objective description of the travel behavior of the study subject. In addition, collecting GPS data for research purposes does not require additional time and resources from the participants (Edwards & Griffin, 2013) while providing obvious advantages in quantity and quality (Korpilo, Virtanen, & Lehvävirta, 2017). Therefore, GPS data has gradually been gaining popularity as a data source for applied analysis of tourism behavior (Bauder & Freytag, 2015; East, Osborne, Kemp, & Woodfine, 2017), route selection (Broach, Dill, & Gliebe, 2012), and movement patterns (Xing, Wang, & Lu, 2020).

In order to test the feasibility and practicability of GPS trajectory data, tourism scholars have carried out research to verify the utility of GPS data in tracking tourists (Hallo et al., 2011; Van der Spek, Van Schaick, De Bois, & De Haan, 2009). The feasibility of utilizing GPS trajectory data has been confirmed in a number of studies analyzing, for example, the activity and movement patterns of tourists in theme parks (Birenboim, Anton-Clavé, Russo, & Shoval; Orellana, Bregt, Ligtenberg, & Wachowicz, 2012) and urban environments (Edwards & Griffin, 2013) as well as the spatiotemporal behavior of first-time versus repeat tourists (McKercher, Shoval, Ng, & Birenboim, 2012). GPS data has even been used to predict subsequent future travel behavior of tourists (Zheng et al., 2017). As an additional means of achieving a deeper understanding of tourists' behavior, GPS trajectory and survey data can be combined (East et al., 2017; Grinberger, Shoval, & McKercher, 2014; Shoval, McKercher, Birenboim, & Ng, 2015).

In summary, while the research on tourist behavior using GPS data has been quite extensive (Li, Xu, Tang, Wang, & Li, 2018) demonstrating its feasibility in tourist behavior research, relatively few studies have taken advantage of this rich data source within the literature on cycling tourism (as discussed in greater detail in Section 2.3).

2.2. Research on tourist behavior patterns

Tourist behavior pattern research analyzes the characteristics and logic of tourists' movement, including their spatial and temporal behavior patterns. Tourist spatial behavior is defined as the process of regional movement of tourists. The mapping of tourists' movements in geographical space is expressed as tourism routes. Based on the theoretical discussion on the spatial behavior pattern of tourists (see e.g., Lew & McKercher, 2002), Lue, Crompton, and Fesenmaier (1993; 1996) have carried out a systematic analysis of tourism routes, putting forward five distinct leisure travel modes: 1) single destination; 2) en route (visiting destinations on the way to and/or from a primary destination); 3) base camp (staying at one primary destination but from it also visiting other destinations in the region); 4) regional tour (visiting a number of destinations in the region but not en route to/from it) and; 5) trip-chaining (visiting multiple destinations in different regions, rather than having only one single destination). Their work has laid the foundation for research on tourists' spatial behavior, and many other scholars have since carried out empirical research based on their influential model (e.g. Stewart & Vogt, 1997; Oppermann, 1995).

Tourists' temporal behavior reflects the differences in activities exhibited by tourists at different time periods. For example, willingness to travel varies over time depending on many factors, such as season, time budget, and personal preferences (Yang, Wu, Liu, & Kang, 2017). Therefore, understanding the behavior patterns of tourists over time and formulating corresponding development strategies can improve their travel experience and satisfaction. Influential examples of research on tourists' temporal behavior include: Kemperman et al. (2004) who compared the activity patterns in theme parks between first-time visitors and repeat visitors, using length of stay to describe and analyze the differences in tourism activities between these groups; Thornton, Shaw, and Williams (1997) who studied the time allocation of tourist groups in various activities and places to analyze the behavior of tourists traveling with children; and more recently Zheng, Mou, Zhang, Makkonen, and Yang (2021) who analyzed the monthly distribution of Chinese tourists in Northern Europe to determine the temporal variation in their travel behavior.

However, the vast majority of previous studies have focused on tourists in general and paid relatively little attention to specific types of tourists, such as cycling tourists. Although the number of cycling tourists in China has gradually increased, there are still relatively few studies on their travel behavior. In order to understand the spatiotemporal behavior of this group of tourists, in-depth exploration of their movement patterns in time and geographical space (such as route preference, time fluctuation characteristics) has become necessary to guide the work of tourism planning officials in attracting cycling tourist to visit the country and specific regions.

2.3. Research on cycling tourism

As a healthy and environmentally friendly means of tourism mobility, cycling tourism has been gradually growing in popularity. The potential of cycling tourism has been reported on decades ago (Lumsdon, 1996; Ritchie, 1998) and subsequent studies have furthered our understanding of its nature and impact.

The primary consideration for any cycling journey is the selection and planning of the cycling route. A well-chosen cycling route can enhance the cycling experience and also help ensure personal safety. Downward (2001) identified and evaluated the factors that cycling tourists (based on a survey) consider important when using recreational bicycle routes, and found that cycling tourists prefer safe, quiet, low-traffic routes that are signed. Additional factors affecting the selection of the cycling route are, for example, good scenery, availability of tourism infrastructure, and slope gradient (Majumdar & Mitra, 2018; Sener, Eluru, & Bhat, 2009). As such, there are many factors that affect tourists' choices of cycling routes, including roads and tourism facilities, but also the preferences of the cycling tourists themselves.

Every cycling tourist has their own motivation for cycling a specific route. For example, Kruger, Myburgh, and Saayman (2015) (using survey data) divided cycling tourists into distinct groups: 1) Regulars, 2) Devotees, and 3) Beginners. The more experienced cycling tourists are naturally more likely to choose more demanding routes than beginners, whose motivation to cycle might be more social (see also Snelgrove & Wood, 2010). Nevertheless, whether the cycling tourist is a beginner, a regular or a devotee, a good cycling experience can be rewarding for tourists both physically and mentally. From this perspective, Lee (2014) has underlined (supported by survey material) the importance of signage and route safety (as in the case of route selection) as the most significant factors contributing to the overall satisfaction of cycling tourists, while, as evidenced by Ritchie (1998) (based on survey data), supply gaps in the existing tourism infrastructure may lead to dissatisfaction, and particularly, loss of (potential) tourism income from cycling tourism.

In summary, while there are some studies on cycling tourism, most of the existing studies on the topic have been 1) carried out by utilizing traditional data sources (i.e. surveys), 2) mainly focused on the perspective of the emotional characteristics of cycling tourists and, most importantly, 3) neglected the spatiotemporal aspects of cycling tourist behavior. Therefore, this paper focuses on the spatiotemporal behavior of cycling tourists by utilizing GPS trajectory data and by applying the Empirical Mode Decomposition (EMD) model, Pearson correlation coefficients and cluster analysis to improve our understanding of cycling tourism for the benefit of tourism management.

3. Methodology

3.1. Case study: Tibet, China

Tibet, located on the southwestern border of the People's Republic of China, is one of the five ethnic minority autonomous regions in China. With an average altitude of more than 4000 m, it is known as the "roof of the world." Although Tibet covers an area of 1.2284 million square kilometers, which accounts for about 1/8 of China's total area, it is sparsely populated, with only 3.51 million people, accounting for 0.25 % of China's total population. Due to the influence of Tibetan Buddhism, Tibet is considered a sacred place and many of its tourist attractions have a strong religious aspect. The Tibetan ethnic group and other ethnic groups living in Tibet have formed a unique Tibetan culture, which is now, with the gradual improvement of the transportation network (now crossed by two main national roads: G317 and G318) attracting more and more tourists (according to Tibet statistical yearbook data, the number of tourist arrivals in Tibet has increased rapidly from 686,116 in 2001 to 40,121,522 in 2019, with an average annual growth rate of 24.7 %) including cycling tourists. Due to the derived tourism income, tourism is generally viewed favorably by both the regional population and the administration of Tibet as a means to develop the local economy.[1]

3.2. Data collection

The main data sources utilized in this paper are:

1) OpenStreetMap (OSM): a free, open source and editable map service that provides users with fairly accurate spatial data (Haklay, 2010). OSM was used to gather the road network data needed for analyzing the road infrastructure related preference characteristics of cycling tourists visiting Tibet (Section 4.3).

2) 2bulu Outdoor Travel website (https://www.2bulu.com/): an interactive outdoor resource sharing and community platform (i.e. travel sharing platform) mainly used in China. The website collects and shares the outdoor sports trajectories of Chinese tourists (notably, the cycling trajectories may also include Tibetan tourists: local tourism cannot be separated from the data) who have voluntarily recorded them with the 2bulu Outdoor Assistant app. Each of these travel trajectories is composed of GPS data points that can also be linked to any photos uploaded on the 2bulu Outdoor travel website by the tourists.

From the 2bulu Outdoor Travel website we obtained 3826 GPS trajectories, voluntarily shared by tourists cycling in Tibet, from January 2009 to December 2019 as our initial data (including 18,635,903 GPS trajectory points). The data mainly contains attribute information such as TrackId (individual journey), UserId (individual user), Time, Latitude and Longitude, Speed and Elevation (Table 1).

GPS positioning is inevitably affected by confounding factors that cause some data errors. Therefore, it is also necessary to process the GPS trajectory data according to the needs of the study. We divided the Tibet Autonomous Region into 45*90 grids, according to the range of longitude and latitude, and used the following rules to clean the data (see Table 2): (1) We removed all trajectory points with missing attribute information from the data. (2) We identified duplicate data where all the field attributes (including timestamp) are the same under the same trajectory (i.e. caused by an error in the app's data collection mechanisms) as well as repeated data collection due to signal instability from confounding factors, such as weather, terrain, etc. All duplicate data were removed. (3) We removed abnormal data based on the recorded speed. Considering the particularity of the studied geographical location, including steep slopes, the maximum cycling speed of tourists in Tibet's countryside, especially on downhill segments of the road, may be much higher than in urban areas. Therefore, we set the speed threshold quite high at 30 m/s. Data with a speed greater than 30 m/s or a negative speed thus indicate either obvious errors in the app's data collection mechanisms or tourists recording motorized travel as cycling by mistake and were excluded from the dataset. After these multiple cleaning procedures, we obtained 3486 GPS trajectories (a total of 17,540,950 GPS data points) as our final data. The GPS data point density distribution of all the cycling trajectories in our dataset are shown in Fig. 1.

3.3. Methods

Three methods – EMD, Pearson correlation coefficient, and cluster analysis – were selected to explore: 1) the temporal patterns (fluctuation patterns), 2) the connection between road infrastructure and journey preferences, and 3) the spatial patterns (places of interest and attractions) of cycling tourism in Tibet.

(1) Temporal patterns: Empirical Mode Decomposition (EMD)

For exploring the fluctuation characteristics of the number of tourist cycling trajectories (i.e. the temporal patterns of cycling tourism in Tibet) we used the EMD model. EMD is a method for decomposing nonlinear and non-stationary data into a multiple Intrinsic Mode Function (IMF) and a residual. IMF is an adaptive method of time-frequency analysis developed by Huang et al. (1998). The IMF component reflects the fluctuation characteristics of the original time series in different time scales, whereas the residual component reflects the long-term trend of the original data. The EMD algorithm is able to process and analyze nonlinear and non-stationary data, which enables us to explore latent time series relationships in our data on cycling trajectories. The specific steps of the algorithm are as follows:

Step 1: For the original time series data $x_0(t)$, upper and lower

[1] https://www.doc88.com/p-1496981565899.html.

Table 1
GPS trajectory example data.

TrackId	UserId	Time	Lng	Lat	Speed (m/s)	Elevation(m)
bmzIgTDAFbU%253D	801,097	2016/05/17 07:57:23	93.13	31.93	15.25	4450.00
UD375sjAhLI%253D	1,482,814	2017/06/07 17:33:19	97.00	28.49	6.65	1706.53
3aj00vSUKQ0%253D	14,131,746	2018/11/10 05:57:38	97.44	30.08	1.98	4724.72

Table 2
GPS initial data preprocessing.

Num	Variable	Description of cleaning rules
1	Attribute	Eliminate points that lack an attribute, such as lat, lng, speed, userId, trackId, etc.
2	Data Point	If $P_1[attr] = P_2[attr] = P_i[attr]$ & $[P_1, P_2, P_i] \in$ same trajectory, remove duplicate data $[P_2, P_i]$, retain P_1.
3	Speed	If $V_i<0$ m/s or $V_i>30$ m/s, remove P_i

envelopes $u_0(t)$ and $l_0(t)$ are determined according to their upper and lower extreme points.

Step 2: The average envelope $m_0(t)$ is determined on the basis of the average values of the upper and lower envelopes. The first IMF $c_0(t)$ and residual $r_0(t)$ components are obtained by calculating the difference between the original data $x_0(t)$ and the average envelope $m_0(t)$.

$$m_0(t) = \frac{u_0(t) + l_0(t)}{2} \quad (1)$$

$$c_0(t) = x_0(t) - m_0(t) \quad (2)$$

$$r_0(t) = m_0(t) \quad (3)$$

Step 3: The residual $r_0(t)$ is used as the original data for the next iteration round to derive a series of IMF and residual components $r_n(t)$. The decomposition results are expressed as follows:

$$x(t) = \sum_{i=0}^{n-1} c_i(t) + r_n(t) \quad (4)$$

(2) Road infrastructure: Pearson correlation coefficient

Pearson correlation coefficient is a well-known and widely used method reflecting the relationship between characteristics and response, which measures the linear correlation between variables. It is utilized here to investigate the tourists' cycling trajectories vis-à-vis the road infrastructure in Tibet. National, provincial, county, and township roads and GPS trajectory lines converted from GPS track points are analyzed with kernel density estimations to extract their raster density values and further analyzed with the Pearson correlation coefficient to determine the route preference degrees of cycling tourism in Tibet.

(3) Spatial patterns: Cluster analysis

Tourists may be attracted to certain areas along their cycling route and take photos to record them. These areas may be specific scenic spots or road sections with unique scenery. In order to trace these AOIs (Areas of Interest) that attract cycling tourists to Tibet, we apply the HDBSCAN algorithm to cluster the locational information associated with the photos voluntarily uploaded by cycling tourists to 2bulu. The HDBSCAN clustering algorithm – that combines hierarchical and density clustering – is an efficient and convenient clustering algorithm (Mou & Yuan et al., 2020a). The algorithm uses variable mutual reach distance to separate clustering results of different densities from sparse noise points to facilitate the identification and extraction of clusters of different densities. The mutual reach distance $d_{mreach\text{-}k}(a,b)$ is defined as:

$$d_{mreach-k}(a,b) = \max\{core_k(a), core_k(b), d(a,b)\} \quad (5)$$

where $core_k(a)$ represents the cluster radius in the HDBSCAN algorithm under the conditions of the minimum clustering parameter k, and d(a,b) indicates the Euclidean distance between a and b. The algorithm steps are as follows:

Step 1: Change the space according to density/sparseness.

Step 2: Construct the minimum spanning tree of the distance weighted graph.

Step 3: Build the cluster hierarchy.

Step 4: Compress the cluster hierarchy according to the minimum cluster size.

Step 5: Extract stable clusters from the compressed tree.

4. Results

4.1. Descriptive overview

Fig. 2a shows the annual change in the number of tourist cycling trajectories in Tibet. Based on the increasing number of cycling

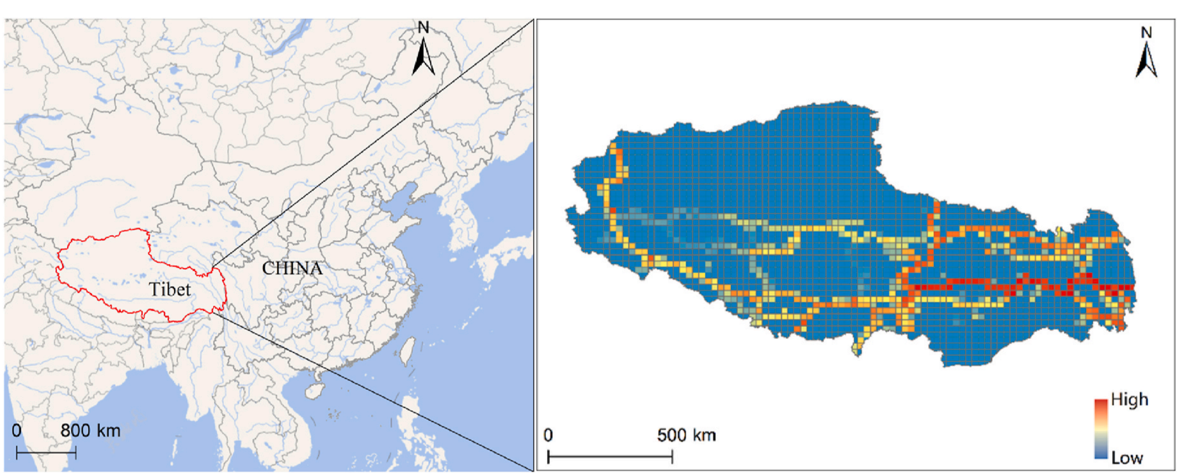


Fig. 1. The distribution of GPS trajectory points for cycling tourists in Tibet.

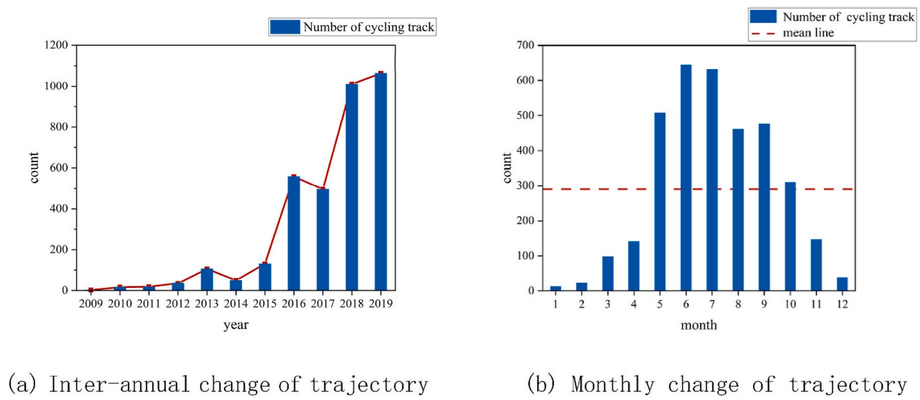


Fig. 2. Time characteristics of trajectories of cycling tourists from 2009 to 2019.

trajectories, it seems that cycling tourism (and the use of 2bulu) has rapidly increased in popularity in recent years. According to the GPS trajectory data (Fig. 2b), we can see that the cycling trajectories of tourists in Tibet are mainly concentrated around the summer period from May to October (87 % of all cycling trajectories). Thus, cycling tourism in Tibet is greatly affected by seasonal factors. From Fig. 3, it can be seen that most cycling tourists' GPS start points are in Tibet (85.96 %), followed by Sichuan (8.84 %), Yunnan (2.99 %), Xinjiang (1.04 %), Qinghai (0.91 %), and Chongqing (0.26 %). Our results are in line with what has been stated by Lumsdon, Downward, & Cope (2004): tourists commonly take other vehicles (bus, train, etc.) to reach the starting point of their cycling journey.

As shown in Fig. 4a, cycling tourists most commonly spend from one to two days cycling in Tibet (70.56 %) and the distance travelled does not normally exceed 200 km (61.46 %), as shown in Fig. 4b. Most cycling tourists in Tibet engage in medium or short distance cycling, while a small proportion pursue more physically and mentally demanding long-distance cycling.

4.2. Temporal patterns of cycling tourism in Tibet

Since the number of recorded cycling trajectories in Tibet is very small from 2009 to 2011, we chose to focus on data from January 2012 up to December 2019 (96 months) in order to improve the accuracy of the results of our EMD decomposition, and finally obtained four IMF and residual (Res) components. The initial non-EMD processed data of monthly cycling trajectories is denoted as "signal" in Fig. 5. The calculated average periods and variance contribution rates (VCR) of each IMF component are shown in Table 3. From Fig. 5 and Table 3, we can see that the number of cycling trajectories in Tibet shows a fluctuating growth trend:

(1) The residual component is the most significant scale component: its variance contribution rate is the largest, reaching 30.12 %. Therefore, it plays a leading role in the temporal fluctuation process of cycling tourism in Tibet. Furthermore, the clear rising trend of the residual component indicates that the number of cycling trajectories in Tibet is increasing.
(2) The IMF1 and IMF2 components denote fluctuation patterns of 3–4 and 10–11-month cycles, respectively. According to the original signal data, the peaks in the number of cycling trajectories in Tibet in different years are concentrated in June, July and September. As such, the IMF1 and IMF2 components show the seasonal fluctuations of the cycling trajectories in Tibet. The IMF2 component, indicating the quasi-one-year periodic fluctuation (Fig. 5), has undergone eight obvious fluctuations between 2012 and 2019. However, we can see that 2014 (months 25–36) showed a significant abnormal state. Two major traffic accidents in Tibet on August 9 and 18 – resulting in 47 deaths, 11 injured, and 13 missing – is a possible reason for this decrease in the number of cycling trajectories in Tibet in 2014. The VCR of IMF1 and IMF2 are 27.90 % and 29.35 %, respectively, underlining the importance of the seasonal characteristics of Tibet cycling trajectories. This result was further verified by the decomposition of daily cycling trajectories (results of this analysis can be obtained from the authors upon request).
(3) The IMF3 and IMF4 components, respectively, denote the cyclical fluctuation patterns of 24-month and 64-month cycles. The VCR of IMF3 and IMF4 indicate that their influence is relatively weak compared to the IMF2, IMF3 and residual components. The 24-

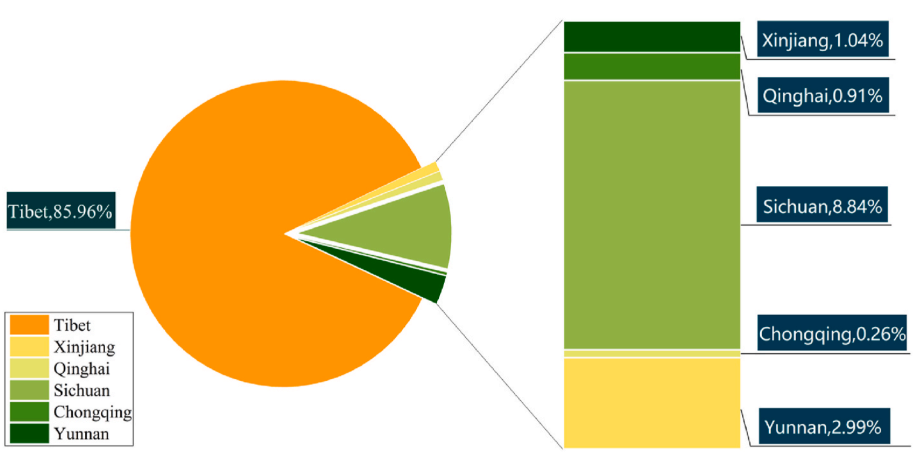
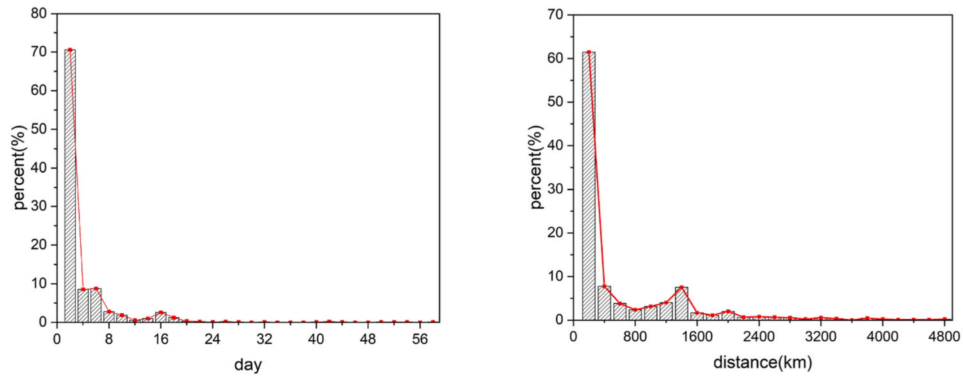


Fig. 3. Distribution of tourist cycling start locations.



(a) Distribution of cycling time (b) Distribution of cycling distance

Fig. 4. Time-distance distribution of cycling tourists in Tibet.

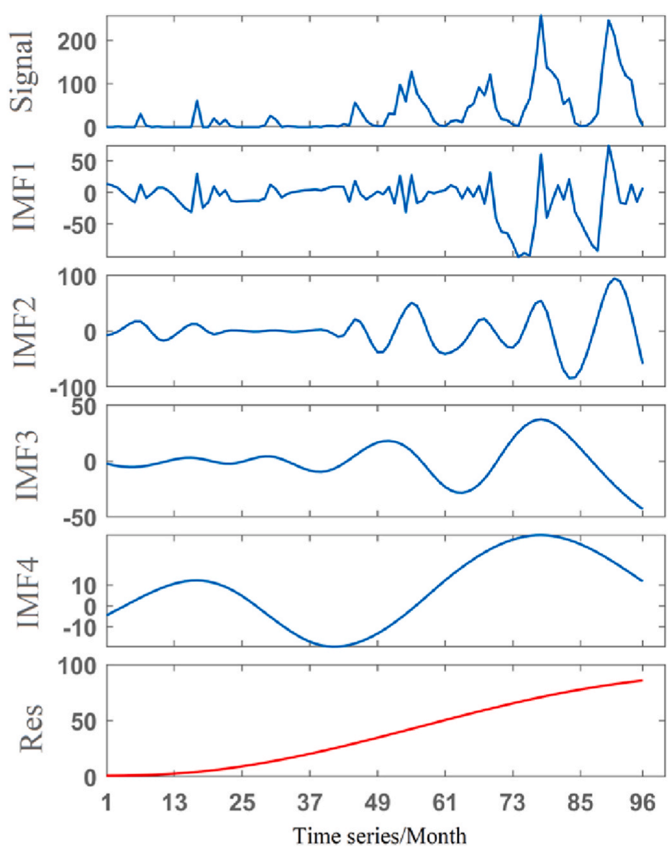


Fig. 5. Decomposition of monthly cycling trajectories.

Table 3
The cycle and variance contribution rate (VCR) of each component of monthly cycling trajectory.

IMF component	IMF1	IMF2	IMF3	IMF4	Res
cycle/month	3.76	10.10	24.00	64.00	–
VCR/%	27.90	29.35	6.49	6.14	30.12

month fluctuation cycle of cycling trajectories in Tibet is consistent with the cycle length, 24–32 months, of China's tourism industry (Chen, Liu, Wang, & Xu, 2005). Therefore, the IMF3 component is likely to show results that are affected by the overall development cycle of China's tourism industry. Similarly, the 64-month fluctuation cycle indicated by IMF4 is consistent with findings indicating the existence of long-term economic cycles, 60–72 months, in China (Liu, Zhang, & Zhang, 2005). As such, it seems that the fluctuations in the popularity of cycling tourism in Tibet are basically in line with China's overall tourism and macroeconomic development. However, from the IMF4 component, we can also see that there are two obvious fluctuations during our observation period. Firstly, the release (in October 2011) of the film "Zhuanshan" about cycling in Tibet likely promoted cycling tourism in Tibet as (potentially) indicated by the upward trend in cycling trajectories in 2012 and 2013. Secondly, the above-mentioned traffic accidents are a likely reason for the sharp drop in the number of cycling trajectories from 2013 up until the first half of 2015. The year 2015 was the 50th anniversary of the founding of the Tibet Autonomous Region, which resulted in extensive visibility and news coverage in the media: a likely reason for the subsequent upward trend in the number of cycling trajectories in Tibet as shown by IMF4 in Fig. 5.

4.3. Road infrastructure and preference characteristics of cycling tourists in Tibet

Fig. 6 shows the overall spatial density distribution patterns of tourist cycling trajectories converted from GPS points (A), national roads (B), provincial roads (C), and county and township roads (D) in Tibet. As can be seen from the figure, the density distribution of cycling tourists is relatively high in central and eastern parts, while it is relatively low in the western parts of Tibet, indicating that the central and eastern parts of Tibet are the most attractive areas for tourists to cycle.

In order to further explore the specific preferences of cycling tourists in Tibet, we respectively extracted the density raster matrix of tourists' cycling trajectories and various types of roads (national roads, provincial roads, county and township roads) and calculated the correlation between the tourist cycling trajectory density raster matrix and the other matrices (Table 4).

From Table 4, we can observe that there is a high and statistically significant (p-value < 0.01) correlation between cycling trajectory and national road matrixes (0.704), while the correlation with provincial and county and township roads is significantly lower. From Fig. 7, where we have fitted the cycling trajectory density values and the national highway density value from 2012 to 2019, we can see that the degree of fit between the two shows an overall upward trend (Fig. 7), indicating that over time, more and more tourists have chosen to cycle on national roads. As shown in Fig. 6, the Sichuan-Tibet Southern Line G318 (marked in blue in the figure) is the most popular route among cycling tourists in Tibet, arguably because of safe road conditions, relatively

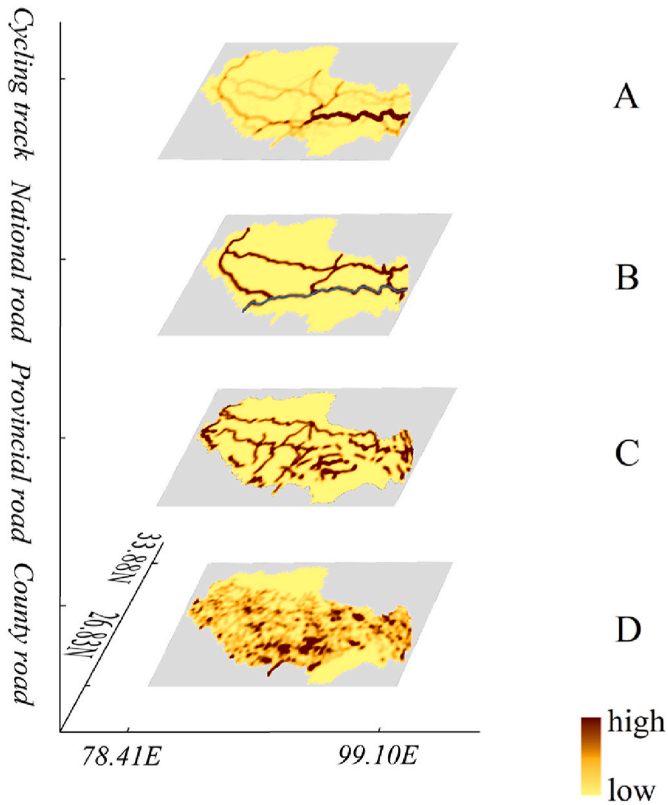


Fig. 6. Line trajectory of tourists' cycling and the spatial density distribution of various roads.

Table 4
Correlation between cycling trajectory and different roads.

	National road	Provincial road	County and township road
Correlation coefficient	0.704	0.229	0.344

complete service facilities (i.e. tourism infrastructure), and diverse scenery along the route.

4.4. Spatial patterns of cycling tourism in Tibet

Fig. 8 shows the spatial flow of cycling tourists from origin to destination in Tibet (thus excluding areas outside Tibet). Based on the number of inbound cycling tourists (Fig. 9), Chengguan District, with the largest "inflow," is the most popular AOI among the cycling tourists in Tibet. Situated in Lhasa, the capital of Tibet, it is the location of many famous scenic spots and popular tourist attractions. Through spatial clustering analysis of the photos taken and shared by the cycling tourists, we found that the most popular specific AOIs are (as expected) Potala Palace, Jokhang Temple, Tibet Intangible Cultural Heritage Museum and Norbulingka Scenic Area (Fig. 10a). Additionally, the counties east of Lhasa (Gongbogyamda County, Bayi District, Bowo County, Baxoi County and Zogang County) also have a large inflow of cycling tourists as they need to be passed to cycle along the most popular G318 National Road (see Section 4.3).

From Fig. 9, we can see that Baxoi County has the second largest inflow of cycling tourists in Tibet. Ranwu Lake, known as the "West Tian Yao Lake" in this county, is a major AOI for cycling tourists. Moreover, there is another special AOI in Baxoi County (marked with a box in Fig. 10b) called the "72 Turns on the Nujiang River," where a steep slope is crisscrossed via a section of winding road. The highest point of the road section is at 4700 m above sea level, making it an extremely demanding route but also indicating that challenges are an important attraction for cycling tourists. Finally, the inflow of cycling tourists to Damxung County, due to the Qinghai-Tibet Line G109 crossing the county, is relatively large (particularly from adjacent counties). The main AOIs are concentrated in Nam Co (one of the three holy lakes in Tibet) Scenic Area and Nyainqentanglha Mountain (Fig. 10c).

5. Discussion

Regarding the spatial characteristics of cycling trajectories in Tibet, the study found that cycling tourism is mostly concentrated on the central and eastern parts of the region. Tourists show a clear preference for cycling on national roads (this preference has become stronger over time), while provincial and county and township roads are relatively less attractive to cycling tourists. The reasons may be as follows: (1) Lower risk: level of risk is an important factor influencing tourists' cycling route preferences; (2) More complete logistical support and tourism services; and (3) Good road trafficability; allowing tourists to cycle smoothly and enhance their cycling experience. Compared with provincial, county and township roads, Tibet's national roads are safer. Good tourism infrastructure is also an important condition for attracting tourists to cycle (Winters, Teschke, Grant, Setton, & Brauer, 2010). Studies have underlined the importance of improved cycling infrastructure for attracting new and inexperienced cycling tourists to a given region (Poorfakhraei, 2015). As the national roads are essential transportation routes, the tourism infrastructure along the way is more mature and developed than along the smaller and less frequently travelled provincial, county and township roads of Tibet. In many areas of Tibet, especially in remote areas, the road conditions of provincial and county and township roads are poor, including many road sections that cannot be navigated smoothly with a bicycle. For the above reasons, it can be inferred that the preference of cycling tourists in Tibet for national roads will not change in the short term, because improving the road conditions of provincial, county and township roads and tourism infrastructure is a gradual, expensive and long-term process.

However, the question of how to improve the appeal of provincial, county and township roads in the future for cycling tourists is a problem that must be solved to promote the sustainable and sound development of cycling tourism in Tibet. Therefore, from the perspective of tourism management, it is nonetheless necessary to start strengthening the basic services (tourism infrastructure) and road infrastructure along the other cycling routes, besides the by far most popular G318, to meet the cyclists' needs. This would provide tourists with safer and better cycling experiences and, further, promote the development of Tibet's cycling tourism industry. Having a higher number of good quality routes to choose from could increase the length of stay of the cycling tourists (according to the cycling trajectories, cycling tourists commonly spend only 1–2 days in Tibet), which would in turn likely increase their tourism spending during their journey (see e.g. Adongo, Badu-Baiden, & Boakye, 2017) and attract repeat tourists. Therefore, it would further increase the impact that cycling tourism has on the local economy of Tibet and, moreover, spread the economic benefits arising from cycling tourism more evenly across the region. Finally, in the very extreme case, potential congestions along G318 would lead to decreased tourism satisfaction (see Dickinson, 2010).

The cycling time of tourists is generally concentrated in the summer, late spring and early autumn. This is closely related to Tibet's unique geographical location and climate conditions. Therefore, cycling is largely affected by seasonal climate and weather conditions (Gebhart & Noland, 2014; Wadud, 2014). The roads in Tibet from winter to early spring are covered with snow and ice, and the temperatures are low, which naturally has a major negative impact on cycling tourism. Therefore, there are obvious seasonal fluctuations in the number of tourist cycling trajectories. However, offering safe guided winter cycling tours and accompanied tourism products (e.g. rental of fat bikes with

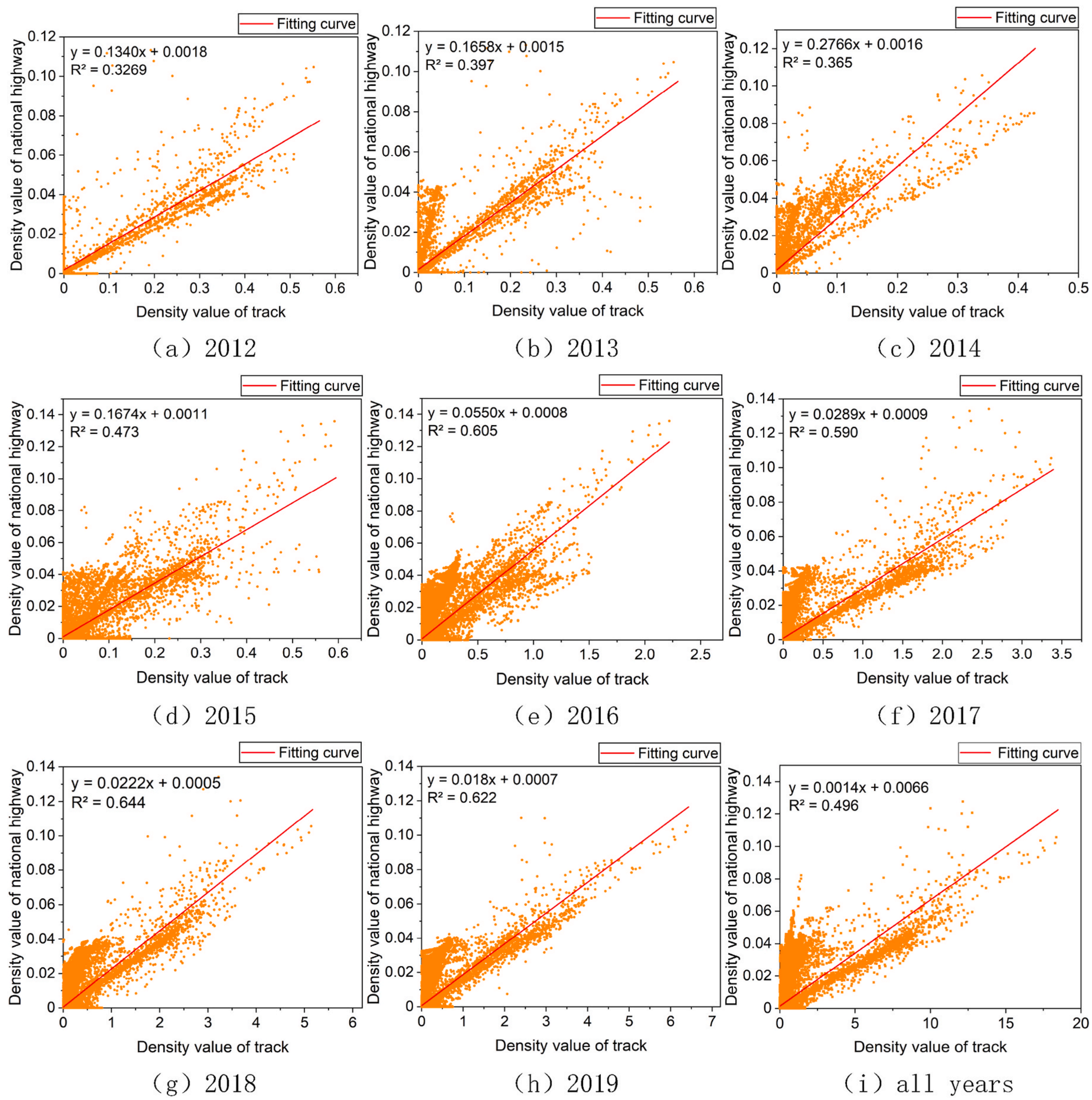


Fig. 7. Fitting curve of cycling trajectory and national highway density values from 2012 to 2019.

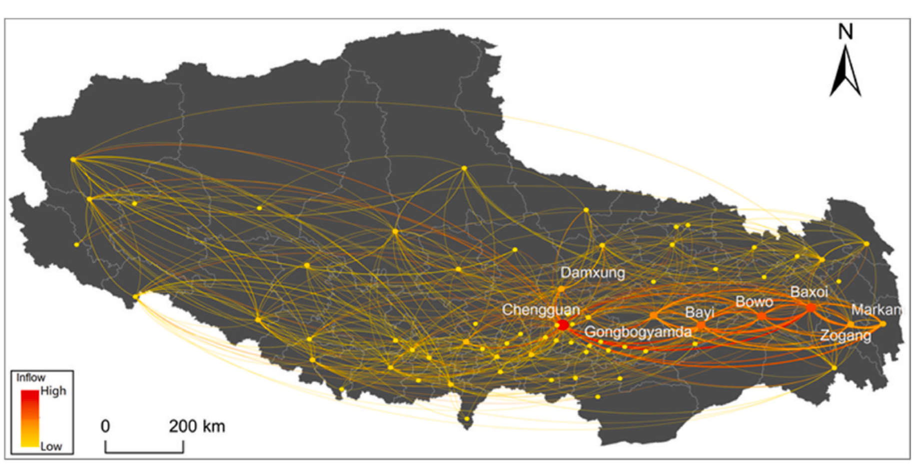


Fig. 8. Inflow characteristics of cycling tourists in Tibet's counties.

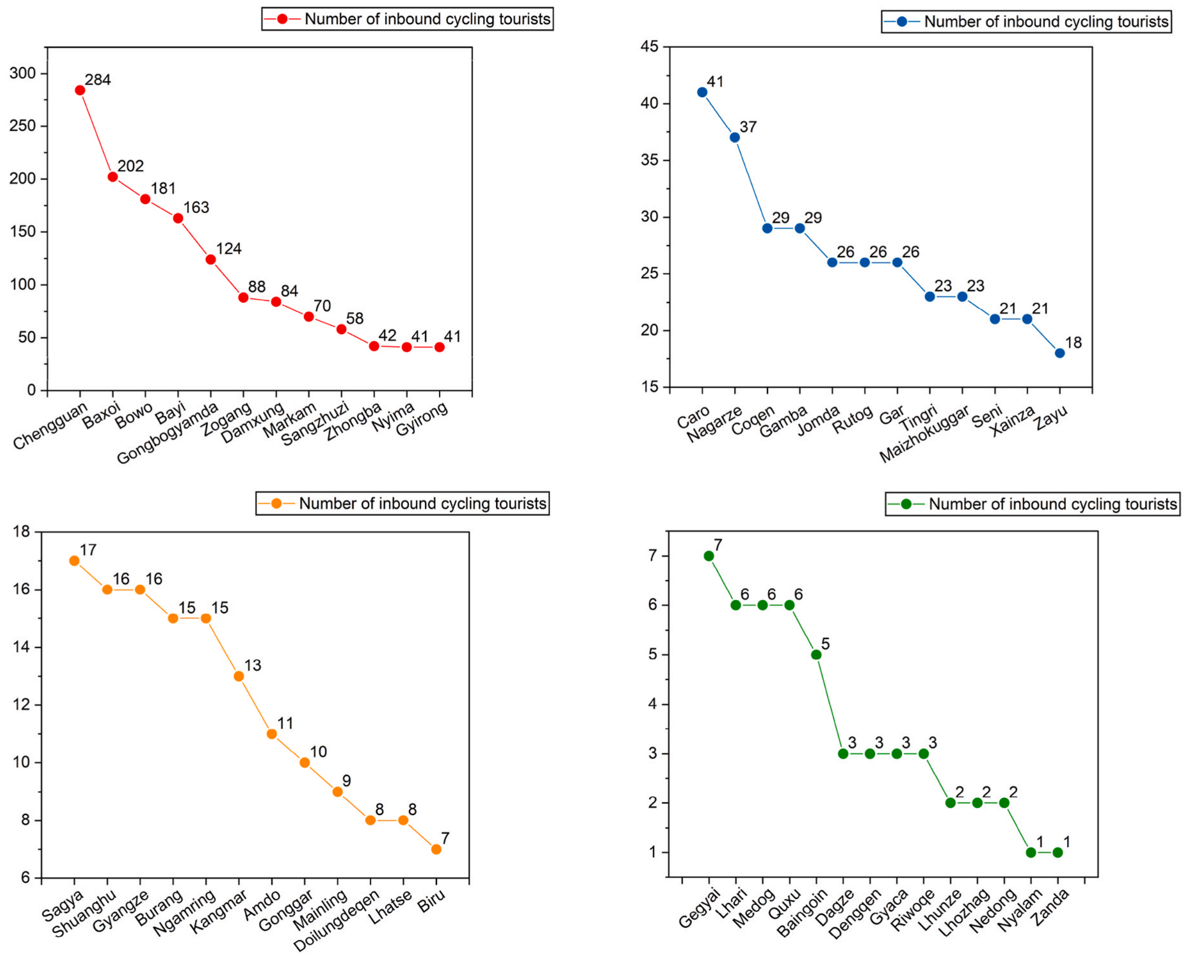


Fig. 9. Inflow of cycling tourists in Tibet's counties (excluding counties with zero inflow).

studded tires) in Tibet might be an exotic adventure for more experienced cyclists seeking challenges (see e.g. Meitz & Ringhofer, 2017).

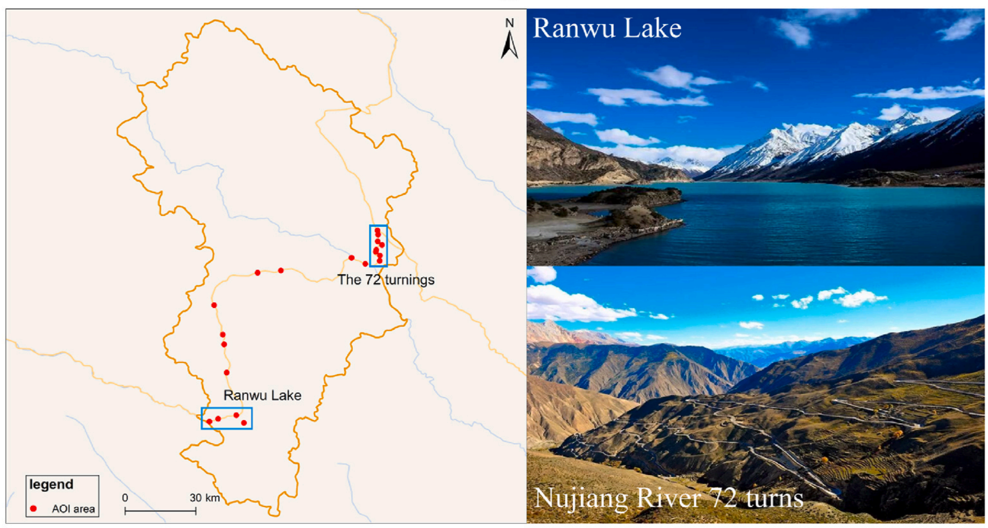
During the research period (2012–2019), the number of cycling trajectories generally showed a rapid upward trend. Despite some abrupt decreases in the growth trend (likely caused by traffic accidents), the temporal fluctuation of cycling tourists in Tibet was mainly consistent with the cyclical fluctuations of China's tourism industry (2–3 year cycles) and economy (5–6 year cycles). Therefore, it is recommended that the local governments and relevant tourism organizations devise reasonable cyclical strategies (discounts, guided tours, marketing campaigns, etc.), based on the evidenced fluctuation in the number of cycling trajectories, to minimize the harmful effects of tourism "slumps" on the tourism industry and the local economy of Tibet.

The inflow characteristics of cycling tourism in Tibet show that the areas along the G318 road of the Southern Sichuan-Tibet Line (Lhasa Chengguan District, Gongbogyamda County, Bayi District, Bowo County, Baxoi County, etc.) have formed a connected cycling chain, which is visited by many cycling tourists. The most popular cycling AOIs are religious-cultural sites (such as Potala Palace, Jokhang Temple and Nam Co Lake) or pertain to physical challenges (the 72 Turns on the Nujiang River). From this perspective, it would seem advisable that the local governments and relevant tourism organizations should market similar scenic spots, religious-cultural sites and challenging physical elements that might appeal to cycling tourists. This could, again, increase length of stay or appeal to repeat tourists. For example, the less popular G317 (than G318) has higher altitudes and lower temperatures requiring higher physical adaptability of cycling tourists and could thus be marketed at the more experienced segment of cycling tourists specifically looking for physical challenges.

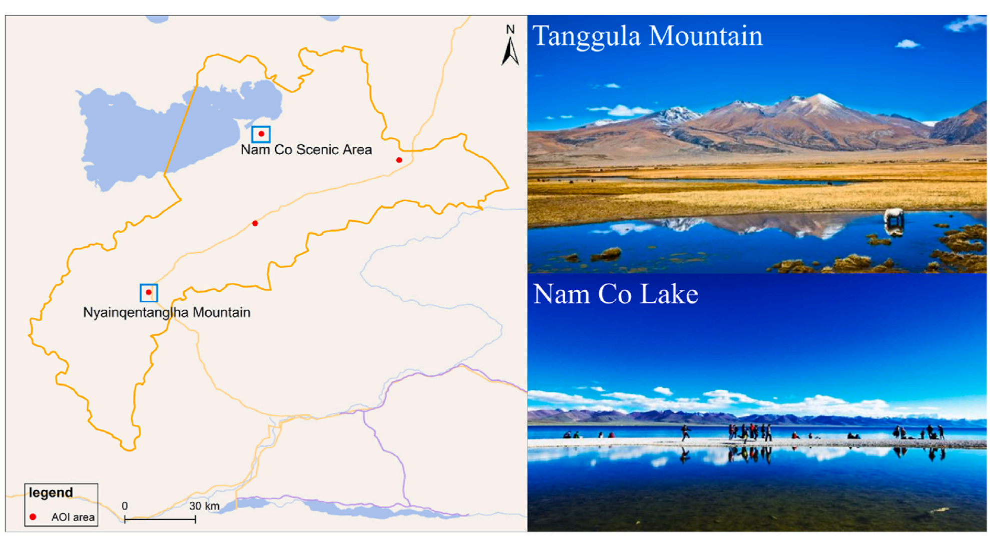
It is worth noting that, except for the areas within China which are closer to Tibet, as shown in Fig. 3 in Section 4.1, also Kathmandu (in Nepal) is a popular starting point for foreign non-Chinese cycling tourists (one can, for example, find several firms offering guided tours between Lhasa and Katmandu). Therefore, there seem to be differences between the preferences of foreign tourists and Chinese tourists in various aspects, such as attraction preferences and cultural preferences, which may lead to some differences in their route choices compared to Chinese tourists. However, as our research focuses on Chinese cycling tourists (i.e. 2bulu users), our data does not cover foreign cycling tourists. Naturally, understanding the spatiotemporal behavior of foreign cycling tourists in Tibet and formulating corresponding tourism strategies based on the potential differences between them and Chinese cycling tourists is an issue worthy of further in-depth analysis.

In addition, although the development of cycling tourism can help to accelerate the growth of the local economy, over-tourism may at the same time have a negative impact on the local cultural heritage. For example, because of the fragility of its plateau ecosystem, the commercial development of tourism in Lhasa has greatly affected the local ecological environment. Furthermore, due to the commercial nature of the tourism industry, Lhasa has also experienced some of other the negative aspects of tourism development: destruction of cultural customs and living habits of local residents (Xiao & Chen, 2020). Therefore, in order to maximize the positive effect of cultural heritage as a tourism resource, relevant departments of Tibet should promote the coordinated development of cultural heritage protection and tourism industry, so as to achieve a win-win solution for both environmental, social and cultural protection and economic development.

(a) Lhasa Chengguan District



(b) Baxoi County



(c) Damxung County

Fig. 10. Tourist cycling AOIs (Chengguan District, Baxoi County, Damxung County).

6. Conclusion and directions for further research

Understanding the spatiotemporal behavior of cycling tourists provides pivotal information for local governments and relevant tourism organizations interested in planning cycling routes and developing cycling tourism. Traditionally, such efforts have had to rely on official statistics or survey data, but technological developments have allowed researchers to experiment with novel data sources allowing real-time data availability. GPS trajectory data is an example of these novel data sources, as it has unique advantages: 1) it records the location of cycling tourists continuously in real-time and 2) it can be visualized (as shown in this paper) into easily interpretable "infographics" to guide tourism management. Such data can be accessed through social media sites, where the users voluntarily share their cycling journey trajectories and combined with other data sources such as road infrastructure data. As such, the data provides rich information at a low cost. In this paper, GPS trajectory data and methods to analyze it were introduced by utilizing the Tibet Autonomous Region as a case study example. The paper explored the spatiotemporal behavior of Chinese cycling tourists in Tibet by applying EMD, Pearson correlation coefficient and cluster analysis. The empirical findings of the study can be summarized as follows:

- Based on the number of cycling trajectories the popularity of cycling tourism in Tibet has increased rapidly in recent years.
- Affected by the climate, the number of cycling trajectories has obvious seasonal fluctuation characteristics accompanied with longer cycles coinciding with China's tourism industry and economic cycles.
- The most popular "hotspots" for cycling tourists are concentrated in the central and eastern parts of Tibet. These hot spots consist of popular religious-cultural sites, scenic spots and road sections offering physical challenges.
- Cycling tourists commonly prefer national roads (rather than provincial, county and township roads), G318 being the most popular route, arguably due to the high quality of road (safety) and tourism infrastructure (availability of tourism services).

From an academic perspective, the methodology applied in this study proved to be a fitting tool for investigating research questions related to tourist behavior patterns in recreational trips with multiple destinations (e.g. regional tours) vis-à-vis tourism (road) infrastructure and distance between destinations (cf. Lue et al., 1993; 1996). The results also bring forth a number of potential development paths that the local government and relevant tourism organizations might follow to increase the appeal of cycling tourism in Tibet for the benefit of the economy of the region (see Section 5). While the results presented here pertain to one specific region, the main goal of the paper was to introduce ways to apply GPS trajectory data for the benefit of tourism management. If an appropriate social media data source exists, the visualizations and methods presented in this paper can be applied in other regions with relative ease and low cost.

Finally, it has to be noted that there are still some shortcomings in the chosen data and approach that lead to our subsequent suggestions for further research:

(1) The data represents only a small sample of all cycling tourists in Tibet and inevitably entails some bias, since not all cycling tourists use the 2bulu sharing platform. In addition, since our research focuses on Chinese tourists, the available data lacks the cycling trajectories of foreign tourists in Tibet. Since the inclusion of foreign cycling tourists might change the results to a certain extent, finding good alternative data sources to include foreign cycling tourists into the analysis would be a valuable line of further research.

(2) Tourists who cycle in groups follow their team, which limits their choices of individual cycling routes. Additionally, the data lacks sociodemographic information (such as age, gender, economic income, etc.). Therefore, we were unable to evaluate the characteristics of different tourist segments. In the future, attempts to combine online cycling data with survey data could significantly improve the precision of the analysis (Li, Yang, Shen, & Wu, 2019).

(3) The current study focuses on the overall analysis of cycling tourists. Segregating cycling data into day trips vs. multi day trips is an interesting direction that could reflect the behavioral differences between one-day cycling trippers and tourists on long-distance cycling holidays. An evident direction for further studies would, therefore, be to segregate the GPS trajectory data into day trips vs. multi day trips (potentially supplemented with alternative data sources, such as surveys) for a more detailed analysis.

Credit author statement

Naixia Mou: Methodology, Writing- Original draft preparation, Project administration, Funding acquisition. **Zhiwen Liu:** Software, Visualization, Writing- Original draft preparation. **Yunhao Zheng:** Conceptualization. **Teemu Makkonen:** Writing- Reviewing and Editing. **Tengfei Yang:** Validation. **Lingxian Zhang:** Data curation, Supervision.

Impact statement

In this paper, a novel cycling trajectory data from 2bulu.com (an interactive outdoor resource sharing and community platform), is used to carry out a detailed analysis of cycling tourists' spatiotemporal behavior. Tibet Autonomous Region, a popular high-altitude cycling area, was selected as the case study area. The utilized data and methods help to detect the spatiotemporal behavior patterns of cycling tourists, providing useful information for tourism management departments to formulate tourism development and marketing strategies.

Declarations of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Adongo, C. A., Badu-Baiden, F., & Boakye, K. A. A. (2017). The tourism experience-led length of stay hypothesis. *Journal of Outdoor Recreation and Tourism, 18*, 65–74. https://doi.org/10.1016/j.jort.2017.02.003

Bauder, M., & Freytag, T. (2015). Visitor mobility in the city and the effects of travel preparation. *Tourism Geographies, 17*(5), 682–700. https://doi.org/10.1080/14616688.2015.1053971

Birenboim, A., Anton-Clavé, S., Russo, A. P., & Shoval, N. (2013). Temporal activity Patterns of theme Park visitors. *Tourism Geographies, 15*(4), 601–619. https://doi.org/10.1080/14616688.2012.762540

Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice, 46*(10), 1730–1740. https://doi.org/10.1016/j.tra.2012.07.005

Chen, Y., Liu, P., Wang, L., & Xu, C. (2005). Research on the fluctuation cycle of China's tourism industry based on spectral analysis. *Hunan Social Sciences*, (2), 104–107. https://doi.org/10.3969/j.issn.1009-5675.2005.02.027 (in Chinese).

Cui, Q., Xu, H., & Yang, Y. (2014). Secular pilgrimage: Tourist experience in Tibet. *Tourism Tribune, 29*(2), 110–117. https://doi.org/10.3969/j.issn.1002-5006.2014.02.012 (in Chinese).

Deenihan, G., & Caulfield, B. (2015). Do tourists value different levels of cycling infrastructure? *Tourism Management, 46*, 92–101. https://doi.org/10.1016/j.tourman.2014.06.012

Dickinson, J. E., R.D. (2010). Other People, other times and special Places": A social representations Perspective of cycling in a tourism destination. *Tourism and*

Hospitality Planning & Development, 7(1), 87–89. https://doi.org/10.1080/14790531003661211
Downward P, L. L. (2001). The development of recreational cycle routes: An evaluation of user needs. *Managing Leisure, 6*(1), 50–60. https://doi.org/10.1080/13606710010026368
East, D., Osborne, P., Kemp, S., & Woodfine, T. (2017). Combining GPS & survey data improves understanding of visitor behaviour. *Tourism Management, 61*, 307–320. https://doi.org/10.1016/j.tourman.2017.02.021
Edwards, D., & Griffin, T. (2013). Understanding tourists' spatial behaviour: GPS tracking as an aid to sustainable destination management. *Journal of Sustainable Tourism, 21*(4), 580–595. https://doi.org/10.1080/09669582.2013.776063
Gebhart, K., & Noland, R. B. (2014). The impact of weather conditions on bikeshare trips in Washington, DC. *Transportation, 41*(6), 1205–1225. https://doi.org/10.1007/s11116-014-9540-7
Girardin, F., Calabrese, F., Fiore, F. D., Ratti, C., & Blat, J. (2008). Digital footprinting: Uncovering tourists with user-generated content. *IEEE Pervasive Computing, 7*(4), 36–43. https://doi.org/10.1109/MPRV.2008.71
Grinberger, A. Y., Shoval, N., & McKercher, B. (2014). Typologies of tourists' time–space consumption: A new approach using GPS data and GIS tools. *Tourism Geographies, 16*(1), 105–123. https://doi.org/10.1080/14616688.2013.869249
Haklay, M. (2010). How good is volunteered geographical information? A comparative study of OpenStreetMap and ordnance survey datasets. *Environment Planning B Planning Design, 93*(4), 3–11. https://doi.org/10.1016/j.amjcard.2004.02.006
Hallo, J. C., Beeco, J. A., Goetcheus, C., McGee, J., McGehee, N. G., & Norman, W. C. (2011). GPS as a method for assessing spatial and temporal use distributions of nature-based tourists. *Journal of Travel Research, 51*(5), 591–606. https://doi.org/10.1177/0047287511431325
Han, H., Lho, L. H., Al-Ansi, A., & Yu, J. (2020). Cycling tourism: A perspective article. *Tourism Review, 75*(1), 162–164. https://doi.org/10.1108/TR-06-2019-0268
Han, H., Meng, B., & Kim, W. (2017). Bike-traveling as a growing phenomenon: Role of attributes, value, satisfaction, desire, and gender in developing loyalty. *Tourism Management, 59*, 91–103. https://doi.org/10.1016/j.tourman.2016.07.013
Hjalager, A. (2015). 100 innovations that transformed tourism. *Journal of Travel Research, 54*(1), 3–21. https://doi.org/10.1177/0047287513516390
Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., et al. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society. A, Mathematical, physical, and engineering sciences, 454*(1971), 903–995. https://doi.org/10.1098/rspa.1998.0193
Hu, C., Li, L., & Luo, S. (2015). Cycling Tourists'Experience of scenic byways based on content analysis of travel blogs: A case study of the Sichuan-Tibet section of national highway 318. *Tourism Tribune, 30*(11), 99–110. https://doi.org/10.3969/j.issn.1002-5006.2015.11.014 (in Chinese).
Kaplan, S., Manca, F., Nielsen, T. A. S., & Prato, C. G. (2015). Intentions to use bike-sharing for holiday cycling: An application of the Theory of Planned Behavior. *Tourism Management, 47*, 34–46. https://doi.org/10.1016/j.tourman.2014.08.017
Kemperman, A., & Joh, C. H. (2004). Comparing first-time and repeat visitors activity patterns. *Tourism Analysis, 8*(2), 159–164. https://doi.org/10.3727/108354203774076661
Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning, 157*, 608–617. https://doi.org/10.1016/j.landurbplan.2016.08.005
Kruger, M., Myburgh, E., & Saayman, M. (2015). A motivation-based typology of road cyclists in the Cape town cycle tour, South Africa. *Journal of Travel & Tourism Marketing, 33*(3), 380–403. https://doi.org/10.1080/10548408.2015.1064057
Lamont, M. (2009). Reinventing the wheel: A definitional discussion of bicycle tourism. *Journal of Sport & Tourism, 14*(1), 5–23. https://doi.org/10.1080/14775080902847363
Lee, C. (2014). An investigation of factors determining cycling experience and frequency. *Tourism Geographies, 16*(5), 844–862. https://doi.org/10.1080/14616688.2014.927524
Lew, A. A., & McKercher, B. (2002). Trip destinations, gateways and itineraries: The example of Hong Kong. *Tourism Management, 23*(6), 609–621. https://doi.org/10.1016/S0261-5177(02)00026-2
Li, Y., Sun, Q., Ji, X., Xu, L., Lu, C., & Zhao, Y. (2020). Defining the boundaries of urban built-up area based on taxi trajectories: A case study of Beijing. *Journal of Geovisualization and Spatial Analysis, 4*(1), 1–12. https://doi.org/10.1007/s41651-020-00047-6
Liu, S., Zhang, X., & Zhang, P. (2005). Smoothing the business cycles at a moderately high altitude. *Economic Research, 11*, 10–21. https://doi.org/10.3969/j.issn.1674-8298.2006.01.001 (in Chinese).
Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management, 68*, 301–323. https://doi.org/10.1016/j.tourman.2018.03.009
Li, Y., Yang, L., Shen, H., & Wu, Z. (2019). Modeling intra-destination travel behavior of tourists through spatio-temporal analysis. *Journal of Destination Marketing & Management, 11*, 260–269. https://doi.org/10.1016/j.jdmm.2018.05.002
Lue, C., Crompton, J. L., & Fesenmaier, D. R. (1993). Conceptualization of multi-destination pleasure trips. *Annals of Tourism Research, 20*(2), 289–301. https://doi.org/10.1016/0160-7383(93)90056-9
Lue, C., Crompton, J. L., & Stewart, W. P. (1996). Evidence of cumulative attraction in multidestination recreational trip decisions. *Journal of Travel Research, 35*(1), 41–49. https://doi.org/10.1177/004728759603500107
Lumsdon, L. (1996). Cycle tourism in Britain. *Insights,* (3), 27–32.
Lumsdon, L. (2000). Transport and tourism: Cycle tourism - a model for sustainable development? *Journal of Sustainable Tourism, 8*(5), 361–377. https://doi.org/10.1080/09669580008667373
Lőrincz, K., Banász, Z., & Csapó, J. (2020). Customer involvement in sustainable tourism Planning at lake Balaton, Hungary—analysis of the consumer Preferences of the active cycling tourists. *Sustainability, 12*(12), 5174. https://doi.org/10.3390/su12125174
Lumsdon, L., Downward, P., & Cope, A. (2004). Monitoring of cycle tourism on long distance trails: the North Sea Cycle Route. *Journal of Transport Geography, 12*(1), 13–22. https://doi.org/10.1016/j.jtrangeo.2003.10.007
Majumdar, B. B., & Mitra, S. (2018). Analysis of bicycle route-related improvement strategies for two Indian cities using a stated preference survey. *Transport Policy, 63*, 176–188. https://doi.org/10.1016/j.tranpol.2017.12.016
McKercher, B., Shoval, N., Ng, E., & Birenboim, A. (2012). First and repeat visitor behaviour: GPS tracking and GIS analysis in Hong Kong. *Tourism Geographies, 14*(1), 147–161. https://doi.org/10.1080/14616688.2011.598542
Meitz, A., & Ringhofer, K. (2017). The bicycle and the Arctic – resilient and sustainable transport in times of climate change. In K. Latola, & H. Savela (Eds.), *The interconnected Arctic — UArctic congress 2016*. Cham: Springer Polar Sciences. Springer. https://doi.org/10.1007/978-3-319-57532-2_16.
Mou, N., Yuan, R., Yang, T., Zhang, H., Tang, J. J., & Makkonen, T. (2020a). Exploring spatio-temporal changes of city inbound tourism flow: The case of Shanghai, China. *Tourism Management, 76*, 103955. https://doi.org/10.1016/j.tourman.2019.103955
Mou, N., Zheng, Y., Makkonen, T., Yang, T., Tang, J. J., & Song, Y. (2020b). Tourists' digital footprint: The spatial patterns of tourist flows in Qingdao, China. *Tourism Management, 81*, 104151. https://doi.org/10.1016/j.tourman.2020.104151
Oppermann M. (1995)A Model of Travel Itineraries. Journal of Travel Research, 33(4), 57-61. https://doi.org/10.1177/004728759503300409.
Orellana, D., Bregt, A. K., Ligtenberg, A., & Wachowicz, M. (2012). Exploring visitor movement patterns in natural recreational areas. *Tourism Management, 33*(3), 672–682. https://doi.org/10.1016/j.tourman.2011.07.010
Poorfakhraei, A. R. G. M. (2015). Estimating welfare change associated with improvements in urban bicycling facilities. *Journal of Transportation Engineering, 141*(11), 4015021–4015025. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000799
Ritchie, B. W. (1998). Bicycle tourism in the south island of New Zealand: Planning and management issues. *Tourism Management, 19*(6), 567–582. https://doi.org/10.1016/S0261-5177(98)00063-6
Ritchie, B. W., & Hall, C. M. (1999). Bicycle tourism and regional development: A New Zealand case study. *Anatolia, 10*(2), 89–112. https://doi.org/10.1080/13032917.1999.9686974
Sener, I. N., Eluru, N., & Bhat, C. R. (2009). An analysis of bicycle route choice preferences in Texas, US. *Transportation, 36*(5), 511–539. https://doi.org/10.1007/s11116-009-9201-4
Shoval, N., McKercher, B., Birenboim, A., & Ng, E. (2015). The application of a sequence alignment method to the creation of typologies of tourist activity in time and space. *Environment and Planning B: Planning and Design, 42*(1), 76–94. https://doi.org/10.1068/b38065
Snelgrove, R., & Wood, L. (2010). Attracting and leveraging visitors at a charity cycling event. *Journal of Sport & Tourism, 15*(4), 269–285. https://doi.org/10.1080/14775085.2010.533918
Speakman, C. (2005). Tourism and transport: Future prospects. *Tourism and Hospitality Planning & Development, 2*(2), 129–135. https://doi.org/10.1080/14790530500173647
Stewart, S. I., & Vogt, C. A. (1997). Multi-destination trip patterns. *Annals of Tourism Research, 24*(2), 458–461. https://doi.org/10.1016/S0160-7383(97)80017-5
Su, M. M., & Wall, G. (2009). The Qinghai–Tibet railway and Tibetan tourism: Travelers' perspectives. *Tourism Management, 30*(5), 650–657. https://doi.org/10.1016/j.tourman.2008.02.024
Thornton, P. R., Shaw, G., & Williams, A. M. (1997). Tourist group holiday decision-making and behaviour: The influence of children. *Tourism Management, 18*(5), 287–297. https://doi.org/10.1016/S0261-5177(97)00017-4
Van der Spek, S., Van Schaick, J., De Bois, P., & De Haan, R. (2009). Sensing human activity: GPS tracking. *Sensors, 9*(4), 3033–3055. https://doi.org/10.3390/s90403033
Wadud, Z. (2014). Cycling in a changed climate. *Journal of Transport Geography, 35*, 12–20. https://doi.org/10.1016/j.jtrangeo.2014.01.001
Weed, M., Bull, C., Brown, M., Dowse, S., Lovell, J., Mansfield, L., et al. (2014). A systematic review and meta-analyses of the Potential local economic impact of tourism and leisure cycling and the development of an evidence-based market segmentation. *Tourism Review International, 18*(1), 37–55. https://doi.org/10.3727/154427214X13990420684482
Winters, M., Teschke, K., Grant, M., Setton, E. M., & Brauer, M. (2010). How far out of the way will we travel? Transportation research record. *Journal of the Transportation Research Board, 2190*(1), 1–10. https://doi.org/10.3141/2190-01
Xiao-Ting, H. B. W. (2012). Intra-attraction tourist spatial-temporal behaviour Patterns. *Tourism Geographies, 14*(4), 625–645. https://doi.org/10.1080/14616688.2012.647322
Xiao, R., & Chen, S. (2020). Influence of tourism activities on environmental culture of tourist destination: A case study of Lhasa, Tibet. *Tourism Overview, 2020*(2), 181–182 (in Chinese).
Xing, Y., Wang, K., & Lu, J. J. (2020). Exploring travel patterns and trip purposes of dockless bike-sharing by analyzing massive bike-sharing data in Shanghai, China. *Journal of Transport Geography, 87*, 102787. https://doi.org/10.1016/j.jtrangeo.2020.102787

Yang, L., Wu, L., Liu, Y., & Kang, C. (2017). Quantifying tourist behavior Patterns by travel motifs and geo-tagged Photos from flickr. *ISPRS International Journal of Geo-Information, 6*(11), 345. https://doi.org/10.3390/ijgi6110345

Zheng, W., Huang, X., & Li, Y. (2017). Understanding the tourist mobility using GPS: Where is the next place? *Tourism Management, 59*, 267–280. https://doi.org/10.1016/j.tourman.2016.08.009

Zheng, Y., Mou, N., Zhang, L., Makkonen, T., & Yang, T. (2021). Chinese tourists in Nordic countries: An analysis of spatio-temporal behavior using geo-located travel blog data. *Computers, Environment and Urban Systems, 85*, 101561. https://doi.org/10.1016/j.compenvurbsys.2020.101561

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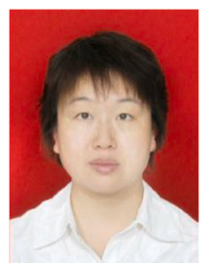

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