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Evolution characteristics of the spatial network structure of tourism efficiency in China: A province-level analysis

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ABSTRACT

The optimization of spatial network connections for tourism efficiency is a prerequisite for the high-quality development of the tourism economy. There is limited understanding, however, of the evolution characteristics of the spatial network structure of tourism efficiency in the extant literature. In this study, super data envelopment analysis (DEA) and social network analysis (SNA) were employed to explore the evolution characteristics of the spatial network structure of tourism efficiency in China at the provincial level from the years 2011– to 2016. The results show that overall tourism efficiency in China exhibited a slight decline. The order of the spatial distribution features by region was eastern, central, northeastern and western. This study demonstrates that the network density of tourism efficiency decreased during the sample period . Additionally, the results indicate that there was a rigid network hierarchy structure, and the core-periphery structure of the tourism efficiency network exhibited clusters.

1. Introduction

In numerous developing countries, the tourism industry plays an indispensable role in the process of socioeconomic development and economic recovery (Dogru & Bulut, 2018). In China, tourism is regarded as one of the most significant industries for the development of regional economies, the promotion of supply-side structural reform (SSR), and the improvement of residents' livelihoods (Li, Liu, & Song, 2019b). Statistics from the Ministry of Culture and Tourism of China (MCTC) showed that, in 2017, the tourism industry made an overall contribution of RMB 8.77×10^4 billion (US$$1.30 \times 10^4$ billion). The tourism industry has thus represented a vital contributor to all-around regional development. With the rapid growth of the tourism economy in China, however, regional tourism resources have become over-exploited and the regional ecological environment has deteriorated. The unbalanced development among provinces has hindered the sustainable development of the tourism industry (Xu, Wang, Li, Tang, & Shao, 2019). The Chinese government has therefore emphasized that tourism development should take both efficiency and quality into consideration. The United Nations' Sustainable Development Goals (SDGs) stress the efficient allocation of resources and the achievement of balance between input and output.

Improvement of the efficiency of resource allocation to achieve the SDGs has received increased attention in academic circles (UNDP, 2016; Zhang, Tu, Zhou, & Yu, 2020). Song and Li (2019) demonstrated that sustainable development is relevant to the tourism industry. Tourism efficiency is defined as "the ability of tourist destinations to exploit the capacity of their hotels, travel agencies and scenic spots (areas) to maximize the demand for tourists" (Niavis & Tsiotas, 2019, p. 3). The optimization of tourism efficiency would promote the efficient allocation of tourism resources and accelerate tourism sustainable development. Consequently, there has been a growing interest in tourism efficiency (Song & Li, 2019).

Tourism efficiency represents a reflection of the investment of tourism resources and its allocation and utilization (Zhou, Xu, & Lee, 2019). Furthermore, tourism efficiency could help appropriately channel the tourism industry's intensive use of capital according to the input and output of tourism resources (Niavis & Tsiotas, 2019). Tourism efficiency research may be classified into two groups. The first is the efficiency of the tourism sector. The hotel industry is one of the largest sectors in the tourism industry. Researchers have performed studies to assess the efficiency of hotel operations (Baker & Riley, 1994; Morey &

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Dittman, 1995; Tarim, Dener, & Tarim, 2000) and to explore the factors that contribute to the improvement of hotels' operations (Huang, Ho, & Chiu, 2014; Oliveira, Pedro, & Marques, 2013). Data envelopment analysis (DEA) and stochastic frontier analysis (SFA), based on production frontier analysis, generally have been applied to evaluate the efficiency of hotels (Mendieta-Peñalver, Perles-Ribes, Ramón-Rodríguez, & Such-Devesa, 2016). The research paradigms of operational efficiency of the hotel industry have increasingly been used to inform an evaluation of other tourism sectors' efficiency, including travel agencies (Fuentes, 2011; Assaf, 2012; Sellers-Rubio & Nicolau-Gonzálbez, 2009; Topolšek, Mrnjavac, & Kovačić, 2014), scenic spots (Cao, Huang, Cheng, & Xu, 2015; Cao, Huang, Jin, & Xu, 2016; Kytzia, Walz, & Wegmann, 2011), and tourism transportation departments (Colladon, Guardabascio, & Innarella, 2019; Ferández, Coto-Millán, & Díaz-Medina, 2018).

A second body of literature related to tourism efficiency has focused on tourist destinations. With the availability of statistical data and improved research methods, scholars have examined the tourism efficiency of destinations at different levels, such as the countries (Blake et al., 2006; Corne, 2015; Qiu, Fang, Yang, & Zhu, 2017; Zha, Yuan, Dai, Tan, & He, 2020), urban agglomerations (Liu, Zhang, & Fu, 2017a,b; Zhou et al., 2019), and provinces (Zha, He, Liu, & Shao, 2019). The improvement of research methodologies has permitted the introduction of numerous new models that have served to enhance the accuracy of the measurements. Typical examples include bootstrap DEA and two-stage double bootstrap DEA (Chaabouni, 2019; Song & Li, 2019). Researchers have also compared the differences in the tourism development efficiency of various tourist destinations (Chaabouni, 2019; Niavis & Tsiotas, 2019; Song & Li, 2019). A few studies have explored the spatial-temporal characteristics of tourism efficiency through exploratory spatial data analysis (ESDA). For instance, Li and Wang (2020) adopted the spatial autocorrelation model and demonstrated that the overall spatial correlation of tourism efficiency in the Wuling Mountain Area of China was weak. Nevertheless, scholars have failed to devote adequate attention to the spatial network structure of tourism efficiency and the role of different tourist destinations in the spatial network structure. This gap in the research has made it difficult to identify and implement targeted measures to improve the tourism efficiency of different tourist destinations.

As a means by which to address this gap in the literature, this study employed super data envelopment analysis (super-DEA) and social network analysis (SNA) to analyze the evolution characteristics of the spatial network structure of tourism efficiency at the provincial level in China. The study included 30 provinces in China (excluding the Tibet Autonomous Region, Hong Kong, Macao, and Taiwan) as case studies, of which their tourism efficiency was assessed through super-DEA. Compared with other methods, SNA has the advantage of systematically permitting an exploration of the spatial relationship and structure (De Paulo & Porto, 2017). Therefore, SNA was employed to examine the characteristics of the spatial network structure of tourism efficiency. This study makes three contributions to the literature. First, the research advances a novel and critical perspective on the spatial network structure of tourism efficiency based on the use of relational data. Second, this study provides a key model to identify the spatial connection of tourism efficiency. Although the empirical research is based on a sample of 30 provinces in China, the methodology is general, and may be applied to other regions worldwide. Third, this research explores the evolution characteristics of the spatial network structure of tourism efficiency, which complements the existing literature on tourism efficiency. Finally, this study also responds to the call for more quantitative research on tourist destination networks.

The remainder of the article is structured as follows. Section 2 presents the research methodology, including the methods and data sources. Section 3 reports and discusses the empirical results. Finally, section 4 is devoted to conclusions, including the implications of the research and recommendations.

2. Methods

2.1. Assessment of tourism efficiency

2.1.1. Super-DEA

Because the efficiency of all decision-making units (DMUs) in original DEA models reaches the frontier production surface, a horizontal comparison of the efficiency of different DMUs cannot be achieved. This study therefore used a super-DEA model to evaluate the tourism efficiency of 30 provinces in China from 2010 to 2016. Taking into account the uncontrollability of tourism output and the controllability of tourism input, super-DEA-Constant Returns of Scale (CRS) was applied to evaluate and rank tourism efficiency. The details of calculation may be found in Wei, Hu, Zhu, and Yu (2018). The formulae are as follows.

$$\begin{cases} \min\theta \\ \sum_{j=1}^{n} \lambda_j Y_j \geq X_j \theta X_j, j = 1, 2, 3.....,n \\ \sum_{j=1}^{n} \lambda_j Y_j \geq Y_j, j = 1, 2, 3.....,n \\ \lambda_j \geq 0, j = 1, 2, 3.....,n \end{cases} \tag{1}$$

Slack variables $S^-$and $S^+$are introduced into the above equation. Then, we have:

$$s.t \begin{cases} \min\theta \\ \sum_{j=1}^{n} \lambda jXj + S^- = \theta Xi, i = 1, 2, 3......,n \\ \sum_{j=1}^{n} \lambda jYj - S^+ = Yi, i = 1, 2, 3......,n \\ \lambda j \geq 0, j = 1, 2, 3......,n \\ S^+ \geq 0 \\ S^- \geq 0 \end{cases} \tag{2}$$

where (equation (1) and equation (2)) θ is the tourism efficiency; X_j and X_i denote the j type input and the input of the i region, respectively; Y_j and Y_i indicate the j type output and the output of the i region, respectively; S^-represents an input surplus, that is, an unused resource; S^+ means that there is a resource deficit; and λ_j is the weight variable of DMU. When a DMU falls on the optimal production front, the value of efficiency is 1, which is considered effective. Otherwise, it is deemed to be invalid. Its relative efficiency value is calculated by its distance from the optimal leading edge ($1 > \theta > 0$, where θ is not restrained in the above two equations). As θ gets larger, tourism efficiency of the province increases. Otherwise, the tourism efficiency of the province decreases.

2.1.2. The construction of input and output indexes

The evaluation of efficiency is based on the two index systems of input and output in economic productivity. "Land, labor, and capital are commonly defined in the Cobb-Douglas production function as the most basic inputs to economic production activities" (Munguía, Davalos, & Urzua, 2019, p. 4). The lack of statistical data on the utilization of land devoted to tourism has resulted in very few studies that included land elements in the input index system (Song & Li, 2019). Land elements were therefore not included in the input index system in this study. Labor and capital were treated as the input indices. Travel agencies, star-rated hotels, and scenic spots (areas) represent the key components (departments) of tourism economic development (Niavis & Tsiotas, 2019). The statistical data available proved rich and the number of these departments adequately reflected the service and resource elements central to tourism economic development (Li et al., 2014). The number of travel agencies, star-rated hotels, and A-class tourist scenic spots (areas) were therefore defined as capital investment. We defined capital input in line with Song and Li (2019). The index of labor input was represented primarily by the number of tourism industry's employees (Wei et al., 2018). In summary, the initial input indexes in this study consists of the number of tourism industry's employees, the number of travel agencies, the number of star-rated hotels, and the number of A-class scenic spots (areas). The output of the tourism industry is mainly reflected by tourist arrival and tourist receipt (Chaabouni, 2019).

2.2. The spatial network structure of tourism efficiency

2.2.1. Establishing the spatial correlation network of tourism efficiency

Based on graph theory, the aggregation of regional tourism efficiency correlation would form the spatial network structure. Each province serves as a node of the network, and the spatial correlation of tourism efficiency between provinces is a line in the spatial network structure of tourism efficiency (Zhang & Li, 2019). The modified gravity model effectively transforms attribute data into relational data. The present research adopted the modified gravity model to construct the spatial correlation network between the tourism efficiency of various provinces in China, consistent with Chen, Wu, Huang, and Yang (2020). The formula is as follows:

$$Fij = Kij\frac{E_i \cdot E^j}{D_{ij}^{\ 2}}, Kij = \frac{Ei}{Ei + Ej}, Dij^2 = \left(\frac{dij}{gi - gj}\right)^2 \tag{3}$$

In this formula, F_{ij} represents the strength of the tourism efficiency connection between province i and province j. K_{ij} refers to the gravity coefficient, and E_i and E_j represent the tourism efficiency of province i and province j, respectively. d_{ij} is the spherical distance between province i and province j. g_i and g_j denote the GDP of province i and province j, respectively. The spatial correlation matrix of tourism efficiency ($\boldsymbol{F_{ij}}$) in China was calculated by the modified gravity model.

Thomas and Blitzstein (2011) argued that dichotomization could stem from the exclusive use of binary methods, ease of input and data collection, ease of output in graphical representations, and sparsity of structure, but the appropriate threshold must be selected. As emphasized by Baggio (2019, p. 58), "researchers must verify carefully the possible variations that could arise in the measurement of network structure". Hence, the mean value of each line in the matrix ($\boldsymbol{F_{ij}}$) is used as the threshold value, as it is widely used in the dichotomization process (Li, Feng, Li, & Zhang, 2019a; Zhang & Li, 2019). The value is equal to 1 when the spatial correlation intensity F_{ij} is greater than the threshold, indicating that the row has a spatial correlation with the tourism efficiency of the province in the column. Otherwise, the value is equal to 0, which demonstrates that the row has no spatial correlation with the tourism efficiency of the province in the column.

2.2.2. Social network analysis

SNA is a sociological method for the analysis of the network structure among social actors. The use of SNA permits complicated systems comprised of individuals to be represented as networks. At present, the use of SNA is confined not only to the exploration of social linkages between social actors but has also been widely used in spatial structure in regions (Therrien, Jutras, & Usher, 2019). Furthermore, the SNA model has been widely adopted in economics, management, sociology, geography, and other disciplines (Liu et al., 2017a,b; Ma & Xue, 2019; Scott, 2000). By using SNA, the characteristics of spatial network structures may be analyzed and examined.

(1) **Overall network characteristic indexes.** This study focuses on network density, connectedness, hierarchy, and efficiency to analyze the characteristics of the overall network structure.

Network density describes the closeness of the degree of closeness between provinces in the network structure of tourism efficiency. It is defined as the ratio of actual connections to all possible connections. The calculation formula is as follows:

$$D = \frac{L}{N \times (N-1)} \tag{4}$$

where D is the network density, L is the number of actual connections, $N \times (N-1)$is the number of possible connections, and N is the number of points in a network structure.

$$C = 1 - \left[\frac{V}{N(N-1)/2}\right] \tag{5}$$

where C is the network connectedness, V is the number of mutually unreachable point pairs, and N is the number of points.

Network hierarchy describes the extent of asymmetric accessibility among provinces in the network; it is calculated by the following formula:

$$H = 1 - \frac{K}{\max(K)} \tag{6}$$

where H is the network hierarchy, K represents symmetrically reachable points, and *max* (K) is the maximum possible point logarithm.

Network efficiency refers to the connection efficiency between provinces in the correlation network. When network efficiency is low, there are more connections between provinces, the tourism efficiency of bordering provinces is closer, and the spatial correlation network is more stable. The calculation formula is as follows:

$$E = 1 - \frac{M}{\max(M)} \tag{7}$$

where E is the network efficiency, M is the number of redundant lines, and *max* (M) is the maximum number of possible redundant lines.

(2) **Individual network characteristics index.** Three centrality indexes, including point centrality, closeness centrality, and betweenness centrality, are chosen to measure the role of each province in the spatial network structure.

Point centrality represents the ability to communicate with other provinces by measuring the number of nodes connected with a node in another province. As the point centrality increases, the centrality in the association network becomes more intensive. The formula is as follows:

$$De = \frac{n}{N-1} \tag{8}$$

where De is the measure of point centrality, n is the number of nodes connected with the province, and N is the maximum number of nodes connected with the province.

Closeness centrality indicates the degree of independence in the overall spatial network. As closeness centrality increases, the tourism efficiency of the province becomes more correlated with that of other provinces. The calculation formula is as follows:

$$C_{APi}^{-1} = \sum_{i=1}^{n} d_{ij} \tag{9}$$

whereC_{APi}^{-1}represents closeness centrality, and d_{ij} represents the shortest distance between province i and province j.

Betweenness centrality is used to measure the degree to which the network connection of two non-adjacent provinces depends on each other. It reflects the degree to which one province controls the connection with the other provinces. The higher the betweenness centrality, the stronger its control on the connections between other provinces, and the more it is at the center of the association network. The calculation formula is as follows:

$$Cbi = \frac{2\sum_{i}^{n}\sum_{j}^{n} bij(l)}{N^2 - 3N + 2}, i \neq j \neq l, i < j \tag{10}$$

where Cb_i refers to betweenness centrality, b_{ij} is the number of the shortcuts between province i to province j, and $b_{ij}(l)$ is the number of shortcuts between province j and province k.

(3) **Core-periphery structure.** The core-periphery analysis is applied to reflect the position of provinces in the network structure. The model helps to determine whether the province is located in the core or the periphery as well as the connection between the core area and the periphery area. In this study, the core-periphery model is employed to demonstrate the evolutionary characteristics of the core area and periphery area in China.

2.3. Data sources

The data used in this paper span from 2011 to 2016. The data on A-class scenic spots (areas), star-rated hotels, travel agencies, tourism industry employees, tourist arrivals, and tourist receipt were obtained from the China Tourism Statistical Yearbooks for the years 2012 to 2017, the Provincial Statistical Yearbook for the years 2012–2017, and the Statistical Bulletin on National Economy and Social Development (SBNESD) for various provinces from 2011 to 2016. The missing data were pre-processed by using the linear interpolation method. To ensure that the tourism efficiency of various provinces was comparable from 2011 to 2016, the price index was used to deflate GDP, tourism revenue, and other data according to procedures established in previous studies (Song & Li, 2019). The spherical distance of each province interval was calculated using ArcGIS10.2 software.

3. Results and discussion

3.1. Spatial differences and evolution of province-level tourism efficiency in China

The overall change of tourism efficiency during the sample period fluctuated little (Fig. 1): the average value remained between 0.6 and 0.8. At the end of the study period, there was a slight decline. The spatial distribution pattern demonstrated the greatest concentration in the eastern region, followed in order by the central, northeastern and western regions. The eastern region and central region exhibited a trend of steady development. They both yielded a stable average tourism efficiency value of 0.8, higher than the national average level. From 2011 to 2013, the tourism efficiency in the northeast region was higher than the national average level, but then declined rapidly in the years that followed. The tourism efficiency decreased from 1.152 in 2013 to 0.678 in 2014 and continued to decline. These changes could be due to the economic downturn in the northeast region in 2014. The tourism efficiency value of the western region improved significantly from 0.641 in 2014 to 0.810 in 2015, reflecting the gradual spillover effect of the Western Development Strategy (Deng, Hu, & Ma, 2019). The allocation efficiency of the tourism production factors rose, the tourism infrastructure gradually improved, and the level of tourism was continuously enhanced. These initiatives paved a road for the improvement of tourism efficiency in the western region.

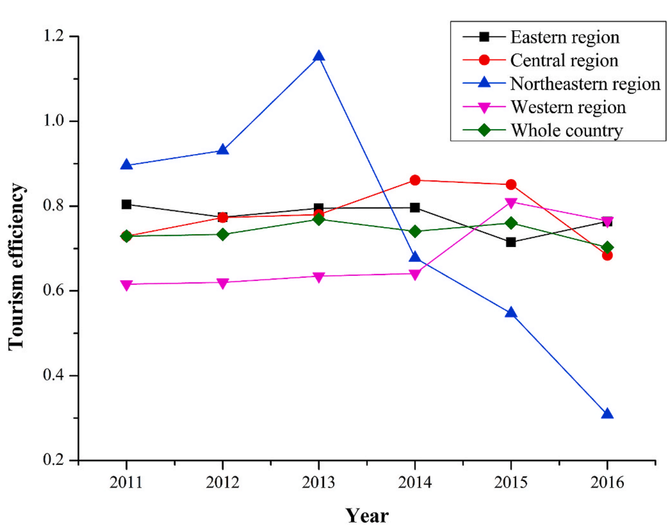

Fig. 1. The average tourism efficiency in the eastern, central, northeastern, and western regions in China from 2011 to 2016.

3.2. Spatial correlation network analysis of province-level tourism efficiency in China

ArcGIS10.2 software was used to draw the spatial correlation network graph of province-level tourism efficiency in China during the sample period. Fig. 2 illustrates the multi-threaded, dense, and complex character of the spatial network structure of tourism efficiency. To further demonstrate the spatial association network of tourism efficiency, the study included a detailed analysis of the overall network characteristics, the individual network characteristics, and the core-periphery structure.

3.2.1. The overall network characteristics

During the sample period, the evolution of network density and the network relationship of province-level tourism efficiency in China reflected variability. The network density value remained between 0.15 and 0.19 (Fig. 3), much lower than the media (0.5). The number of network relationships was far from the maximum (870), reaching their peak in 2015. The network density value was 0.189, and the number of relationships was 161. In 2016, both the network density and the number of network relationships decreased slightly, which could be attributed to the policy of national tourism reform and development. To further promote the transformation and improvement of tourism, several opinions of the State Council on Promoting the Reform and Development of Tourism emphasized that tourism development should focus on the improvement of both quality and efficiency (Li et al., 2019b). Therefore, the tourism industry should pay greater attention to both speed and quality. Moreover, each province should attend to the reorganization of internal tourism cooperation while adjusting tourism industry structure.

The study examined network connectedness, network hierarchy, and network efficiency to measure the overall network correlation characteristics of province-level tourism efficiency in China. Fig. 4 reveals that for the years from 2011 to 2016, the network connectedness of the province-level tourism efficiency network was 1, indicating that the overall network structure had strong connectivity, accessibility, and robustness. There were direct and indirect connections, as well as significant spatial correlation and spillover effects among different provinces. The network hierarchy held at the middle and upper levels. Increased variations among provinces suggested that a hierarchical spatial network structure prevailed, with high tourism efficiency in some provinces and low tourism efficiency in others. The overall level of network efficiency was high. Although it decreased in 2015, the network efficiency in the other years remained above 0.7, which indicates that redundant relationships resulted in the instability of the network structure of tourism efficiency. The government should promote the normalization of cross-regional tourism cooperation and enhance two-way spillover of inter-provincial tourism development to achieve the coordinated development of tourism quality and efficiency.

3.2.2. Individual network characteristics

By using three centrality indexes, namely point centrality, closeness centrality, and betweenness centrality, this study provided an analysis of the individual network characteristics of province-level tourism efficiency in China. Out-degree centrality manifested as the spillover effect

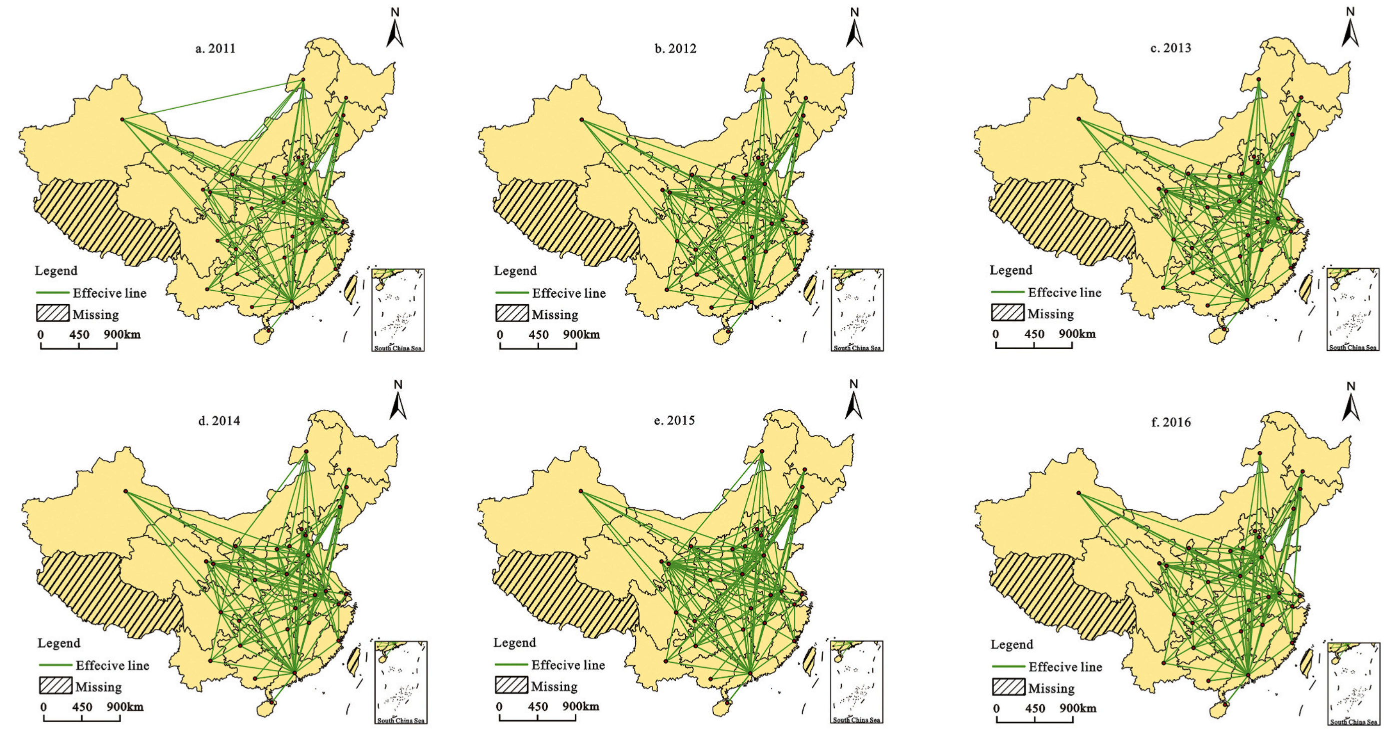

Fig. 2. Spatial correlation network of province-level tourism efficiency in China from 2011 to 2016.

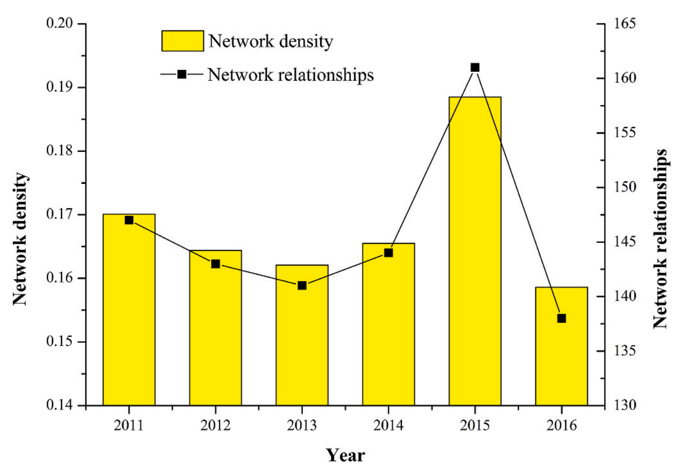

Fig. 3. The network density and relationships of province-level tourism efficiency in China from 2011 to 2016.

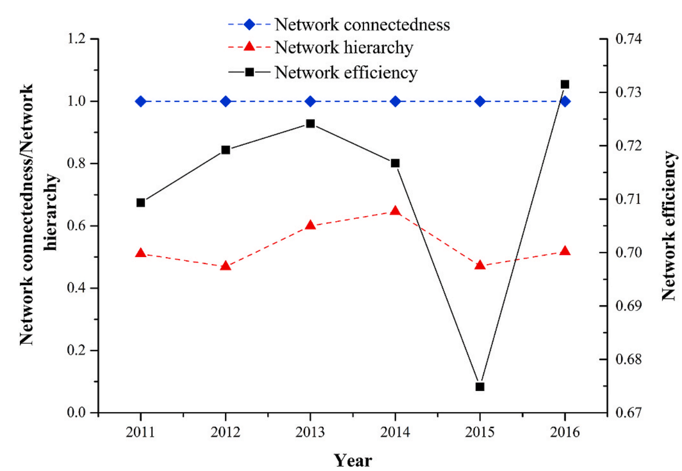

Fig. 4. Network connectedness, network hierarchy, and network efficiency of province-level tourism efficiency in China from 2011 to 2016.

of tourism efficiency, whereas the in-degree centrality reflected the concentration effect of tourism efficiency. In order to identify the evolution characteristics of the individual network of province-level tourism efficiency in China, this study selected the years 2011 and 2016 as two points in time and analyzed their corresponding centrality characteristics (Table 1).

(1) **Point degree.** The overall change of the point centrality of province-level tourism efficiency was slow, and the development of inter-regional tourism efficiency was not equal among provinces (Table 1). The point centrality of Jiangsu, Shandong, and Guangdong provinces proved far greater than the others. Moreover, these three provinces demonstrated great influence and were absolutely central in the spatial network structure of tourism efficiency. The in-degree centrality of the three provinces was greater than 20, the out-degree centrality was relatively low, and the agglomeration effect was far greater than the radiation effect. The Guangxi Zhuang Autonomous Region and Hainan Province exhibited the lowest point centrality. Both in-degree centrality and out-degree centrality were relatively low. Moreover, their radiation and concentration effects were weak. The provinces of Guangdong, Jiangsu, and Shandong exhibited the highest in-degree centrality. These provinces were rich in tourism resources and had a high level of tourism economic development. Moreover, greater levels of income from tourism promoted regional polarization effects. Consequently, these provinces represented the agglomeration center of tourism efficiency.

The out-degree centrality for all the provinces in China was greater than 0, indicating that the tourism efficiency of each province had a spatial radiation effect. Furthermore, the regional differences between provinces with high or low out-degree centrality were large; the spatial

Table 1
Centralities of the spatial association network of China's provincial tourism efficiency from 2011 to 2016.

Province	2011					2016				
	Out-degree centrality	In-degree centrality	Point centrality	Closeness centrality	Betweenness centrality	Out-degree centrality	In-degree centrality	Point centrality	Closeness centrality	Betweenness centrality
Beijing	4	3	13.79	52.72	0.18	4	2	13.79	52.72	0.06
Tianjin	6	6	24.13	56.86	0.73	4	4	20.69	55.76	0.37
Hebei	6	5	20.69	52.72	0.47	5	3	20.69	55.76	0.20
Shanxi	5	3	17.24	54.71	0.29	5	5	24.13	56.86	0.56
Inner Mongolia	5	7	31.03	59.18	0.90	4	0	13.79	53.70	0.06
Liaoning	6	2	20.69	55.76	0.24	3	0	10.34	52.72	0.06
Jilin	4	1	13.79	53.70	0.07	5	0	17.24	54.71	0.29
Heilongjiang	5	1	17.24	54.71	0.12	5	0	17.24	54.71	0.29
Shanghai	4	6	20.69	55.76	0.43	4	3	13.79	53.70	0.21
Jiangsu	4	23	79.31	80.55	19.76	3	24	82.75	82.85	21.46
Zhejiang	4	4	20.69	52.72	0.54	4	7	27.58	54.71	1.25
Anhui	3	3	17.24	54.71	0.38	3	2	13.79	53.70	0.21
Fujian	4	0	13.79	53.70	0.28	4	0	13.79	53.70	0.21
Jiangxi	5	5	20.69	55.76	0.60	4	3	20.69	55.76	0.54
Shandong	6	22	75.86	76.31	15.57	6	22	75.86	76.31	15.92
Henan	10	12	58.62	70.73	5.80	7	9	48.27	65.90	3.54
Hubei	5	1	17.24	54.71	0.13	6	0	20.69	55.76	0.43
Hunan	5	1	17.24	54.71	0.43	5	1	17.24	54.71	0.28
Guangdong	5	25	86.20	87.87	29.40	4	26	89.65	90.62	30.64
Guangxi	2	1	6.89	50.87	0.02	2	1	6.89	50.87	0.02
Hainan	1	0	3.44	47.54	0	1	1	3.44	48.33	0
Chongqing	4	8	31.03	58.00	1.49	5	2	20.69	55.76	0.28
Sichuan	5	2	17.24	54.71	0.19	7	8	34.48	60.41	1.48
Guizhou	2	5	17.24	52.72	0.27	2	6	20.69	54.71	0.52
Yunnan	6	0	20.69	55.76	0.41	4	1	13.79	53.70	0.10
Shaanxi	5	1	17.24	54.71	0.19	5	6	27.58	58.00	0.21
Gansu	7	0	24.13	56.86	0.43	6	2	24.13	56.86	0.13
Qinghai	6	1	20.69	55.76	0.25	8	0	27.58	58.00	0.28
Ningxia	6	0	20.69	55.76	0.25	7	0	24.13	56.86	0.31
Xinjiang	8	0	27.58	58.00	1.13	6	0	20.69	55.76	0.49
Mean	4.93	4.93	26.43	57.95	2.70	4.60	4.60	26.20	58.13	2.68

radiation effect of the tourism efficiency for each province crossed the traditional administrative boundary restrictions and showed extensive spatial correlation. In 2011 and 2016, the in-degree centrality of the Ningxia Hui Autonomous Region and the Xinjiang Uygur Autonomous Region was 0, showing that both provinces had only one-way spatial connection with the other provinces to improve the quality and efficiency of the tourism industry. The radiation effect from other provinces had not resulted in a sufficient agglomeration effect.

(2) **Closeness centrality.** The distribution of closeness centrality was relatively balanced, with narrow regional differences. The closeness centrality of numerous provinces ranged from 50 to 70, indicating that the tourism efficiency of each province in the overall spatial network could more quickly generate intrinsic connections with other provinces. The overall spatial network demonstrated a strong correlation, high flow efficiency, and relatively smooth spatial agglomeration as well as spatial radiation of tourism efficiency. The province with the highest closeness centrality in 2011 and 2016 was Guangdong Province, which held a prominent core position in the overall network. Diversified tourist routes deepened the breadth and depth of tourism efficiency radiation. These findings demonstrated that Guangdong Province enjoyed abundant tourism resources, attractive tourism-linked economic benefits, more interactions between other provinces, and high-levels of economic development from tourism. The superior geographical advantages made it a central actor for inter-regional exchanges and cooperation. In contrast, Hainan Province showed the lowest level of closeness centrality. The province's marginal geographical location contributed to its position at the tail end of the tourism efficiency spatial network.

(3) **Betweenness centrality.** The distribution of betweenness centrality appeared to be consistent with those of point centrality and closeness centrality. However, quite a few provinces had a high level of betweenness centrality. The difference between most provinces was large, and the polarization was significant. The provinces of Guangdong, Jiangsu, and Shandong had the highest level of betweenness centrality, with a total value of 68.038 in 2016. They accounted for 84.476% of the national tourism efficiency and betweenness centrality. The indicator demonstrated that the three provinces played the role both as bridges and intermediaries, because they could control the flow of tourism economic factors. The betweenness centrality of Hainan Province was consistently 0, indicating that it had weak inter-connectivity with other provinces and could improve spatial correlation.

3.2.3. *Analysis of the core-periphery structure*

In this study, UCINET (University of California at Irvine Network) 6.0 software was used to elaborate a core-periphery structure chart of province-level tourism efficiency in China in 2011 and 2016 (Fig. 5). Several interesting results can be summarized. First, the core-periphery structure of the province-level tourism efficiency network in China gradually evolved during the sample period and the core areas were basically clustered. In 2011, the core areas were mainly located in the Inner Mongolia Autonomous Region (IMAR), Tianjin City, Hebei Province, and Shanxi Province. In 2016, some core areas shifted. The IMAR ceased to form a core area, thus weakening its agglomeration function. Additionally, the provinces of Sichuan, Shaanxi, and Gansu became core areas. Second, there also were changes in the number of core provinces. There were nine core provinces in 2011 and ten core provinces in 2016. The six provinces that consistently comprised part of the core were Tianjin City and the provinces of Hebei, Shanxi, Jiangsu, Henan, and Guangdong. The overall core-periphery structure gradually developed in a group-like manner with enhanced spatial connections. Third, the

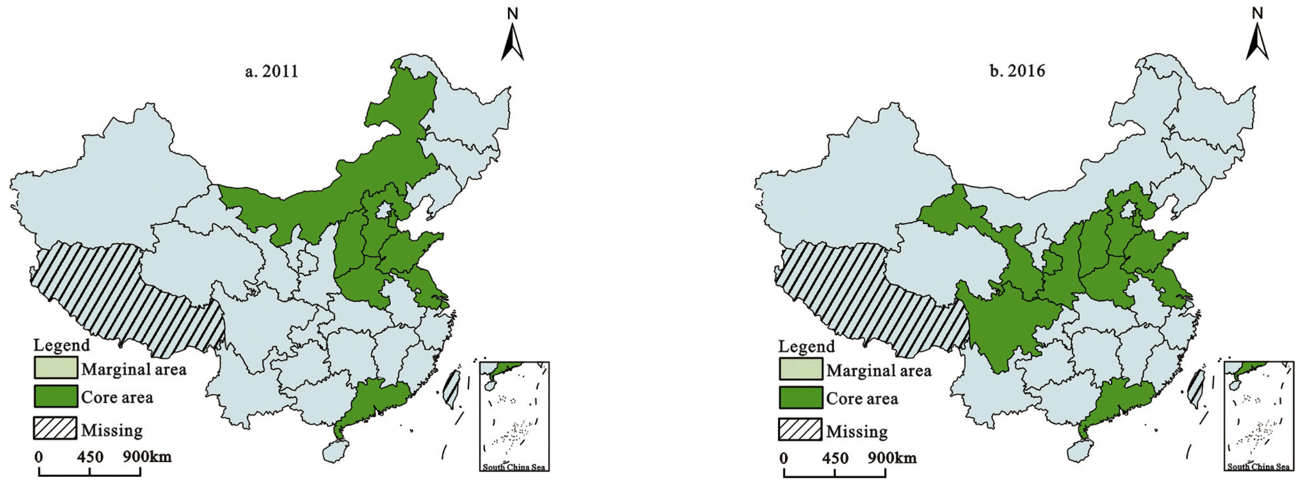

Fig. 5. Core-periphery structure of province-level tourism efficiency in China.

network density converges inside the core area, periphery area, core area to periphery area, and periphery area to core area. Table 2 illustrates that the internal network density in the core area decreased slightly, from 0.514 in 2011 to 0.422 in 2016. The internal network in the core area was relatively closely connected, but the overall network structure was not stable. Tourism industrial improvements and transformations resulted in these changes. The network density of the core area to the periphery area decreased from 0.381 in 2011 to 0.355 in 2016. The network density between the periphery area and core area was relatively low and decreased from 0.074 in 2011 to 0.070 in 2016. These values attest to the hierarchical character of the structure.

4. Conclusions and implications

4.1. Conclusions

Despite its importance, the spatial network structure of tourism efficiency has not received adequate attention in tourism research. This study has significant theoretical and practical implications for approaches to tourist destination networks. The study's theoretical contribution centered on the use of SNA to examine the evolution characteristics of spatial network structure of tourism efficiency. The research therefore served to overcome an omission created through an overdependence on the application of attribute data. The focus on the role of various regions in the spatial network structure of tourism efficiency provided insights into practical policy solutions that would prove useful to decisionmakers who strive to establish coordination mechanisms among the members in tourist destinations. In this regard, several conclusions may be drawn from this research.

(1) During the sample period, tourism efficiency was generally stable nationwide, except for a slight decline at the end of the sample period. Spatially, the distribution pattern was approximately: eastern region > central region > northeastern region > western region. The tourism efficiency values in the eastern region and central region are higher than the national average value, and the tourism efficiency values in the western region and northeast region have opposite evolutionary trends. The western region lags in the early stage and exhibits a catch-up trend in the later stage.

(2) The spatial network structure of tourism efficiency in different provinces is multithreaded, dense, and complicated in China. The overall fluctuations of network density and network correlation degree decrease, which indicated that the spatial network structure of tourism efficiency became loosely linked during the sample period; a cooperation mechanism for tourism development in various provinces should be established as soon as possible. The network connectedness value is always 1, and the spatial correlations and spillover effects between provinces are significant. The network hierarchy is above the average value. It increases at a small scale and is volatile. The network efficiency is high and above the average value, but the spatial network is still unstable.

(3) The overall change of point centrality was slow, and the development of inter-regional tourism efficiency is not balanced. The distribution of the closeness centrality is relatively balanced, and the difference between different provinces is small. The distribution of betweenness centrality is balanced, which is in line with the trends of point centrality and closeness centrality. Province-level tourism efficiency in China shows apparent core-periphery structure characteristics. The overall core-periphery structure development tends to be group-centered, and the spatial connection is strengthened.

Table 2
Core–periphery structure density matrix of province-level tourism efficiency in China.

Network density	2011		2016	
	Core area	Periphery area	Core area	Periphery area
Core area	0.514	0.074	0.422	0.070
Periphery area	0.381	0.060	0.355	0.039

4.2. Recommendations

The research was designed to identify possible areas for improvement, with specific implications for tourist destinations management and organization. First, a crucial aim for high-quality tourism-linked economic growth would be to alleviate the imbalanced tourism efficiency among the different regions of China. Therefore, the establishment of coordination and cooperation mechanisms is of great significance for both the satisfaction of tourism demand and to assure sustainable development in tourist destinations. Second, the spatial network structure of tourism efficiency proved both complex and dynamic. Furthermore, various provinces have played the different roles of core and periphery in the network structure. For example, Guangdong, Jiangsu, and Shandong Provinces played the role of both bridges and intermediaries in the exchange and communication of tourism economic factors such as capital, talents, information, and technology. Therefore, these provinces could strengthen cooperation with regard to tourism economic development and improve accessibility of tourist flows. However, marginal areas, such as the Xinjiang Uygur Autonomous Region, Qinghai Province, and Heilongjiang Province, should actively emulate other provinces' best practices of tourism management and strive to match the achievements of the well-connected provinces. Third, the findings from this research showed that the distance and position of a province impacted the stability of the network structure of tourism efficiency. Improvement and promotion of transportation and information infrastructure proves crucial as a means to strengthen the connections in the spatial network structure of tourism efficiency.

The continuous rise in the density of China's transportation network and the consistent innovation of transportation technology has resulted in the declining impact of spatial distance between different administrative regions on the structure of the tourism efficiency spatial network. Future research could include a "time distance" variable as a means by which to modify the gravity model and achieve greater accuracy in the corresponding calculations. The spatial network structure of tourism efficiency gradually changed through regional interactions. It would be beneficial to analyze the key factors that affect the spatial network structure of tourism efficiency. Such a focus would demand government attention to the planning of tourism development and adoption of a scientific decision-making process.

Author statement

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; and I have drafted the work or revised it critically for important intellectual content; and I have approved the final version to be published; and I agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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