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How to Decouple Tourism Growth from Carbon Emissions? A Spatial Correlation Network Analysis in China

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Abstract: This research aims to analyze the spatial correlation network of the decoupling between tourism growth and carbon emissions in China's 31 provinces to promote the overall decoupling through regional cooperation. This study scientifically measures the decoupling index from 2009 to 2019 based on a "bottom-up" method and the Tapio decoupling model. It analyzes the spatial correlation network of the decoupling and its driving factors by using social network analysis. The conclusions show that the decoupling between China's tourism economic growth and carbon emissions was dominated by an expansive connection, which indicates a nonideal decoupling state. Among the regions, decoupling was stronger in the eastern provinces and weaker in the middle and western districts. The spatial correlation outside the plates was more significant, while the internal correlation was weaker. Beijing and Shanghai were in the center of the network, and the eastern developed provinces were in the subcentral place, both of which had more muscular control over the network. In contrast, the middle and western regions were on edge positions, playing passive roles in the network. In addition, the economic development level was the most vital driving force behind the spatial correlation, followed by spatial adjacency and government policy. In contrast, the industrial structure and technological level were negative influencing factors. These research findings indicate potential interprovincial cooperation in terms of tourism decarbonization, which provide a profound reference for the whole sustainable development of China's tourism industry.

Keywords: tourism economic growth; carbon emission; decoupling theory; spatial correlation network; influencing factor; social network analysis

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1. Introduction

The global tourism economy experienced continuous growth from 2009 to 2019, and international tourist arrivals and revenue increased by 4% and 3% in 2019, respectively [1]. While actively promoting economic growth, tourism contributes to 8% of global greenhouse gas emissions. China's tourism industry ranks second in carbon emissions among all countries, after the United States [2]. Against this background, the Chinese government has attached great importance to the environmental problems brought about by tourism and has successively issued policies to emphasize the necessity and urgency of green development in tourism.

Given the contribution of tourism to global warming, academics have devoted significant efforts to scientifically examining the relationship between tourism's economic growth (TEG) and carbon emissions (CEs) including quantifying the CEs/carbon footprint induced by tourism [2–6], exploring the influence of tourism development on CEs [7–10], and measuring the ecological footprint [11–13] and eco-efficiency [14–17] of tourism. Among these

studies, quite a few have strengthened the negative impacts of tourism on the environment. However, some scholars have also found that tourism positively affects environmental protection. Gössling et al. [18] discovered that tourism revenue can be used for ecosystem protection in Seychelles, which makes inbound tourism a possible channel for safeguarding biodiversity. Ali et al. [19] suggested that tourism helps to reduce resource depletion. Kongbuamai et al. [20] and Katircioglu et al. [21] concluded that tourism improves environmental quality.

Tourism development does not necessarily lead to environmental damage and an increase in CEs. On the contrary, tourism can promote environmental protection by generating financial revenue and rationally utilizing natural resources. To depict the relative impact of tourism on the natural environment, eco-efficiency is used to calculate the environmental cost of tourism's economic benefits, which is the ratio of tourism's revenue to CEs [14]. Another way is to explore the decoupling nexus between the tourism economy and environmental indicators. Decoupling originates from physics, which initially refers to the weakening or disappearance of the relationship between physical variables. Zhang [22] first applied decoupling theory to an economic study exploring the association between economic output and CEs. Based on the decoupling model proposed by Tapio [23], decoupling analyses have been extensively applied to economic production and CEs in all economic sectors [24,25], whole industry sectors [26], the transportation industry [27], construction industry [28], fishery sector [29], electricity sector [30], agricultural sector [31], manufacturing industry [32], etc.

In the tourism research field, scholars have also employed the decoupling index to examine the relationship between TEG and environmental performance. Tang et al. [33] calculated the decoupling index between CO_2 emissions and tourism revenue from 1990 to 2012 in China, pointing out that the decoupling changed from negative to weak positive. Qin and Li [34] analyzed the decoupling correlation and the driving factors between TEG and environmental pressure in China. Zha et al. [35] depicted the decoupling status and its influencing factors between tourism development and CEs in Chengdu city, China, discovering that the decoupling was generally weak between 1991 and 2018, and the different decoupling status was influenced by heterogeneous factors. Xiong et al. [36] uncovered the decoupling state between TEG and CEs from 2007 to 2019 in China's 30 provinces and the driving factors of tourism-related CEs, discovering that the decoupling was mainly weak positive and the influencing elements differed across various provinces.

Previous literature has researched the spatial characteristics of the decoupling relations between TEG and CEs and explored the driving forces behind this decoupling phenomenon and tourism-induced CEs. However, most studies have highlighted spatial differences rather than linkages, which cannot depict the spillover mechanism between different regions. Therefore, a spatial correlation perspective and an exploration into the formation forces of this correlation are theoretically meaningful. The tourism development of Chinese provinces has a noticeable Matthew effect, with a higher level of economic development leading to a higher level of tourism development [37]. The imbalance of interprovincial development in China has become a hindrance to the sustainable development of tourism [38]. On the contrary, a reasonable spatial network structure promotes the flow of tourism elements, including capital, technology, talents, and information in different geographic spaces [39], thereby strengthening the economic connection, spatial integration, and coordinated development of tourist destinations [40]. Therefore, it is of great practical significance to deeply explore the spatial correlation network (SCN) of China's provincial tourism and the driving factors behind the network.

This paper aimed to construct the SCN of the decoupling between tourism economic output and CEs in China's 31 provinces/cities/districts (hereinafter referred to as provinces) and clarify the formation causes of the network. Specifically, a "bottom-up" approach was firstly used to measure the tourism-driven CEs, a Tapio decoupling model (TDM) was then applied to calculate the decoupling index, an improved gravity model was further introduced to construct the SCN of the decoupling, and a social network analysis (SNA)

was lastly employed to explore the structural characteristics and influencing factors of the spatial correlation. Based on the results of the analysis, this paper proposes suggestions to promote the collaborative decoupling of China's interprovincial TEG and CEs, thereby improving the overall green development level of China's tourism industry.

2. Methods and Data Sources

2.1. "Bottom-Up" Measurement of CEs in Tourism

Tourism is a nontraditional industry with a solid correlation and vague range, which lead to difficulties in measuring its CEs. At present, there are "top-down" and "bottom-up" methods for the measurement of tourism-related CEs. The "top-down" method is based on tourism satellite account data. Since China's tourism satellite account has not been fully established, this study adopted a "bottom-up" method to measure the CEs of China's tourism industry. Drawing on existing studies [33,41,42], this paper defined the CEs from tourism transportation, tourism accommodation, and tourism activities as the main sources of CEs from the tourism industry. Specifically, based on previous research results [43–45], the CEs of these three aspects were calculated by multiplying the number of tourists by their corresponding CE coefficients, which were finally added up to obtain tourism's CEs.

2.2. Tapio Decoupling Model

The TDM is an application of decoupling theory to the decoupling relationship between economic development and the natural environment, which mainly considers the ratio between the change rate of economic output and the change rate of environmental factors [23]. This paper introduces the decoupling model into the tourism industry to study the decoupling relationship between TEG and CEs. The model was constructed as Equation (1).

$$D_i = \% \frac{C_i^t - C_i^0}{T_i^t - T_i^0} = \% \frac{\Delta C}{\Delta T} \quad (1)$$

where D_i denotes the decoupling index of area i; C_i^t and C_i^0 represent tourism's CEs in region i in the tth year and the base year, respectively; T_i^t and T_i^0 represent tourism's economic output in region i in the tth year and the base year, respectively, which are reflected by the total tourism revenue. There are eight types of decoupling status based on the decoupling index (Table 1).

Table 1. Criteria for judging the decoupling status between TEG and CEs.

Decoupling Type	Decoupling Status	Judging Criteria
Decoupling	Strong decoupling	$\Delta T > 0, \Delta C < 0, D < 0$
	Weak decoupling	$\Delta T > 0, \Delta C > 0, 0 < D < 0.8$
	Recessive decoupling	$\Delta T < 0, \Delta C < 0, D > 1.2$
Connection	Recessive connection	$\Delta T < 0, \Delta C < 0, 0.8 < D < 1.2$
	Expansive connection	$\Delta T > 0, \Delta C > 0, 0.8 < D < 1.2$
Negative decoupling	Expansive negative decoupling	$\Delta T > 0, \Delta C > 0, D > 1.2$
	Weak negative decoupling	$\Delta T < 0, \Delta C < 0, 0 < D < 0.8$
	Strong negative decoupling	$\Delta T < 0, \Delta C > 0, D < 0$

2.3. Social Network Analysis

Spatial correlation analysis mainly uses the Granger test [46] and SNA [47]. Since the VAR-based Granger test is sensitive to the time lag of panel data, this study firstly establishes a spatial correlation matrix by using the improved gravity model (Equation (2))

and analyzed the structural features and factors of the SCN based on SNA including centrality analysis, CONCOR analysis, and QAP analysis.

$$S_{ij} = \frac{G_i}{G_i + G_j} \cdot \frac{T_i \cdot T_j}{\frac{D_{ij}^2}{(g_i - g_j)^2}} \quad (2)$$

where S_{ij} denotes the spatial correlation strength of the decoupling between province i and j; G_i and G_j represent the GDP in province i and j; T_i and T_j represent the decoupling indexes in province i and j; g_i and g_j denote the per capita GDP of province i and j; D_{ij} refers to the shortest distance between province i and j.

2.4. Data Sources

The data for calculating tourism's CEs were mainly from the China Tourism Statistical Yearbook and its copies (2010–2020), Sixty Years of New China Statistical Data Compilation, China Tourism Sampling Survey Data, China Transportation Yearbook, the Statistical Yearbook of the 31 provinces, the National Statistical Bulletin, and the annual statistical report of the tourism industry. Other data were mainly from the China Statistical Yearbook (2010–2020). When calculating CEs, the number of people participating in tourism-related activities in a few regions were missing, which was compensated for by using the trend average method. This method filled in the missing values by using the moving average, which not only considered the actual moving average, but also the moving average of the trend value, thereby obtaining a more stable trend sequence than a random sequence, minimizing the error of the estimated value.

3. Characteristics of the Spatial Correlation Network of Decoupling

3.1. Overall Characteristics of the SCN

This study measured the mean value of the national decoupling index between TEG and CEs from 2009 to 2019. According to the National Development and Reform Commission, this paper divided China's 31 provinces into three regions: east, middle, and west. The east included the 11 provinces of Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the middle consists of the 10 provinces of Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi; the west consisted of the ten provinces of Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang. This paper calculated the decoupling index in each region and depicts the spatial difference.

As shown in Figure 1, weak decoupling and expansive connection repeatedly alternated in the eastern region during the study period. The holding of major events, such as the 2008 Olympic Games and the 2010 World Expo, made green and low-carbon tourism popular, and the CEs of the tourism industry was controlled to a certain extent, which led to the weak decoupling between TEG and CEs between 2009 and 2010. However, with the increasingly fierce tourism competition in the eastern region, the growth rate of tourism development has slowed down, and the CEs brought by tourism development have remained high, making the decoupling state unstable. The central region was dominated by expansive connection, except for a weak decoupling state in 2010. This shows that the solidification effect of tourism's CEs in the central region was profound, which makes it difficult to change the decoupling state. The western region showed weak decoupling in 2010 and 2018–2019, with expansive connection in the remaining years.

The national TEG and CEs were weakly decoupled in 2010 and 2019, indicating that the growth rate of China's tourism CEs was lower than the economic growth rate. However, the remaining years were all expansive connections, indicating that TEG and CEs had similar growth rates. In general, the decoupling of China's TEG and CEs was dominated by expansive connection, with weak decoupling in 2010 and 2019. Among all the regions, the decoupling of the eastern region was stronger than the middle and western regions.

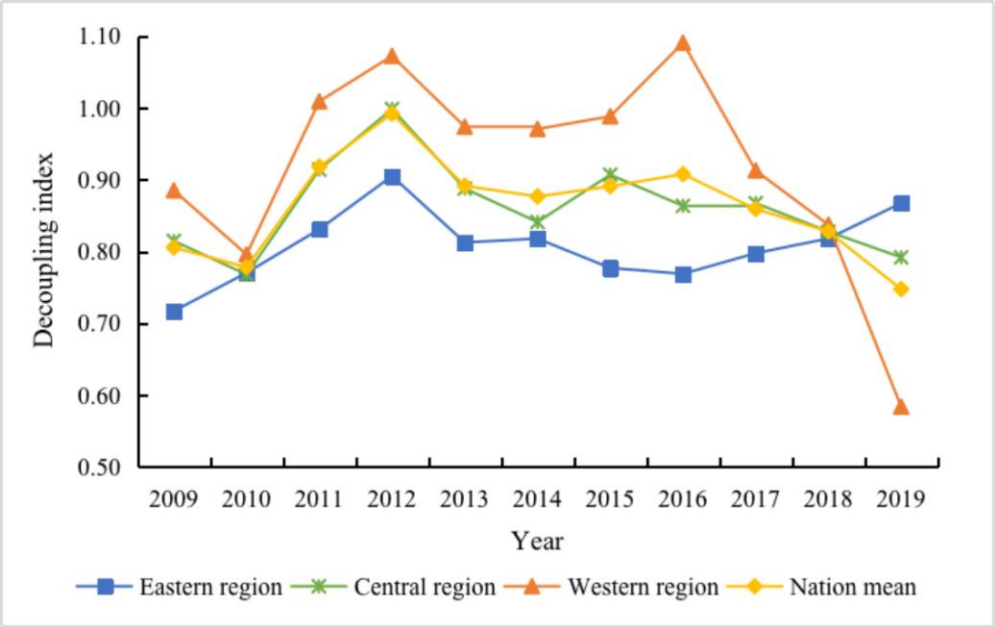


Figure 1. Decoupling index between China's TEG and CEs from 2009 to 2019.

Based on the decoupling index between TEG and CEs in China's 31 provinces and an improved gravity model, this paper firstly established a spatial correlation matrix. Then, taking the average value of each row of the matrix as the comparison value, a value greater than the comparison value was recorded as 1, and the rest were recorded as 0, thereby establishing a binary matrix of spatial correlation. Finally, UCINET6 was used to draw the spatial topology map of the decoupling. This study selected the 4 years of 2009, 2012, 2015, and 2019 for comparative analysis. The results are shown in Figure 2. In the figures, each node represents a province, the connection between the nodes indicates a spatial relationship between the two provinces, and the arrow represents the direction of the spatial overflow.

The results of the analysis show that from 2009 to 2019, the spatial correlation of the decoupling between China's TEG and CEs became increasingly close, with each province not only spatially correlated with neighboring provinces but also with cross-regional provinces. Among all of the provinces, Beijing and Tianjin were always the center of the association network, and the eastern coastal areas, such as Jiangsu, Zhejiang, Shanghai, Guangdong, and Fujian, were located in the subcenters. With the advancement of time, provinces in the middle and western regions, such as Anhui, Hubei, Hunan, Chongqing, and Inner Mongolia, gradually moved closer to the central area, leading to more central and subcentral areas in the network.

The characteristics of the SCN (Figure 3) show that from 2009 to 2019, the number of network relationships of the decoupling between China's TEG and CEs fluctuated wildly, with the most connections in 2010 and 2012, indicating again that the hosting of the Olympic Games and World Expo improved the spatial correlation strength. Network density reflects the density of the network relationships. The higher the density, the stronger the network correlation. During the study period, the network density was the largest in 2010 and 2012, which was 0.187. Network efficiency indicates the number of redundant relationships in the network. The more redundancy, the lower the efficiency. The overall network efficiency fluctuated around 0.650. The network grade indicates the asymmetric reachability of the network. The higher the grade, the greater the difference between the core and periphery provinces. From 2009 to 2019, the network grade fluctuated around 0.4, with the smallest value in 2010 and 2012, indicating that the difference between the core–periphery provinces narrowed in these two years.

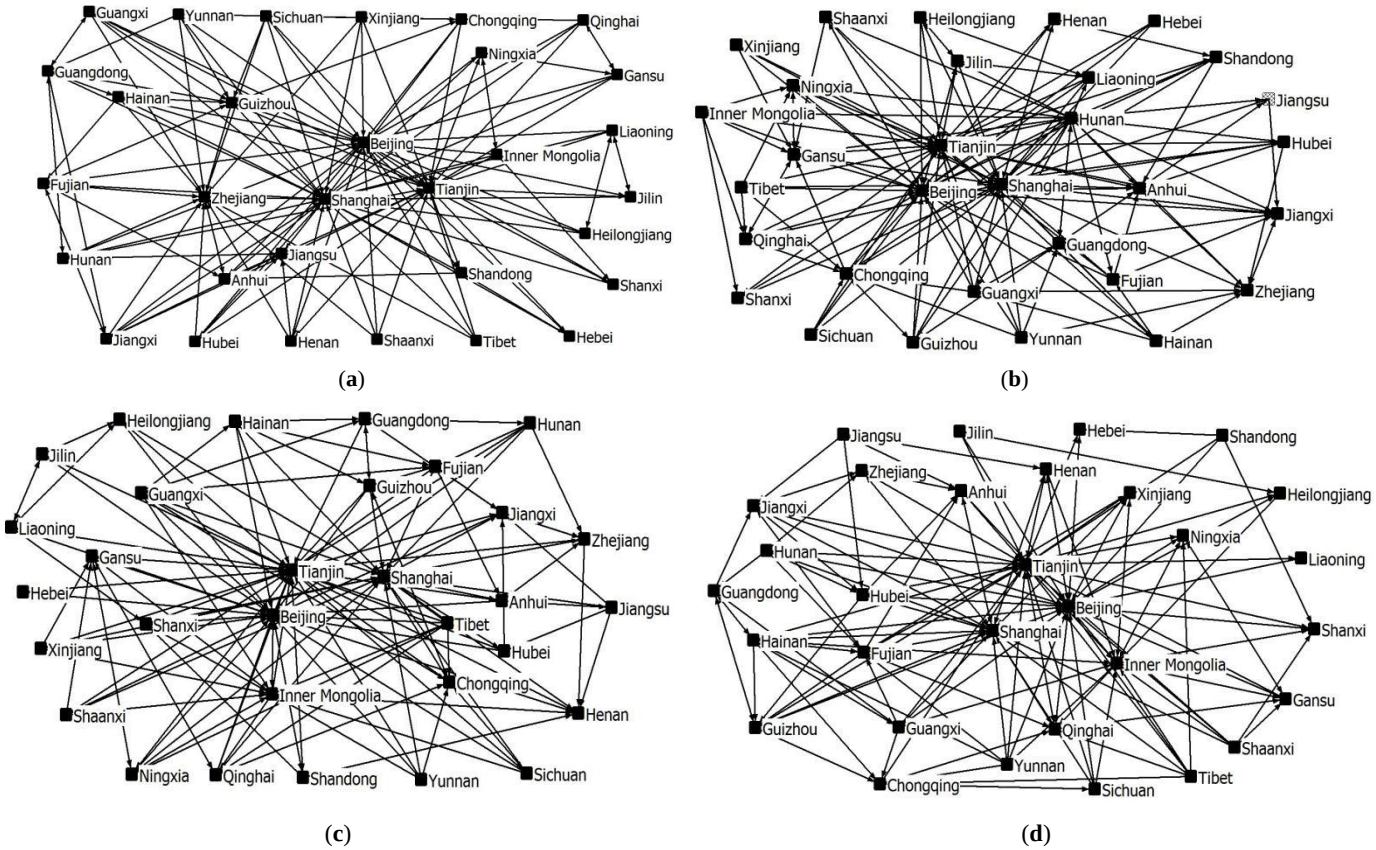


Figure 2. Spatial topology map of the decoupling between China's TEG and CEs: (**a**) 2009; (**b**) 2012; (**c**) 2015; (**d**) 2019.

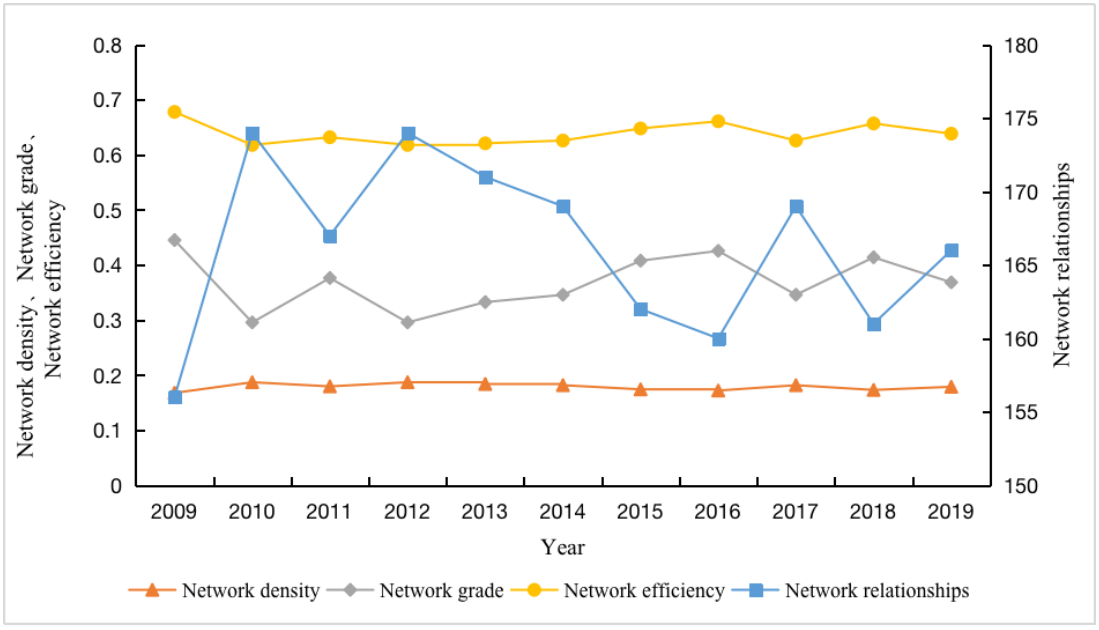


Figure 3. Overall characteristics of the SCN of the decoupling between China's TEG and CEs from 2009 to 2019.

3.2. Individual Characteristics of the SCN

This study used centrality to describe the individual characteristics of the provinces including the centrality of degree, closeness, and betweenness. Degree centrality reflects the number of relationships a node has, consisting of out-degree and in-degree. The higher

the degree centrality, the more relationships a node has, and the closer it is to the network's center. From 2009 to 2019, the average degree centrality of China's 31 provinces was 27.097, and the degree centrality of 6 provinces exceeded the average value. These provinces were mainly developed eastern regions, which had strong economic growth, advanced technology, and talent gathering. In particular, the degree centrality of Beijing, Tianjin, and Shanghai exceeded 50, with and in-degree greater than out-degree, indicating that these provinces enhanced their decoupling effect by attracting spatial overflow from other provinces. However, Liaoning, Hebei, Jilin, Heilongjiang, Ningxia, and Shandong were in the bottom five in terms of degree centrality. These regions were at the fringes of the spatial network, because they were geographically remote and had less inflow from other regions.

The closeness centrality reflects the average length of the shortest paths from a node to other nodes. Higher closeness centrality demotes a closer distance of a node to other nodes and easier reception of spillovers from outside. As can be seen from Table 2, the average closeness centrality of 31 provinces was 57.181, of which 11 provinces had a closeness centrality greater than the average, and their total value accounted for 35.48% of the total. Among the 11 provinces, the eastern developed regions were of the majority, indicating that eastern provinces were more likely to connect with other regions. The provinces that ranked among the last five in terms of closeness centrality were the same as for degree centrality, indicating that these provinces had difficulty in connecting with other provinces and had less influence on other regions.

Table 2. The centrality characteristics of the 31 provinces.

Province/City/District	Degree Centrality				Closeness Centrality		Betweenness Centrality	
	Out-Degree	In-Degree	Centrality	Ranking	Centrality	Ranking	Centrality	Ranking
Beijing	8	23	76.667	2	81.081	2	22.475	2
Tianjin	9	26	86.667	1	88.235	1	31.795	1
Hebei	2	3	10.000	12	50.000	13	0.010	23
Shanxi	3	5	16.667	10	52.632	11	0.171	21
Inner Mongolia	6	14	50.000	4	66.667	3	5.134	4
Liaoning	2	1	6.667	13	49.180	14	0.010	23
Jilin	3	1	10.000	12	50.000	13	0.010	23
Heilongjiang	4	3	13.333	11	50.847	12	0.087	22
Shanghai	5	15	53.333	3	60.000	5	7.281	3
Jiangsu	4	1	26.667	7	57.692	7	2.966	5
Zhejiang	4	4	26.667	7	58.824	6	1.925	7
Anhui	5	5	23.333	8	55.556	9	1.694	9
Fujian	8	5	36.667	5	61.224	4	1.895	8
Jiangxi	6	6	26.667	7	57.692	7	0.227	18
Shandong	4	0	13.333	11	50.847	12	0.087	22
Henan	4	4	16.667	10	53.571	10	1.654	9
Hubei	6	3	26.667	7	57.692	7	1.930	6
Hunan	7	0	23.333	8	56.604	8	1.349	12
Guangdong	4	4	26.667	7	56.604	8	1.895	8
Guangxi	8	2	26.667	7	56.604	8	1.515	10
Hainan	9	4	33.333	6	58.824	6	1.925	7
Chongqing	4	7	26.667	7	56.604	8	0.844	14
Sichuan	5	1	16.667	10	52.632	11	0.260	17
Guizhou	5	5	26.667	7	57.692	7	1.502	11
Yunnan	7	0	23.333	8	55.556	9	0.362	16
Tibet	6	0	20.000	9	53.571	10	0.260	17
Shanxi	6	0	20.000	9	53.571	10	0.577	15
Gansu	5	4	20.000	9	53.571	10	0.182	20
Qinghai	4	8	26.667	7	55.556	9	0.847	13
Ningxia	4	4	13.333	11	50.847	12	0.010	23
Xinjiang	4	3	16.667	10	52.632	11	0.225	19
Average	5	5	27.097	-	57.181	-	2.939	-

Betweenness centrality calculates the number of the shortest paths through a node. Greater betweenness centrality means stronger control of a node over the shortest path of the network, and the greater its influence on the relationship between other nodes. During the study period, the average betweenness centrality of the 31 provinces in China was 2.939. The betweenness centrality of Beijing, Tianjin, Shanghai, Jiangsu, and Inner Mongolia was higher than the average level, signifying that these provinces were "controllers" in the spatial network. However, Ningxia, Liaoning, Jilin, and Hebei's betweenness centrality ranked among the bottom four, making them in the "controlled" position.

3.3. Clustering Characteristics of SCN

Using the CONCOR analysis of UCINET6, this study divided the 31 provinces into four plates based on the spillover relationship numbers (Table 3). The first plate was the "net benefit" plate including Beijing and Tianjin. The relationships outside the plate were greater than the number of intra-plate connections, and the receiving relationships were greater than the spillover relationships. The second plate was the "two-way spillover" plate, which had a comparatively larger number of relationships, both inside and outside the plate. The plate included six provinces with superior geographical locations and strong strengths in all aspects, thereby becoming the main inflow and outflow sources in the SCN. The third plate was the "agent" plate, with the actual internal relationship ratio being close to the expected internal relationship ratio. The plate incorporated 12 provinces, such as Inner Mongolia and Jilin, which mainly acted as a bridge in the spatial network, transporting the overflow from the developed eastern provinces to the underdeveloped areas in the middle and western regions and transporting the resources in the opposite direction. The fourth plate was the "net spillover" plate, with the number of spillover relationships greater than the number of receiving relationships and the actual internal relationship ratio much higher than the expected internal relationship ratio. This plate included 11 provinces, such as Hunan and Henan, which mainly received spatial overflow inside the plate and received less external overflow.

Table 3. The sectoral division of the decoupling between TEG and CEs in 31 provinces in China.

Plate	Province/City/District	Receiving Relationships		Spillover Relationships		Expected Internal Relationship Ratio (%)	Actual Internal Relationship Ratio (%)
		Inside the Plate	Outside the Plate	Inside the Plate	Outside the Plate		
Plate one: "Net benefit" plate	Beijing, Tianjin	2	13	2	4	3.33%	33.33%
Plate two: "Two-way overflow" plate	Jiangsu, Guangdong, Zhejiang, Fujian, Hubei, Shanghai	6	20	6	20	16.67%	23.08%
Plate three: "Agent" plate	Inner Mongolia, Jilin, Heilongjiang, Hebei, Qinghai, Shanxi, Liaoning, Ningxia, Shandong, Gansu, Chongqing, Shanxi	23	22	23	32	36.67%	41.81%
Plate four: "Net spillover" plate	Hunan, Henan, Guangxi, Guizhou, Yunnan, Tibet, Anhui, Hainan, Jiangxi, Sichuan, Xinjiang	26	15	26	14	33.33%	65.00%

Figure 4 shows that the total intra- and inter-plate spillover relationships were 57 and 70, respectively, indicating that the inter-plate spillovers dominated the spatial spillovers of the decoupling between TEG and CEs in China's 31 provinces.

According to the density and image matrix inside and between the plates (Table 4), the density of plate two (0.167) and plate three (0.159) was comparatively higher, signifying that there was a larger correlation within the second and third plates. On the contrary, plate one and plate four had greater density with other plates, denoting that the two plates had larger spatial spillovers from the outside than the inside.

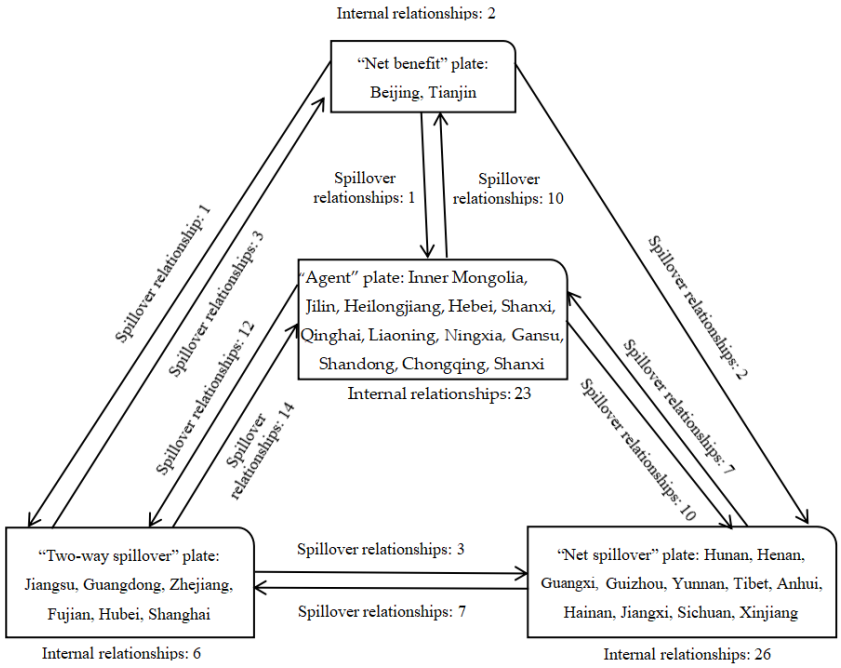


Figure 4. Intra- and inter-plate spillover relationships of the decoupling between China's TEG and CEs.

Table 4. Intra- and inter-plate density matrix and image matrix of the decoupling between China's TEG and CEs.

Plate	Density Matrix				Image Matrix			
	Plate One	Plate Two	Plate Three	Plate Four	Plate One	Plate Two	Plate Three	Plate Four
Plate one	0.000	0.000	0.542	0.182	0	0	1	1
Plate two	0.333	0.167	0.028	0.303	1	0	0	1
Plate three	0.958	0.014	0.159	0.015	1	0	0	0
Plate four	1.000	0.394	0.106	0.036	1	1	0	0

4. Influencing Factors of the Spatial Correlation of Decoupling

4.1. Model Construction

The factors affecting the spatial correlation of the decoupling between China's TEG and CEs are complex and diverse and need to be considered from multiple aspects. This paper firstly selected the influencing factors from seven aspects: economy, technology, structure, policy, population, location, and energy consumption [48–53]. The spatial correlation difference matrix of the decoupling between TEG and CEs in China's 31 provinces was taken as the dependent variable and the interprovincial correlation difference matrix of the factors as the independent variable to construct the research model (Equation (3)). Lastly, QAP was used to test the correlation and regression relationships.

$$C = f(E, T, S, G, P, L, N) \quad (3)$$

where C is the spatial correlation matrix of the decoupling between China's TEG and CEs; E is the economic factor, which is represented by the difference matrix of interprovincial per capita GDP; T is the technical factor, which is denoted by the interprovincial difference matrix of the number of three domestic patent application authorizations; S is the structural element, which is proxied by the interprovincial difference matrix of the proportion difference of tertiary industry; G is government policy, which is measured by the interprovincial difference matrix of the fiscal expenditure of energy conservation and environmental protection; P is population factor, which is reflected by the interprovincial difference matrix of domestic and foreign tourists; L is the spatial adjacency matrix, which

is one if two provinces are adjacent, otherwise 0; *N* is the energy use, which is represented by the difference matrix of energy use.

4.2. QAP Correlation Analysis

This paper adopted QAP to conduct the correlation analysis between the spatial correlation of the decoupling and its influencing factors, and the results are shown in Table 5. The correlation coefficients of the economic factors, structural factors, technical factors, government policies, and spatial adjacency were all significantly positive, indicating that the differences in the economic development level, industrial structure, technological level, government policy, and geographical location between provinces exerted an obvious impact on the decoupling between TEG and CEs. In addition, the values of the correlation coefficients showed, in descending order of influence strength, that the significant factors were economic factors, structural factors, spatial adjacency, government policies, and technical factors. However, the impact of energy consumption and population elements were not significant, suggesting that they are not important for the spatial correlation of decoupling.

Table 5. Correlation analysis of the spatial correlation structure of the decoupling between China's TEG and CEs and its influencing factors.

Influencing Factors	Correlation Coefficients	*p*-Value	Mean	Standard Deviation	Minimum Value	Maximum Value	$p > 0$	$p < 0$
Economic factors	0.387	0.000	0.000	0.072	−0.161	0.389	0.000	1.000
Structural factors	0.263	0.006	0.000	0.079	−0.125	0.384	0.006	0.994
Technical factors	0.061	0.019	0.000	0.075	−0.133	0.408	0.806	0.195
Population factors	0.003	0.453	0.000	0.047	−0.170	0.186	0.453	0.547
Policy factors	0.079	0.012	0.000	0.068	−0.151	0.370	0.127	0.873
Energy consumption	−0.002	0.359	0.001	0.078	−0.131	0.432	0.359	0.641
Spatial adjacency	0.168	0.000	0.000	0.039	−0.123	0.152	0.000	1.000

4.3. QAP Regression Analysis

To reduce the interference of the correlation between the influencing factors on the influence strength, this paper conducted a QAP regression analysis based on 10,000 random permutations. The results (Table 6) show that the explanation degree of the influencing factors on the spatial correlation was 20.9%. Among all of the factors, the regression coefficients of the economic factors, government policies, and spatial adjacency were positive and significant, indicating that the differences in the level of economic development, government policies, and spatial adjacency between provinces facilitated the formation of the SCN of the decoupling. The regression coefficients of the structural elements and technological elements were negative and significant at the 10% significance level, indicating that the smaller the gap between regional industrial structure and technology, the more conducive to the formation of the SCN of the decoupling.

Table 6. Regression analysis of the spatial correlation structure of the decoupling between China's TEG and CEs and its influencing factors.

Influencing Factors	Unstandardized Regression Coefficients	Standardized Regression Coefficients	*p*-Value	Probability 1	Probability 2
Intercept term	−0.022	0.000			
Economic factors	0.000	0.425	0.000	0.000	1.000
Structural factors	−0.001	−0.013	0.044	0.556	0.444
Technical factors	−0.000	−0.080	0.067	0.934	0.067
Policy factors	0.000	0.046	0.027	0.194	0.807
Spatial adjacency	0.254	0.236	0.000	0.000	1.000

5. Conclusions and Discussion

5.1. Conclusions

This paper was firstly based on a "bottom-up" method and the TDM to calculate the decoupling index between TEG and CEs in China's 31 provinces from 2009 to 2019.

Then, a spatial correlation matrix of the decoupling was constructed based on an improved gravity model. In addition, the overall, individual, and clustering features of the SCN were analyzed based on SNA. Lastly, QAP correlation and regression in SNA were used to examine the influencing factors of the spatial correlation. Through the above research, the main conclusions are as follows.

Firstly, except for 2010 and 2019, the decoupling between China's TEG and CEs was an expansive connection from 2009 to 2019, which indicates a nonideal decoupling state. Among the regions, the decoupling was stronger in the eastern provinces and weaker in the middle and western districts.

Secondly, from the characteristics of the SCN, the spatial correlation strength, stability, and level differences of the decoupling fluctuated wildly during the study period, which all reached the best state in 2010 and 2012. In addition, Beijing and Shanghai were located in the center of the correlation network, and the developed eastern provinces were situated in the subcenters, which were prone to spatial spillover relationships with other provinces. The middle and western regions were at the edge of the network, which resulted in difficulties in terms of spatial spillovers with other provinces.

Thirdly, in terms of spatial agglomeration and inter-plate correlation, Beijing and Tianjin were located in the "net benefit" plate, the developed eastern regions were primarily in the "two-way spillover" plate, and the western and central provinces mainly belonged to the "agent" and "net spillover" plates. The provinces outside the plates had stronger spatial correlation and a higher degree of agglomeration, while the internal correlation and agglomeration of the plates were not obvious.

Lastly, the influencing factors of the spatial correlation of the decoupling between China's TEG and CEs mainly included economic factors, spatial adjacency, government policy, structural factors, and technical factors. Among them, the larger the spatial difference between the first three factors and the smaller the spatial difference between the latter two factors, the more conducive to the formation of spatial correlation of the decoupling.

5.2. Discussion

Firstly, the decoupling state between China's TEG and CEs from 2009 to 2019 was generally consistent with the studies of Tang, Shang, Shi, Liu, and Bi [33]; Zha, Dai, Ma, Chen, and Wang [35]; Xiong, Deng, and Ding [36], who asserted that the decoupling was mainly weak in China, indicating great space for the improvement of decarbonization of China's tourism industry.

Secondly, the overall characteristics of the SCN reflected that the holding of the 2008 Olympic Games and 2010 World Expo had a significant positive effect on the spatial correlation of the decoupling. Moreover, the individual characteristics of the SCN demonstrated the spatial differences between the provinces in the different regions, with the developed eastern provinces being located in the central places of the network. This conclusion confirms the Matthew effect regarding the level of economic development and the level of tourism development in China [37].

Thirdly, the results of the spatial agglomeration indicate, again, the advantageous positions of the developed eastern provinces in the spillover network, which received more spillovers from the outside. In addition, the inter-plate spillover relationships were more important for spatial correlation than the intra-plate ones, highlighting the significance of inter-plate cooperation.

Lastly, in the context of the new era, China has implemented "cross-regional cooperation" and "cross-regional poverty alleviation" to achieve shared prosperity and build a well-off society in all respects. Therefore, regions with larger differences in economic development, governmental policies, and spatial locations are more inclined to establish cooperative relationships and promote the flow of production factors such as technology, talents, and resources. These elements are important driving forces of the decoupling between TEG and CEs, which help to enhance the spatial spillover effect of the decoupling. On the contrary, with similar levels of economic development, governmental policies,

and spatial locations, regions with closer industrial structures and technological strengths are more likely to carry out relevant exchanges and cooperation, thereby enhancing the spatial spillover of the decoupling. This finding is similar to the results of Sun et al. [54], who determined that the smaller the gap between the knowledge base and the industrial structure in China's provinces, the larger the possibility for interprovincial connection of innovation.

5.3. Policy Implications

Based on the above empirical conclusions, this paper puts forward the following policy recommendations. First, the state should increase the assistance and financial transfer payment for talents and technologies in the middle and western regions and continuously improve the construction infrastructure for innovation and research, thereby creating a good technology research and development environment for the middle and western regions. In this way, a green innovation and development highland can be formed in the middle and western regions, and the overall low-carbon development level of tourism in the middle and western regions will be improved.

Second, the developed eastern regions, with a better level of decoupling between tourism development and CEs, should actively participate in "cross-regional cooperation" and "cross-regional poverty alleviation" by exporting talent, technologies, and resources to the middle and western regions, thereby increasing spatial spillovers and reducing regional differences.

Third, the middle and western regions with a poor level of decoupling should firstly improve their strength in terms of economy, industrial institutions, government policies, technology, etc., so as to improve the level of decoupling. Meanwhile, they should seize cooperation opportunities, such as "cross-regional cooperation" and "cross-regional poverty alleviation", to attract spatial overflow from developed areas. In particular, they should strengthen contacts with members outside the plates, thereby positioning themselves closer to the network's center and changing from a "passive" role to an "active" role in the association network.

Last, all provinces should follow the trend of collaborative innovation and facilitate the flow of talent, technology, and capital, thus promoting intra- and inter-plate cooperation in terms of tourism decarbonization. At the same time, the state should clarify the positions and roles of every province; stimulate the radiation driving effect of Beijing, Tianjin, Shanghai, and other eastern provinces; encourage and support their cooperation with middle and western provinces.

5.4. Research Limitations and Future Research Directions

Since the Tourism Statistical Yearbook was changed to the Chinese Cultural Relics and Tourism Statistical Yearbook in 2021, the statistical caliber is different from previous statistical yearbooks. Therefore, the research data in this paper were from 2019. When relevant data are available, the study period can be extended. In addition, this paper analyzed the impact of representative factors on the decoupling between TEG and CEs in China from a macro perspective, and future research can explore the impact of a single important factor in detail.

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