MEASUREMENT, TEMPORAL AND SPATIAL EVOLUTION OF TOURISM ECO-EFFICIENCY IN CHINA BASED ON DATA MINING

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Abstract. Ecological efficiency is commonly applied to evaluate the ecological and economic effects of sectors such as agriculture, industry, and mining. As the environmental issues associated with tourism become more evident, the concept of ecological efficiency is increasingly incorporated into tourism studies. In this paper, based on the research of domestic and foreign literatures on ecological efficiency, an evaluation index system of ecological efficiency in line with tourism development is constructed. Based on data mining, Carbon emissions and tourism consumption across 30 provinces in China from 2010 to 2020 are estimated, with the analysis of the results conducted using the coefficient of variation and Moran index. The trends in tourism eco-efficiency are evaluated for their alignment with the requirements of sustainable development, particularly the United Nations Sustainable Development Goals (SDGs). The results show that the carbon emissions of China's tourism industry are increasing, and the carbon emissions among tourism departments are quite different. Due to the implementation of tourism development policies, the eco-efficiency of tourism across China and its regions has generally shown consistent improvement. However, when considering the time aspect, regional disparities in China's tourism ecological efficiency remain. Strong spatial correlation exists among regions, and the coupling coordination between population density, industrial structure, and technological innovation is significantly influenced by these factors; The coupling coordination between population density, industrial structure, and technological innovation is greatly influenced by these factors.
Keywords: *data mining, ecological efficiency of tourism, space-time evolution, carbon emission reduction, regional disparities, coupling coordination model*

Introduction

Tourism, as one of the national strategic pillar industries, is a crucial foundation for advancing the development of ecological civilization and a beautiful China. However, with the development of tourism, unsustainable practices such as irrational exploitation of tourism resources, overcrowding at tourist destinations, and extensive development models have hindered the improvement of regional ecological civilization. In particular, tourism has become a source of carbon emissions that cannot be ignored. This has a notable impact on the country's overall strategic plan for reaching peak carbon dioxide emissions and achieving carbon neutrality (Cao et al., 2020). As a result, in the context of the growing demand for high-quality tourism development in the new era, there is increasing focus on achieving a harmonious and sustainable balance between tourism and the environment. On the basis of continuously improving tourism efficiency and ecological efficiency, by continuously enhancing tourism efficiency and ecological efficiency, a coupled and coordinated development pattern of the two should be

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fostered, which is not only an urgent need for high-quality tourism development but also a critical mission for building a Beautiful China, but also the important mission of building a beautiful China.

Most scholars at home and abroad believe that carbon emissions have aggravated global climate change to a great extent, while the consumed by human activities is an important driving factor of carbon emissions, and tourism-related activities will also consume fossil and produce carbon emissions (Liu et al., 2021; Diawol et al., 2021). As a key sector of the national economy, the ecological efficiency of tourism and its impact are crucial factors to consider, which is based on the input of tourism resources such as consumption and environmental pollution such as carbon emission, can be improved, the answers to these questions need the support of empirical data. Wang et al. (2020) argues that “ecological efficiency provides a better assessment of how economic activities affect the environment”, and the core of ecological efficiency lies in “minimum input and maximum output”. Ye and Ou (2019) and Geng et al. (2021) considers tourism ecological efficiency a key indicator for assessing the balance between the benefits of tourism development and its environmental impact. Liu et al. (2021) think that with the current development scale and speed of tourism, it is set to become the leading sector contributing to global greenhouse gas emissions. Yuan (2019) puts forward the research method of systematically analyzing the consumption of tourism, He is a trailblazing researcher who evaluates the environmental impact of tourism by examining its carbon emissions. His work focuses on analyzing the ecological efficiency of transportation within the tourism sector, accommodation, and activities, it was discovered that the efficiency levels vary significantly across different sectors of tourism. According to Chen et al., (2019), air travel is the leading factor driving both resource consumption and carbon emissions within the tourism transportation sector. Everett et al. (2019) pointed out through research that the global greenhouse gas emissions from transportation are increasing at a rate of 2% every year, and among all tourism modes, air tourists have the highest carbon emission intensity per person (Zhang et al., 2021). With the increasing dependence of tourism on air transportation, the air tourism industry is anticipated to experience a continuous increase in both carbon emissions and energy usage (Li et al., 2019).

Tourism eco-efficiency is grounded in the principles of eco-efficiency theory, low-carbon tourism and sustainable development. By combing the related literatures at home and abroad, it has been observed that the literature on tourism eco-efficiency covers a broad range of topics and viewpoints, and diverse research methods and means. Nowadays, data mining technology is one of the research hotspots in the field of database and artificial intelligence. Its main purpose is to extract easily understandable, hidden, potential, unknown and meaningful information from massive data information (Haibo et al., 2020; Kongbuamai et al., 2020). In view of the above, this paper will select the tourism eco-efficiency evaluation index which can reflect the investment of tourism resources, environmental impacts, and economic outputs. To analyze regional disparities in tourism ecological efficiency, the coefficient of variation and Moran index will be applied. By comparing with the ecological efficiency value for sustainable development, the paper will assess the state of regional tourism sustainability. Furthermore, the study will explore the spatial patterns of ecological efficiency across China, focusing on aspects such as pattern scale, intensity, and texture, while exploring the temporal and spatial evolution, as well as the regional disparities and clustering of ecological efficiency.

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Compared with existing literature, this study innovates in three aspects. First, it integrates data mining techniques (e.g., Apriori algorithm) with the Super-SBM (Slack-Based Measure Model) model for the first time, extracting hidden association rules from tourism consumption and carbon emission data to dynamically analyze influencing factors of tourism eco-efficiency, thus overcoming the limitation of traditional DEA models that only focus on efficiency measurement. Second, it constructs a “time-space-factor coupling” analytical framework, systematically revealing the evolution of provincial tourism eco-efficiency in China through coefficient of variation, Moran index, and spatio-temporal gravity migration, which complements the shortage of single-dimensional analyses in prior studies. Third, the study improves the traditional coupling coordination model by incorporating driving factors such as population density, industrial structure, and technological innovation, quantifying the interaction mechanism between tourism efficiency and ecological efficiency to provide more precise policy targets for regional sustainable tourism development.

Research method

Indicator selection and data source

This study focuses on 30 provinces and cities across four key regions of China, using them as units for research and decision-making. According to the regional classification framework set forth by the National Bureau of Statistics, the areas are divided into four categories: eastern, northeastern, central, and western regions. The analysis covers a period of 11 years, from 2010 to 2020.

This study utilizes panel data from 30 provinces (municipalities and autonomous regions) in China spanning 2010–2021. Tourism-related data, including tourism revenue, tourist arrivals, and the number of star-rated hotels, are sourced from the *China Tourism Statistical Yearbook (2010–2021)*. Socio-economic indicators such as GDP, population density, and energy consumption are obtained from the *China Statistical Yearbook (2010–2021)*, while carbon emission data are calculated according to the *Guidelines for Compiling Provincial Greenhouse Gas Inventories*.

To mitigate the impact of inflation, all monetary indicators (e.g., tourism revenue) are deflated to 2010 constant prices using the Consumer Price Index (CPI). The adjustment formula is: Real Value = Nominal Value × (CPIbase year / CPIreport year), where the base-year CPI (Consumer Price Index) (2010) is set to 100, and CPI values for each year are retrieved from the corresponding *China Statistical Yearbook*. For example, with a nominal tourism revenue of 3,419.5 billion yuan and a CPI of 101.4 in 2015, the real revenue is adjusted to 3,419.5 × (100 / 101.4) ≈ 3,372.3 billion yuan.

Generally speaking, the more indicators, the more it can reflect the true efficiency value. Nevertheless, numerous studies indicate that in the DEA (Data Envelopment Analysis) model, the ratio of indicators to decision-making units should be maintained at no more than one-third, with the number of indicators being less than or equal to one-third of the decision-making units. There are 9 indicators and 30 decision-making units in this paper, which is in line with the principle of indicator quantity in DEA model (Chen and Qing, 2019). environment, and economy indicators related to tourism eco-efficiency. In this study, these three types of indicators are classified into expected output indicators, unexpected output indicators, and input indicators, as illustrated in *Figure 1*.

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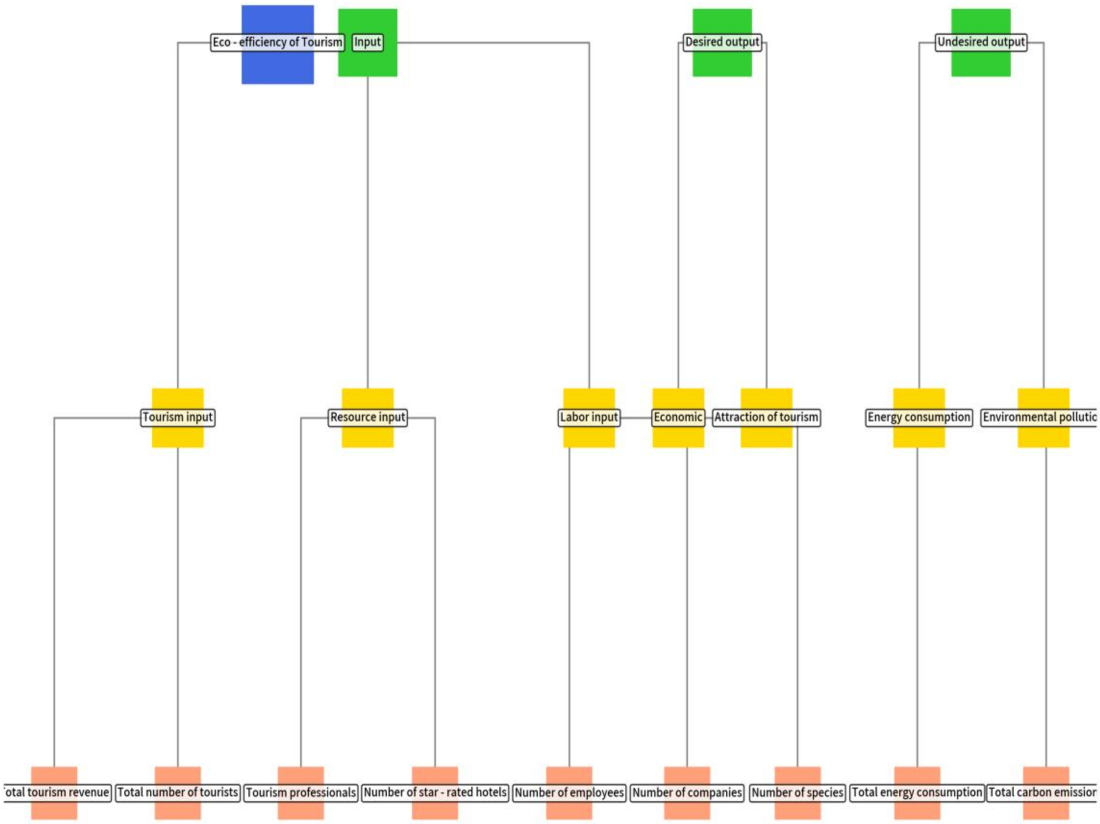

Figure 1. *Composition of eco-efficiency index of tourism*

Expected output index

In reality, the tourism output effect should also include the satisfaction of tourists participating in tourism activities and the attraction of regional tourism. However, it is difficult to quantify the difference in tourists' satisfaction perception and the attraction of tourism through data, and it is not advisable to select the principle according to DEA (Data Envelopment Analysis) indicators. Therefore, this study adopts indicators such as total tourism revenue and the overall number of tourists as proxies for tourism satisfaction and attraction, serving as representations of the anticipated output metrics.

Undesired output index

In this research, carbon emissions associated with tourism are utilized as a measure of environmental pollution., that is, undesirable output. Carbon emission is the most important aspect of tourism's impact on the environment at present, which comes from the consumption of. To measure the carbon emission of tourism, we must first identify the relevant departments of tourism. According to the results of previous literature studies, it has been identified that the main contributors to carbon emissions in tourism include transportation, lodging, and a range of tourist activities.

Tourism resources input index

In this paper, tourism professionals is chosen as the labor input, the total consumption of tourism is taken as the input, the yearly investment in tourism-related

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fixed assets is regarded as the capital input. The number of star-rated hotels, A-level tourist attractions, and travel agencies is used as a measure of the region's ability to accommodate tourists and the level of tourism development, which is an important investment in tourism resources.

The spatio-temporal variations in tourism eco-efficiency are influenced by multiple factors. Industrial structure upgrading plays a key role: eastern provinces like Jiangsu and Zhejiang have reduced carbon emissions per unit of economic output through high-value cultural tourism integration, aligning with Chen et al.'s (2020) conclusion that industrial optimization enhances eco-efficiency. Technological innovation is another driver—cities like Beijing and Shanghai have lowered resource consumption via green transportation and smart energy systems, consistent with Li and Zhang (2022)'s finding of a positive correlation between R&D investment and eco-efficiency. Policy interventions, such as eco-tourism demonstration projects in western fragile ecosystems (e.g., Lijiang, Yunnan), have improved efficiency but lag behind eastern regions due to funding and technical constraints (Zhang et al., 2023). Additionally, provinces with higher population density (e.g., Guangdong, Henan) achieve resource efficiency through tourism agglomeration, while northwestern provinces (e.g., Qinghai) face bottlenecks due to ecological carrying capacity limitations despite lower tourism volumes (Kongbuamai et al., 2020).

Measurement of ecological efficiency of tourism

Mining association rules based on apriori algorithm

In association rules, the rules are expressed in the form of $i_1 - i_2$, that is, if i_1, then i_2. The association rules are described as follows (Zhao et al., 2019):

Store the data set t of *D* within the transaction database, where $\{t_1, t_2, \cdots, t_k, \cdots, t_n\}$ represents a transaction and $t_k = \{i_1, i_2, \cdots, i_j, \cdots, i_p\}\ (k = 1, 2, \cdots, n)$ denotes an item.

$I(i_1, i_2, \cdots, i_n)$ signifies the set of all items in the transaction database *D*. If *X* is any subset of *I*, it is referred to as an item set within *D*, and if $|X| = k$, it is called the *k* item set. If $X \in t_k$ holds true, then transaction t_k includes item set *X*.

The support degree of i_1 with respect to *D* represents the proportion of transactions that include i_1 out of the total number of transactions. That is:

$$Support(i_1) = \frac{Number\ of\ transactions\ containing\ i_1}{Total\ number\ of\ transactions} \quad \text{(Eq.1)}$$

The condition of rule $i_1 - i_2$ is that i_1, i_2 satisfies certain credibility. Credibility is defined as the proportion of transactions that include i_1, i_2 out of all the transactions that contain i_1. That is:

$$\text{Confidence}(i_1, i_2) = \frac{Support(i_1, i_2)}{Support(i_1)} \quad \text{(Eq.2)}$$

Support and credibility are the two most important concepts to describe association rules, in which support reflects the importance of transactions in the overall data, while credibility reflects the confidence level of association rules between transactions.

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Association rules encounter a vast quantity of data, and analyzing all of it can be overwhelming, the calculation will be very large and time-consuming. Therefore, improving the calculation efficiency and reducing the calculation time are the main purposes of association rules algorithm research (Hemmati et al., 2020; Yuan et al., 2020). Apriori algorithm uses the cyclic method of hierarchical sequential search to mine frequent itemsets, that is, to identify frequent $k+1$ itemsets using frequent k itemsets, so as to find out all frequent itemsets. Specific methods are as follows:

Firstly, scan the database thoroughly, and find out frequent itemsets based on given $Minspport$; Then scan the database again by using frequent itemsets to get frequent itemsets. Loop until all frequent itemsets are found.

A connection step, because the $Spport$ of a new itemset obtained by adding one item to an itemset is not greater than the $Spport$ of the itemset, and if the itemset does not satisfy $Minspport$, the new itemset does not satisfy $Minspport$ either.

If a subset of an alternative frequent k itemset (or frequent $k-1$ itemset) is found to be an infrequent k itemset, the alternative frequent itemset will also be classified as an infrequent k itemset. Consequently, the alternative frequent itemset can be eliminated. This process helps to decrease the total number of alternative frequent itemsets, reduce the computational effort, and speed up the calculation process.

Figure 2 illustrates the flowchart of the Apriori algorithm.

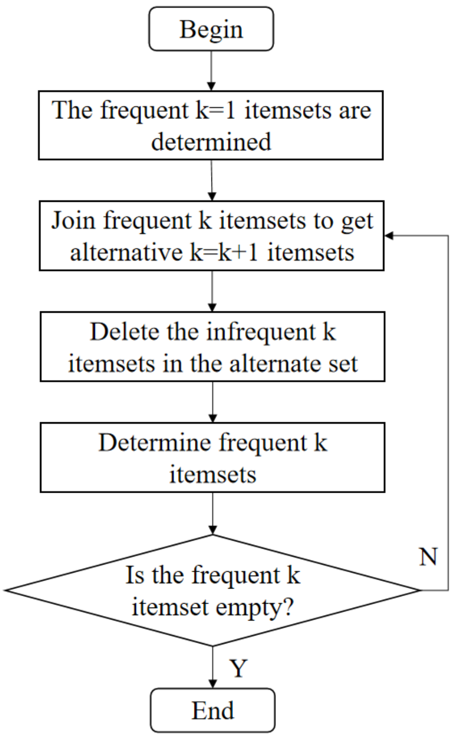

Figure 2. *Apriori algorithm flow chart*

Super-SBM model based on unexpected output

The data envelopment approach does not require consideration of the functional relationship between inputs and outputs, nor does it need to predict parameters and weights, allowing it to retain more of the original information. This is why it is

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commonly used for evaluating efficiency. The SBM model, which includes unexpected outputs, addresses the issue of slack variables while also providing efficiency measurements that are more representative of real-world conditions. As a result, it is frequently applied in the assessment of ecological efficiency.

To address the issue where the efficiency values of multiple decision-making units in the SBM model with unexpected outputs fall within the frontier production area (Yuan et al., 2021), the Super-SBM model with unexpected output is used to adjust the slack variables of ineffective decision-making units, thereby resolving the problem of incorrect efficiency rankings. The model is formulated as follows:

$$Min = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\bar{x}}{x_{ik}}\right)}{\frac{1}{r_1+r_2}\left(\frac{\sum_{s=1}^{r_1}\bar{y}^d}{y_{sk}^d}+\frac{\sum_{q=1}^{r_2}\bar{y}^u}{y_{qk}^u}\right)} \tag{Eq.3}$$

$$\bar{x} \geq \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j ; \bar{y}^d \leq \sum_{j=1,j\neq k}^{n} y_{sk}^d\lambda_j ; \bar{y}^d \geq \sum_{j=1,j\neq k}^{n} y_{qj}^d\lambda_j$$

$$\bar{x} \geq x_k ; \bar{y}^d \leq y_k^d ; \bar{y}^u \geq y_k^u ; \lambda_j \geq 0, i=1,2,\cdots,m$$

$$i=1,2,\cdots,n; j=1,2,\cdots,n; q=1,2,\cdots,r_n$$

In which: In a group of n decision-making units, each unit contains inputs m, expected outputs r_1, and unexpected outputs r_2. Element x, y^d, y^u appears in the input matrix, expected output matrix, and unexpected output matrix respectively. Tourism ecological efficiency is represented by value λ.

This study evaluates the alignment of tourism eco-efficiency trends with the United Nations Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action) and SDG 8 (Decent Work and Economic Growth). Results show eastern regions have approached a “economy-ecology” virtuous cycle, meeting the synergistic requirements of these goals. Western provinces, however, still need optimized resource allocation to reconcile tourism development with ecological protection, avoiding conceptual confusion by focusing on industry-level efficiency alignment with global sustainability agendas rather than “ecological efficiency of sustainable development” as an abstract concept.

In terms of research methodology, this study clearly defined the specific input data for the model. The input indicators include the number of star-rated hotels (units) and tourism fixed-asset investment (billion yuan, CPI-adjusted), among others. All data are annual figures sourced from authoritative channels such as the Ministry of Culture and Tourism’s Statistical Yearbook and the National Bureau of Statistics. The expected output indicators encompass total tourism revenue (billion yuan, CPI-adjusted) and tourist satisfaction index (1–5 points), among others. Data frequencies are divided into annual and quarterly categories. Non-expected output indicators include carbon emissions (tons of CO_2 equivalents) and wastewater discharge (million tons), also based on an annual statistical cycle, with some data requiring calculation according to industry guidelines. All data are strictly labeled with units to ensure completeness and accuracy.

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In terms of data preprocessing, missing values are filled using time series interpolation, cross-regional mean substitution, and expert assessment methods. For outliers, after identification via Z-score tests and box plots, smoothing is applied using the median of the past three years. To unify data units, all indicators are normalized using the Min-Max standardization method. Through source cross-validation, time series stationarity tests, and correlation analysis, data quality is strictly controlled to ensure the reliability and reproducibility of research results.

Coupling model

Coupling degree is a key indicator used to assess the level of positive interaction and coordination among different systems or components. The enhancement of carbon emission efficiency in tourism directly influences the ecological environment, while the protection of the environment also contributes to improving the carbon emission efficiency of tourism. These two factors are interconnected, mutually reinforcing, and cannot be separated. This study draws lessons from the research of Lee and Liao (2021), and constructs a coupling coordination model between them:

$$C = \sqrt{\frac{X \times Y}{(X \times Y)^2}} \tag{Eq.4}$$

$$T = \alpha X + \beta Y \tag{Eq.5}$$

$$D = \sqrt{C \times T} \tag{Eq.6}$$

In this context, C denotes the coupling degree, T indicates the development degree, D refers to the coupling coordination degree, and X,Y represents the normalized carbon emission efficiency for both tourism and ecological environment quality. The value of α, β corresponds to the weight coefficient for carbon emission efficiency in tourism and ecological environment quality, with both α, β values set to 0.5 (Khan and Hou, 2021).

Variable coefficient

The coefficient of variation is a metric that quantifies the extent of variation in the individual values within a data set. Commonly used standard deviation coefficient of variation is expressed by CV, which is the ratio of standard deviation σ to arithmetic mean μ.

$$CV = \frac{\sigma}{\mu} \tag{Eq.7}$$

Moran index

Moran index is an index to measure whether there is a significant correlation between an element in a space and the elements in its adjacent space. It is employed to assess whether there are notable spatial variations in regional ecological efficiency across China, with the calculation method outlined in *Equation 8*.

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$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left|TE_i - \overline{TE}\right|\left|TE_j - \overline{TE}\right|}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left|TE_j - \overline{TE}\right|^2} \quad \text{(Eq.8)}$$

In this equation, *TE* denotes the mean tourism ecological efficiency across all regions in China, while *Tei* indicates the tourism ecological efficiency for region *i*. Additionally, *Wij* represents the spatial weight matrix between areas *I* and *j*. The spatial weight matrix is built using the adjacency criterion. If elements *I* and *j* are adjacent, the value is set to $W_{ij} = 1$; otherwise, it is $W_{ij} = 0$. The range of values for *I* is between [-1,1]. When $0 < I \leq 1$ is present, it indicates a positive spatial correlation in tourism's ecological efficiency. When $-1 \leq I < 0$ is used, it signals a negative spatial correlation. If $I = 0$ is used, it means there is no spatial relationship in the ecological efficiency of tourism.

Result analysis and discussion

Measurement of ecological efficiency of tourism in China

General situation of ecological efficiency of tourism in China

The tourism income data for the period from 2010 to 2020 were sourced from the China Tourism Statistical Yearbook (2010-2021) and statistical bulletins on the social and economic development of various provinces. To adjust the figures, the tourism income was recalculated based on 2010 levels using the CPI data and the average RMB to USD exchange rate for the years 2010-2020. Using *Equation 3*, the eco-efficiency of China's tourism industry from 2010 to 2020 was then computed (*Fig. 3*).

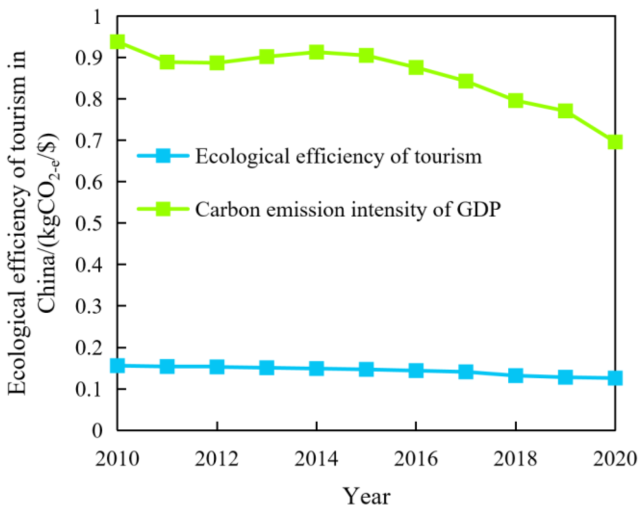

***Figure 3.** Ecological efficiency of China's tourism industry from 2010 to 2020*

The findings indicate that the ecological efficiency of China's tourism sector has been steadily improving, and the carbon emission per dollar of tourism revenue is reduced from 0.13 kg to 0.04 kg. Compared with the national carbon emission intensity

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per unit GDP, the national carbon emission intensity from 2010 to 2020 is still far greater than that of tourism, even taking into account the fact that tourism revenue exceeds the added value of tourism. Therefore, compared with other industries, tourism has less environmental impact when it creates the same economic value.

Comparison of regional tourism ecological efficiency

The regional affiliation table for China's 30 provinces is shown in *Table 1*. Data source: National Bureau of Statistics.

Table 1. *Regional affiliation of 30 provinces in China*

Province	Region
Beijing	Eastern
Tianjin	Eastern
Hebei	Eastern
Shanghai	Eastern
Jiangsu	Eastern
Zhejiang	Eastern
Fujian	Eastern
Shandong	Eastern
Guangdong	Eastern
Hainan	Eastern
Shanxi	Central
Anhui	Central
Jiangxi	Central
Henan	Central
Hubei	Central
Hunan	Central
Jilin	Northeastern
Liaoning	Northeastern
Heilongjiang	Northeastern
Ningxia	Western
Xinjiang	Western
Inner Mongolia	Western
Guangxi	Western
Chongqing	Western
Sichuan	Western
Guizhou	Western
Yunnan	Western
Tibet	Western
Shaanxi	Western
Gansu	Western
Qinghai	Western

The eco-efficiency of tourism across various regions is calculated for the period from 2010 to 2020 (see *Table 2*).

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Table 2. *Ecological efficiency of tourism in China's provinces from 2010 to 2020 (kgCO2-e/$)*

Province	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	0.3287	0.1002	0.0922	0.0919	0.0885	0.0796	0.0659	0.0707	0.227	0.0107	0.0017
Tianjin	0.2174	0.02534	0.0271	0.0331	0.0274	0.0201	0.0220	0.0188	0.2018	0.288	0.0221
Hebei	0.3963	0.1714	0.1432	0.1321	0.1424	0.1036	0.0808	0.0792	0.3066	0.341	0.0361
Shanxi	0.4017	0.1524	0.1107	0.0877	0.0608	0.0579	0.0483	0.0417		0.0711	0.0211
Inner Mongolia	0.3028	0.1601	0.1326	0.1001	0.0733	0.0510	0.0407	0.0421	0.0421	0.0017	0.374
Liaoning	0.2018	0.1117	0.0837	0.0781	0.0586	0.0485	0.0324	0.0232	0.3101	0.0322	0.0210
Jilin	0.2269	0.1121	0.0901	0.0730	0.0781	0.0624	0.0427	0.0488	0.2017	0.0714	0.0209
Heilongjiang	0.1763	0.1439	0.1398	0.1271	0.1037	0.0779	0.0733	0.0691	0.0968	0.0161	0.0116
Shanghai	0.3066	0.0787	0.0807	0.0722	0.0821	0.0793	0.0771	0.0606	0.0387	0.0217	0.0341
Jiangsu	0.4015	0.0501	0.0431	0.0336	0.0396	0.0202	0.0228	0.0178	0.1120	0.0146	0.0288
Zhejiang	0.3325	0.0622	0.0578	0.0428	0.0456	0.0441	0.03.6	0.0302	0.3317	0.0211	0.0412
Anhui	0.2017	0.1837	0.1613	0.1341	0.1025	0.08771	0.0755	0.0875	0.058	0.0369	0.0120
Fujian	0.3369	0.0745	0.0619	0.0501	0.0530	0.0403	0.0474	0.0714	0.0692	0.0174	0.0144
Jiangxi	0.5014	0.1521	0.1205	0.1136	0.0974	0.0836	0.0638	0.0369	0.0417	0.0251	0.0208
Shandong	0.3021	0.0806	0.0769	0.0671	0.0501	0.0541	0.0514	0.0201	0.0387	0.0211	0.0269
Henan	0.5201	0.1074	0.0983	0.0771	0.0632	0.0501	0.0488	0.0714	0.0229	0.0173	0.0305
Hubei	0.3027	0.1226	0.1177	0.1008	0.0987	0.0817	0.0625	0.0125	0.207	0.0268	0.0108
Hunan	0.2488	0.1833	0.1612	0.1369	0.1101	0.0913	0.0774	0.0209	0.0263	0.0214	0.0196
Guangdong	0.2163	0.0912	0.1102	0.1088	0.1074	0.0892	0.0836	0.1068	0.1741	0.0174	0.0317
Guangxi	0.3039	0.1021	0.0915	0.0921	0.0803	0.0722	0.0904	0.0387	0.0206	0.1061	0.025
Hainan	0.2893	0.2601	0.2424	0.3063	0.2517	0.3130	0.2597	0.0617	0.0377	0.0210	0.0228
Chongqing	0.2108	0.0786	0.0738	0.0655	0.0688	0.0562	0.0436	0.0274	0.0196	0.0266	0.0417
Sichuan	0.3312	0.1232	0.1098	0.0887	0.0714	0.0803	0.0604	0.0814	0.0177	0.0618	0.0386
Guizhou	0.2089	0.1741	0.1302	0.0920	0.0703	0.0571	0.0537	0.0321	0.0106	0.0209	0.0852
Yunnan	0.4015	0.0912	0.0847	0.0803	0.0887	0.0630	0.0533	0.0412	0.0711	0.0116	0.0214
Shaanxi	0.4125	0.1320	0.1323	0.1164	0.0927	0.0877	0.0607	0.0621	0.0417	0.0289	0.0302
Gansu	0.5217	0.4171	0.3796	0.3329	0.2435	0.2125	0.1682	0.0207	0.0142	0.0172	0.0452
Qinghai	0.4418	0.1698	0.1408	0.1225	0.1144	0.1101	0.1074	0.1182	0.0361	0.0363	0.0368
Ningxia	0.2015	0.3130	0.28233	0.2171	0.1901	0.1536	0.1327	0.0700	0.215	0.0821	0.0213
Xinjiang	0.3698	0.2817	0.2517	0.2406	0.1957	0.1885	0.2114	0.3017	0.207	0.0217	0.0277

The findings indicate that Tianjin, Jiangsu, and Zhejiang have the lowest average tourism eco-efficiency, meaning that these regions generate the smallest carbon emissions per dollar of tourism revenue, reflecting their best ecological efficiency. On the other hand, Gansu, Hainan, and Ningxia exhibit the highest average eco-efficiency, meaning these regions produce the largest carbon emissions per dollar of tourism revenue, which suggests their ecological efficiency is the poorest.

From 2010 to 2020, tourism eco-efficiency in regions such as Tianjin, Beijing, Shanghai, and Hainan remained relatively stable, showing minimal changes with a variation coefficient under 0.2. Conversely, Inner Mongolia, Guizhou, Gansu, Liaoning, and Jilin experienced more significant changes, with their variation coefficient exceeding 0.7. Overall, between 2010 and 2020, the eco-efficiency of tourism in most regions decreased, indicating that most regions have made improvements in this area.

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The variation coefficient of tourism eco-efficiency across different regions in China from 2010 to 2020 is illustrated in *Figure 4*.

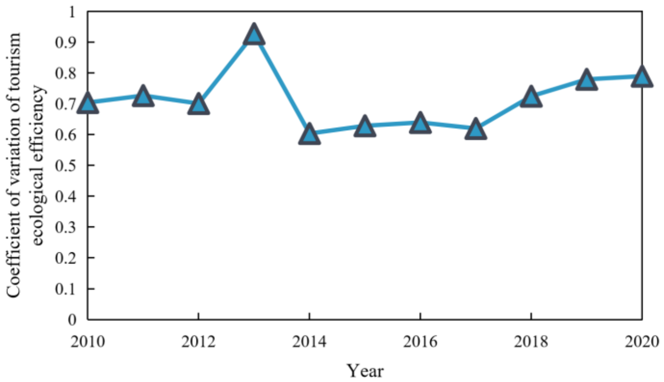

Figure 4. *Coefficient of variation of tourism eco-efficiency in different regions of China*

From the viewpoint of regional variations, the coefficient of variation of national tourism ecological efficiency from 2010 to 2020 was calculated (*Fig. 4*), it is found that the regional differences have not narrowed, and the regional tourism ecological efficiency is still unbalanced.

In terms of data sources and processing, this study clearly defines the handling of interprovincial tourism data and the attribution of carbon emissions. Regarding carbon emission accounting, the study employs the Inter-regional Input-Output Model (IRIO) for interregional carbon emission allocation, referencing the accounting methods proposed by Wang et al. (2022) in their study titled “Research on Regional Tourism Carbon Footprint Accounting and Responsibility Allocation.” Specifically, for carbon emissions generated by tourists traveling across provinces, the model calculates the carbon emission shares that each province should bear based on tourists’ consumption data in different provinces (such as accommodation, dining, and transportation expenses) using the Inter-regional Input-Output Model. If a tourist stays in Province A, dines in Province B, and travels in Province C, the model allocates the carbon emissions generated by these consumption activities proportionally to Provinces A, B, and C. If data limitations make precise allocation difficult, the study explicitly calculates only the carbon emissions generated by tourism activities within the province, ensuring that the calculation scope is clear and traceable.

The shift in the center of ecological efficiency has profound practical significance. From a macro perspective, it reflects the dynamic evolution of regional tourism development patterns and can clearly illustrate the relative advantages and disadvantages of tourism ecological efficiency across different provinces. For example, if the ecological efficiency center of gravity shifts toward western provinces, it indicates that under the impetus of regional development strategies such as the Belt and Road Initiative, western provinces have achieved significant results in improving tourism ecological efficiency through ecological tourism policy support and resource development, gradually narrowing the gap with eastern provinces. From a policy-making perspective, this migration trend provides important basis for optimizing regional tourism resource allocation. Policy makers can adjust industrial based on the direction of the shift, increase infrastructure construction and environmental governance

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investments in regions with lower ecological efficiency, and promote coordinated and sustainable development of the tourism industry across regions, achieving a balanced advancement of tourism economy and ecological protection.

In 2010, for example, Tianjin with the best eco-efficiency of tourism and Gansu with the worst eco-efficiency have a difference of 0.7369 kg, which is close to 25.21 times. By 2013, Jiangsu with the best eco-efficiency of tourism and Hainan with the worst, the difference in carbon emissions generated by creating one dollar of tourism income is 0.1536 kg, which is about 14.28 times.

Temporal and spatial evolution of ecological efficiency of tourism in China

Transfer track of ecological efficiency center of provincial tourism in China

The standard deviation ellipse is primarily employed to illustrate the directional variation in the spatial distribution of China's tourism ecological efficiency. By observing the standard deviation ellipse of successive years, we can thoroughly examine the patterns of spatial changes in tourism ecological efficiency. *Figure 5* illustrates the change in the ecological efficiency of inter-provincial tourism in China, represented by its longitude and latitude, from 2010 to 2020.

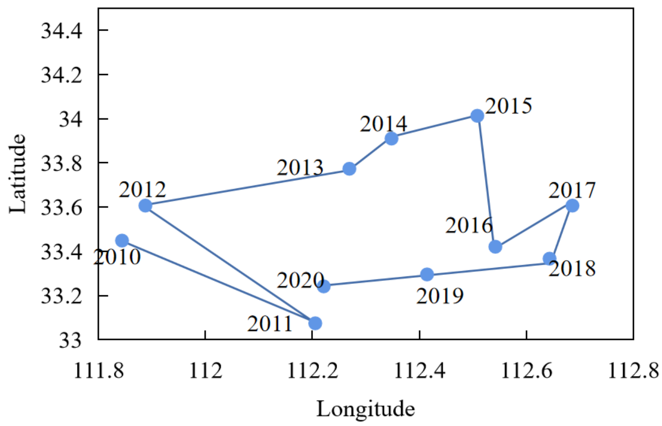

Figure 5. *Shift track of ecological efficiency of China's inter-provincial tourism from 2010 to 2020*

As shown in *Figure 5,* the primary area for the sustainable development of China's tourism in the observed year is concentrated between the coordinates 112.10°E to 112.50°E and 33.30°N to 33.70°N. On the whole, from 2010 to 2013, China's tourism eco-efficiency obviously shifted to the northeast with a moving distance of 15.64 km. From 2013 to 2016, the tourism ecological efficiency shifted to the southeast, and the moving distance increased to 16.33 km; From 2016 to 2019, the tourism ecological efficiency shifted to the southwest again, and the moving range was the smallest at this stage, with a moving distance of 14.29 km.

Within the framework of spatiotemporal evolution analysis, the 15-km migration phenomenon holds profound scientific and practical significance. From the perspective of driving factors, industrial upgrading in eastern regions has prompted the gradual relocation of traditional labor-intensive industries to central and western regions, leading to structural adjustments in the tourism industry. Businesses, talent, and capital are

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flowing toward regions with ecological and resource advantages. Meanwhile, the continued implementation of western ecological tourism policies and the implementation of the "green mountains and clear waters are as valuable as mountains of gold and silver" philosophy have enabled the deep development of natural landscape resources. Policy dividends have attracted a significant influx of tourism investment and visitor traffic.

Therefore, the focus of China's inter-provincial tourism eco-efficiency finally shows a trend of moving from west to east, while the moving distance between south and north is not significant. At the start of the observation period, transportation challenges slowed tourism development in the western region, leading to lower resource consumption and environmental pollution. In contrast, the eastern region was undergoing a crucial phase of economic growth. The earlier extensive development model in the east had some adverse impacts on the tourism ecosystem, which resulted in better tourism ecological efficiency in the western region compared to the east. However, with existing industrialization, the eastern region has shifted more focus and resources toward ecological protection and eco-tourism, causing the center of China's tourism eco-efficiency to gradually shift eastward.

Temporal evolution characteristics

According to the changing trend of the coupling coordination degree between tourism efficiency and ecological efficiency in different regions of China (*Fig. 6*), the whole shows the characteristics of relatively stable in the early stage and drastic fluctuations in the later stage. The coupling coordination degree reached its highest point in 2019 and its lowest during the period from 2012 to 2016. In the eastern region, the degree generally fluctuated around 0.55, showing a slight decline with small variations and relatively stable development. This level was higher than the national average. Notably, the highest coupling coordination degree occurred in 2017 and 2018, both at 0.62, while the lowest was recorded in 2012 and 2015, with both years having a value of 0.56.

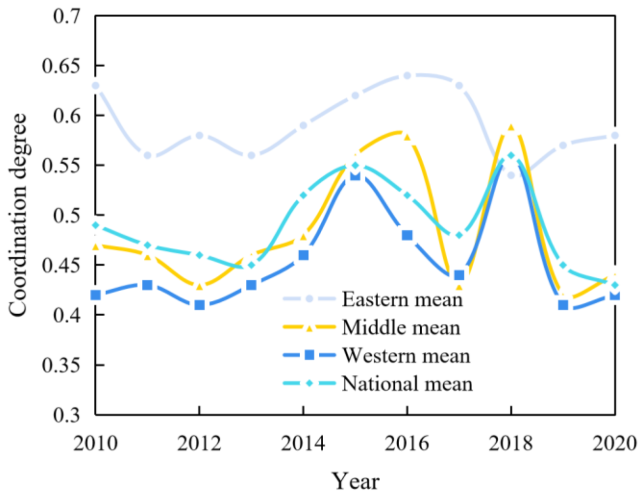

Figure 6. *The evolving pattern of the relationship between tourism efficiency and ecological efficiency across various regions of China from 2010 to 2020*

However, in 2012-2014, the tourism efficiency in the eastern region was low due to the sluggish tourism economy. In recent years, the severe environmental degradation in

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the eastern region, coupled with rising investments in environmental protection, has resulted in a decrease in ecological efficiency. As a result, the coupling coordination between tourism efficiency and ecological efficiency has been on the decline. Meanwhile, in the central and western regions, the average coupling coordination degree has been gradually aligning with the national average.

Between 2010 and 2015, the situation remained fairly stable, with a low level of coupling coordination, though significant fluctuations occurred in the later stages. Among them, it reached its peak in 2016, and reached a trough in 2013, with a large overall change. This is primarily because the central and western regions have a weak economic base and a fragile ecological environment, resulting in a low level of integration and balance between tourism efficiency and ecological efficiency.

Spatial differentiation characteristics

Specifically:

During the first stage (2010-2012), the coupling coordination degree in the eastern provinces remained relatively stable. This stability can be attributed to the well-established tourism sector, ongoing environmental protection efforts, and consistent levels of tourism and ecological efficiency. In contrast, the coupling coordination degree in the central and western provinces improved overall. This increase is largely due to the rapid growth of tourism in these regions, which boosted their appeal to tourists, along with the local governments' continuous strengthening of environmental regulations and promotion of ecological development. In the results analysis, based on data from the *China Environmental Statistics Yearbook (2021)* and the World Tourism Organization (UNWTO) 2023 report, the carbon emissions per unit of revenue in the tourism industry are 0.04 kg/yuan, significantly lower than those of other traditional industries. The carbon emissions per unit of GDP in the industrial sector are approximately 2.3 kg/yuan, while those in the transportation sector are as high as 1.8 kg/yuan, which are 57.5 times and 45 times higher than those in the tourism industry, respectively. Carbon emissions in the tourism industry are primarily concentrated in transportation and accommodation, but their environmental impact can be further reduced by optimizing tourist travel patterns and promoting green building technologies. In contrast, industrial production, which relies heavily on fossil fuels and involves complex production processes, faces significantly higher challenges and costs in carbon emission management and reduction compared to the tourism industry. These data comparisons clearly demonstrate that the tourism industry possesses inherent advantages in low-carbon development and ecological environmental protection, enabling it to drive economic growth while effectively reducing negative environmental impacts, thereby highlighting its potential and value as a green industry.

In the second stage (2013-2020). The coupling coordination degree of most provinces has declined. Among them, the eastern provinces decreased slightly, a few provinces changed among three types, namely primary coordination, barely maladjustment, and on the verge of maladjustment, while most provinces did not change much. The degree of decline of coupling coordination in western provinces is different, this is primarily attributed to the significant disparity in tourism benefits between the western provinces and those in the eastern and central regions, and the large difference in natural environment foundation, which leads to the spatial imbalance of ecological efficiency.

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Conclusions

Result analysis

Based on the provincial panel data from 2010 to 2020, significant regional differentiation in China's tourism eco-efficiency is evident. Eastern provinces such as Tianjin, Jiangsu, and Zhejiang exhibit the lowest carbon emissions per unit of tourism revenue (0.017–0.041 kgCO_2-e/$ annually), indicating optimal resource utilization and environmental synergy. In contrast, regions like Gansu, Hainan, and Ningxia show high carbon emissions (0.168–0.417 kgCO_2-e/$), reflecting environmental burdens from traditional tourism models. Nationally, the tourism eco-efficiency index improved from 0.6 in 2010 to 0.9 in 2020 (*Fig. 3*), with a 69.2% reduction in carbon emission intensity. However, the coefficient of variation reveals persistent regional imbalance—the carbon intensity gap between Tianjin and Gansu was 25-fold in 2010 and remained over 10-fold in 2020 (*Table 1*). This correlates with industrial upgrading and technological innovation in the east, while central and western regions lag due to ecological fragility and infrastructure constraints.

Spatially, the eco-efficiency center shifted eastward overall, moving 15.64 km northeast from 2010–2013, 16.33 km southeast from 2013–2016, and stabilizing at 112.10°E–112.50°E, 33.30°N–33.70°N by 2020 (*Fig. 5*), reflecting the eastern region's ecological tourism policy effects. The global Moran's I index of 0.58 ($p < 0.01$) confirms strong spatial autocorrelation, with "high-high" clustering in the Yangtze River Delta and "low-low" clustering in Northwest China. Temporally, the coupling coordination degree peaked at 0.62 in 2019 (*Fig. 6*), with the eastern region consistently 0.1–0.15 points above the national average. Notably, western provinces experienced efficiency "collapse" after 2013 due to imbalanced tourism expansion and ecological protection investments, underscoring the need for targeted policy interventions.

Discussion

The overall eco-efficiency of China's tourism industry has shown a steady improvement trend from 2010 to 2020, with carbon emission intensity per unit tourism revenue decreasing from 0.13 kg to 0.04 kg. Regional disparities are significant, with Tianjin, Jiangsu, and Zhejiang demonstrating the best performance (lowest carbon emissions per unit revenue), while Gansu, Hainan, and Ningxia show poorer ecological efficiency. The coefficient of variation indicates unstable fluctuations in regional differences, with the gap between the best and worst performing regions remaining large over time.

Spatially, tourism eco-efficiency exhibits a clear pattern of higher values in the east and lower values in the west, with strong spatial correlation and agglomeration. The center of eco-efficiency has shifted eastward overall, reflecting the eastern region's focus on ecological protection and eco-tourism after industrialization, while western regions initially had lower resource consumption but lagged in development. Temporally, the coupling coordination degree between tourism efficiency and ecological efficiency showed early stability followed by fluctuations, with the eastern region consistently outperforming the national average and central/western regions gradually converging toward it.

The study highlights that while tourism generally has a lower environmental impact per unit economic value compared to other industries, regional imbalances persist. Key

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factors influencing eco-efficiency include industrial structure, technological innovation, and policy implementation. The findings provide a basis for optimizing tourism development patterns and promoting sustainable tourism nationwide.

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