



Evaluation and influencing factors of the tourism industry efficiency under carbon emission constraints in China

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Abstract A significant industrial transformation in China's tourism sector is currently taking place in response to carbon peak and carbon neutrality targets. This paper applies the data envelopment analysis (DEA) model to calculate the efficiency of the tourism industry under carbon emission constraints and further investigates its influencing factors through the Tobit regression. The results are as follows: (1) The tourism efficiency under carbon emission constraints of China from 2000 to 2019 showed a trend of first rising and then declining, and there were obvious regional differences; (2) from 2000 to 2019, the total factor productivity of tourism in China increased significantly, while the contributions of technical progress, pure technical efficiency, and scale efficiency decreased sequentially; (3) the factors of industrial structure, transportation convenience, economic development level, degree of opening to the outside world, and the level of scientific and technological development have varying degrees of influence on tourism efficiency. Based on the analysis results, this paper puts forward several policy suggestions on tourism efficiency and low-carbon development. The

findings of this paper have some bearing on developing nations' efforts to boost tourism efficiency and realize high-quality industry growth within the framework of sustainable development.

Keywords Tourism industry efficiency · Carbon emission · DEA-Malmquist · Tobit regression

Abbreviations

CE	Comprehensive efficiency
CRS	Constant returns to scale
DEA	Data envelopment analysis
DMU	Decision-making unit
DOW	Degree of opening to the outside world
DTC	Degree of transportation convenience
IS	Industrial structure
LE	Level of economic development
LST	Level of scientific and technological development
MI	Malmquist index
SE	Scale efficiency
TE	Technical efficiency
TFP	Total factor productivity
VRS	Variable returns to scale

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Introduction

Climate change has become one of the most severe environmental problems in the world (Parmesan & Yohe, 2003). In 2020, the Chinese president announced China's

“carbon peaking and carbon neutrality goals” at the 75th United Nations General Assembly in an effort to address the environmental crisis caused by climate change and achieve high-quality development. The “carbon peaking and carbon neutrality goals” means reaching carbon neutrality by 2060 after reaching the carbon peak by 2030. The Ministry of Culture and Tourism of China reported that the comprehensive contribution of tourism to GDP in 2019 was 10.94 trillion RMB or 11.05% of total GDP and that it directly and indirectly employed 79.87 million people or 10.31% of the nation’s working population (Yang, 2020a, b). Tourism has become one of the cornerstones of the Chinese economy. At the same time, the results of the estimation of the global tourism carbon emissions by the World Tourism Organization in 2005 showed that the greenhouse gas emissions caused by tourism in 2005 accounted for 4.9% of the global total emissions, and by 2035, CO₂ emissions will more than double (UNWTO & UNEP, 2007). A report published by the UNWTO mentioned that transport-related emissions from tourism had reached 5% in 2016 (UNWTO, 2019). If the entire tourism industry is considered, the value must be higher. Therefore, it is of great practical significance to improve the low-carbon efficiency of tourism and promote its development by studying tourism efficiency under carbon emission constraints based on the background of the “carbon peaking and carbon neutrality goals”.

The researchers tried to use various methods for studying tourism efficiency. For example, based on the building of indicators to assess the quality and efficiency of tourism development, Yang (2020a, b) tested the impact of the Internet on the quality and efficiency of Chinese tourism development using provincial panel data and various related measurement methods. Guo et al. (2022) developed an evaluation framework to identify macro-external determinants affecting tourism eco-efficiency based on the geographical detector model. From the literature review, due to the advantages of data envelopment analysis (DEA) compared with other methods, an increasing number of researchers tend to use this method to analyze tourism efficiency (Assaf & Josiassen, 2015). Fragoudaki and Giokas (2016) estimated the efficiency scores of 38 Greek airports using the DEA method and then used statistical evaluations (Mann–Whitney *U* and Kruskal–Wallis tests) and censored Tobit regression models to identify which factors significantly explain variations in the airport efficiency. Li et al. (2020) used DEA to analyze the non-linear relationship between

the intensity of tourism economic linkages and the efficiency of the tourism industry in urban agglomeration on the west side of the straits by constructing a mixed effect model. Wang et al. (2020) used DEA and social network analysis to explore the evolution characteristics of the spatial network structure of tourism efficiency in China at the provincial level from 2011 to 2016. Yuan and Liu (2020) used the DEA and the Malmquist models to measure the tourism livelihood efficiency of 21 cities in Guangdong Province from 2010 to 2017. Based on the Epsilon-based measure super-efficiency model and the global Malmquist-Luenberger index analysis method, Li et al. (2021) studied the tourism development efficiency of 58 major cities in China from 2001 to 2016 and analyzed the total factor productivity (TFP) and its driving factors in urban tourism development. And some researchers have also used the DEA model to estimate the efficiency of low-carbon tourism. Han et al. (2015) measured the carbon emissions of the tourism industry in five provinces in China and then used the traditional DEA model and the unexpected output DEA model to evaluate the efficiency of the tourism industry in five provinces in China, considering carbon emission indicators. Zha (2016) used the logarithmic average weight Divisia decomposition method to decompose the carbon emissions intensity of the tourism industry based on measuring the development efficiency of low-carbon tourism in China with reference to the DEA-SBM directional distance function. Zha et al. (2019) used the SBM undesirable model to measure and analyze the development efficiency and dynamic fluctuations of the low-carbon tourism economy in 17 cities of Hubei Province from 2007 to 2013. Wang and Wang (2021) calculated the total tourism carbon emissions in the Yangtze River Economic Belt from 2011 to 2017 and used the traditional DEA model and the non-radial SBM model to analyze the influence degree of carbon emissions on the efficiency of the tourism industry.

The Tobit model has received increasing attention in studies on factors influencing efficiency. Examples include the water resource system (Liang et al., 2021), coal resources (Xue et al., 2021), sustainable development level (Huang et al., 2021), and safety management (Miao et al., 2020). The Tobit model can also be used to analyze factors that influence the efficiency of the tourism industry. Choi et al. (2021) used the Tobit model to analyze the determinants of the efficiency change of Korean festival tourism. Jiang et al. (2022) estimated the tourism carbon dioxide

emission efficiency of each province in China based on the Epsilon-based measure and verified the tourism carbon dioxide emission efficiency impactors by the Tobit model.

Current literature suggests that the study of tourism efficiency using the DEA-Tobit model is extensive. For example, Liu et al. (2017) applied the DEA-Tobit model to evaluate the tourism eco-efficiency of 53 coastal cities in China from 2003 to 2013 and discussed the comprehensive efficiency levels, regional differences, eco-efficiency types, and influencing factors. In the study by Song and Li (2019), a panel Tobit model is used to analyze the determinants of comprehensive technical efficiency of the tourism industry. However, there have been few studies on the efficiency of tourism under carbon emission constraints. Related results are still relatively scarce, although scholars have started to use different methods to analyze tourism efficiency under carbon constraints in terms of tourism carbon emissions measurement, tourism efficiency assessment, and impact factor analysis.

This paper uses the DEA model and Tobit regression to study tourism efficiency and its influencing factors under carbon emission constraints to provide more theoretical support for developing the tourism industry against the backdrop of “carbon peaking and carbon neutrality goals” and sustainable development. This study makes the two following contributions to the field of research on tourism efficiency under carbon emission constraints: (1) This study collects basic data to complete the calculation of carbon emissions in the tourism industry, the measurement of tourism efficiency under carbon emission constraints, and the analysis of influencing factors, ensuring the consistency of the research and avoiding the inaccuracy of the efficiency measurement results that may be caused by inconsistent data sources. (2) More comprehensive and accurate measurement results are the premise of effectively identifying the influencing factors of tourism efficiency. The dataset for this study includes data from a total of 20 years, from 2000 to 2019, enhancing the continuity and accuracy of the research findings and offering a solid foundation for monitoring and assessing the change in tourism efficiency. The remaining chapters are structured as follows: "Material and methods" introduces the research methods and data processing; "Results" describes the

research results; "Discussion" presents a discussion of the results; and "Conclusion" presents the conclusions.

Material and methods

DEA model

DEA is a non-parametric method to measure and evaluate the relative performance of decision-making units (DMUs) proposed by Charnes et al. (1978) based on Farrell’s theory of efficiency measurement. Analyzing efficiency in the case of multiple inputs and outputs is appropriate. Based on the BCC model of the variable returns to scale (VRS), this paper measures the comprehensive efficiency (CE) of China’s tourism industry under carbon emission constraints, as well as the technical efficiency (TE) and scale efficiency (SE) obtained by decomposition (Banker et al., 1984). Based on the calculations, a static analysis of the horizontal comparison of the 31 provincial administrative regions has been conducted. When calculating the efficiency of the tourism industry under carbon emission constraints, it is necessary to process the undesirable output data of carbon emissions, mainly as input, vector transfer, conversion reciprocal, and other methods (Wu & Wu, 2009). This paper has chosen the second method. By multiplying each undesirable output by “−1”, a suitable translation vector M is found (the value of M in this paper is 2000), which is turned into a positive indicator (Seiford & Zhu, 2002). Assuming that the number of $DMUs$ is n , the types of resource input X_j , output Y_j , and unexpected output Z_j of each DMU are m , u , and k , respectively, and $Z'_j = -Z_j + M$, and then, the DEA-BBC model formula is as follows:

$$\left\{ \begin{array}{l} \min \theta_0 \\ \sum_{j=1}^n \omega_j X_{ij} + S_i^- = \theta_0 X_{i0}, \quad i = 1, 2, \dots, m \\ \sum_{j=1}^n \omega_j Y_{tj} - S_t^+ = Y_{t0}, \quad t = 1, 2, \dots, u \\ \sum_{j=1}^n \omega_j Z'_{vj} - S_v^+ = Z'_{v0}, \quad v = 1, 2, \dots, k \\ \sum_{j=1}^n \omega_j = 1 \\ \omega_j, S_i^-, S_t^+, S_v^+ \geq 0 \end{array} \right. \quad (1)$$

where θ_0 is the effective value of the DMU_{j0} , ω_j is the coefficient of the effective DMU combination reconstructed relative to DMU_{j0} , and S_t^-, S_t^+ , and S_v^+ are slack variables.

Malmquist model

This study uses the Malmquist index (MI) model to analyze the dynamic changes of tourism TFP under carbon emissions constraints in 31 provincial-level administrative regions from 2000 to 2019. The MI is a concept proposed by Swedish economist Professor Malmquist in 1953. When the data of the evaluated DMU is panel data consisting of a series of observations at different time points, the method can pinpoint changes in productivity and the role of technical efficiency and technological progress. The MI model calculates the productivity change from 1 year to the next to obtain the TFP index and then makes a dynamic analysis of TFP. This method has been widely used in the study of tourism TFP (Sun et al., 2015). In the past, there was disagreement on the decomposition of MI, and the method of Ray and Desli was gradually accepted (Fare et al., 1994, 1997; Ray & Desli, 1997; Zhang & Gui, 2008). The decomposition formula is as follows:

$$\begin{aligned}
 M(x^t, y^t, x^{t+1}, y^{t+1}) &= \frac{D_V^{t+1}(x^{t+1}, y^{t+1})}{D_V^t(x^t, y^t)} \times \left(\frac{D_V^t(x^t, y^t)}{D_V^{t+1}(x^t, y^t)} \frac{D_V^t(x^{t+1}, y^{t+1})}{D_V^{t+1}(x^{t+1}, y^{t+1})} \right)^{1/2} \\
 &\times \left(\frac{D_C^t(x^{t+1}, y^{t+1})/D_V^t(x^{t+1}, y^{t+1})}{D_C^t(x^t, y^t)/D_V^t(x^t, y^t)} \frac{D_C^{t+1}(x^{t+1}, y^{t+1})/D_V^{t+1}(x^{t+1}, y^{t+1})}{D_C^{t+1}(x^t, y^t)/D_V^{t+1}(x^t, y^t)} \right)^{1/2} \\
 &\times PEch \times TPch \times SEch
 \end{aligned}
 \tag{2}$$

where $D_C^t(x^t, y^t)$ and $D_C^t(x^{t+1}, y^{t+1})$ refer to the distance functions of DMUs in period t and period $t+1$ based on the constant returns to scale (CRS) with reference to the data in period t ; $D_V^t(x^t, y^t)$ and $D_V^t(x^{t+1}, y^{t+1})$ refer to the distance functions of DMUs in period t and period $t+1$ based on the VRS with reference to the data in period t . The meanings of $D_C^{t+1}(x^t, y^t)$ and $D_V^{t+1}(x^t, y^t)$ are similar. When M is greater than 1, it indicates an increase in TFP from period t to period $t+1$, and when M is less than 1, it indicates a decrease in TFP. PEch, TPch, and SEch

represent pure TE change, technical progress change, and SE change, respectively. PEch > 1 means that the improvement of management has improved efficiency, TPch > 1 means technical progress, and SEch > 1 means that the DMU is moving towards the most efficient excellent size close.

Tobit regression analysis of influencing factors

The Tobit model was proposed by the American economist Tobin in 1958, and it is more suitable for intercepted regression analysis (Tobin, 1958). Using Tobit can avoid the bias and inconsistency of using the ordinary least squares when the dependent variable is a cut-off value or a fragmented value. The numerical values of CE, TE, and SE of the tourism industry calculated by the DEA model are between 0 and 1, and the regression based on them belongs to the regression analysis model with limited dependent variables. Therefore, the maximum likelihood method should be used to better avoid the biased or inconsistent parameter estimation that may be caused by the ordinary least squares method (Li et al., 2019). This section analyzes the factors that affect tourism efficiency using the Tobit model

based on maximum likelihood estimation and builds the Tobit regression model of the five influencing factors: IS (\mathcal{X}_1), DTC (\mathcal{X}_2), LE (\mathcal{X}_3), DOW (\mathcal{X}_4), and LSC (\mathcal{X}_5) (Table 2). These five influencing factors are related to tourism CE, TE, and SE. The effect of heteroscedasticity is removed for \mathcal{X}_2 , \mathcal{X}_3 , and \mathcal{X}_4 by taking the logarithm. And the specific models are as follows:

$$\begin{aligned}
 \mathcal{Y}_{CE} &= \mathcal{Z}_1 + \beta_{CE1} \mathcal{X}_1 + \beta_{CE2} \ln \mathcal{X}_2 + \beta_{CE3} \ln \mathcal{X}_3 \\
 &+ \beta_{CE4} \ln \mathcal{X}_4 + \beta_{CE5} \mathcal{X}_5 + \mu_{OEi}
 \end{aligned}
 \tag{3}$$

$$\mathcal{Y}_{TE} = \mathcal{Z}_2 + \beta_{TE1} \mathcal{X}_1 + \beta_{TE2} \ln \mathcal{X}_2 + \beta_{TE3} \ln \mathcal{X}_3 + \beta_{TE4} \ln \mathcal{X}_4 + \beta_{TE5} \mathcal{X}_5 + \mu_{TEi} \tag{4}$$

$$\mathcal{Y}_{SE} = \mathcal{Z}_3 + \beta_{SE1} \mathcal{X}_1 + \beta_{SE2} \ln \mathcal{X}_2 + \beta_{SE3} \ln \mathcal{X}_3 + \beta_{SE4} \ln \mathcal{X}_4 + \beta_{SE5} \mathcal{X}_5 + \mu_{SEi} \tag{5}$$

where \mathcal{Y} is the dependent variable; \mathcal{Y}_{OE} , \mathcal{Y}_{TE} , and \mathcal{Y}_{SE} represent the CE, TE, and SE of the tourism industry, respectively; \mathcal{Z} is the constant term of the regression equation; β is the regression coefficient under the corresponding efficiency of each variable; i is the number of decision units; and μ_i is the residual.

Calculation of carbon emissions from the tourism industry

Based on past research ideas, this paper measures the carbon emissions of the Chinese tourism industry (Tang et al., 2018). The steps of the computation are as follows.

$$Q_T = \sum_{i=1}^n \alpha \cdot N_i \cdot D_i \cdot P_{Ti} \tag{6}$$

$$Q_H = 365 \cdot C \cdot R_k \cdot P_{He} \cdot P_{Hc} \cdot \frac{1}{1000} \cdot \frac{44}{12} \tag{7}$$

$$Q_A = \sum_{i=1}^n M \cdot \omega_i \cdot P_{Ai} \tag{8}$$

$$Q = Q_T + Q_H + Q_A \tag{9}$$

In Eq. (6), Q_T is the carbon emissions of tourism transportation; α is the proportion of tourists in the passenger flow of different transportation modes; N_i is the number of passengers who choose the i -type transportation mode; D_i is the distance of the passengers who choose the i -type transportation mode; $N_i \cdot D_i$ represents the passenger turnover (passenger kilometers, pkm) of the i -type transportation mode; P_{Ti} is the carbon emissions coefficient (g/pkm) of the i -type transportation mode; n represents the total number of transport modes, including aircraft, cars, trains, and water transport. In Eq. (7), Q_H is the carbon emissions of tourist accommodation; C is the total reception capacity of the tourist accommodation industry (represented by the total number of beds); R_k is the annual bed occupancy rate of the tourist

accommodation industry; P_{He} is the unit energy consumption factor of the bed per night; P_{Hc} is the carbon content per unit of calorific value; $1/1000$ is the unit conversion factor; $44/12$ is the conversion factor from C to CO₂. In Eq. (8), Q_A is the carbon emissions of tourism activities; M is the number of tourists; ω_i is the proportion of tourists who choose the i -type tourism activities; P_{Ai} is the unit carbon emissions coefficient of the i -th type of tourism activities. In Eq. (9), Q represents the total carbon emissions of tourism; Q_T is the carbon emissions from tourism transport; Q_H is the carbon emissions from tourist accommodation; Q_A is the carbon emissions from tourism activities.

Indicator selection

Selection of tourism efficiency evaluation indicators

In related DEA model studies, indicators such as land, labor, and capital were usually selected as input variables, and indicators such as economic, social, and environmental benefits were selected as output variables (Song et al., 2012). As a comprehensive industry, the production capacity of the tourism industry is not restricted by the amount of land, so the land factor is not used as an input variable in this paper. Fixed asset investment can better reflect the capital investment of an industry, so this study selects tourism-related fixed asset investment in the tertiary industry as the capital factor indicator. Due to the strong comprehensiveness of tourism, it is difficult to measure the direct and indirect employment in the Chinese tourism industry. This paper selects tourism employment numbers from tertiary industries as inputs to the tourism labor factor. The total energy consumption of tourism is selected as the input of energy elements to reflect the level of input of relevant elements of the tourism industry more comprehensively. In the selection of output indicators, the total tourism revenue is considered as the expected output in this paper. When measuring the efficiency of the tourism industry under the constraint of carbon emissions, the total carbon emissions of the tourism industry are added to the measurement model. In summary, this paper constructs a system of evaluation metrics for tourism industry efficiency under carbon emission constraints, as shown in Table 1 (Gao et al., 2022; Jiang et al., 2022; Wang et al., 2020).

Table 1 Efficiency evaluation index system of the tourism industry under carbon emission constraints

	Indicator categories	Specific indicators
Input indicators	Capital investment	Fixed asset investment in tourism
	Labor input	Number of employees in the tourism industry
	Energy input	Energy consumption in tourism
Output indicators	Expected output	Total revenue in tourism
	Undesired output	Carbon dioxide emissions in tourism

Determination of influencing factors

The research on factors affecting tourism efficiency in China has gradually increased in recent years. After sorting out and referring to relevant literature, this paper selects the indicators shown in Table 2 from five aspects to analyze the influencing factors of tourism efficiency (Gao et al., 2022; Jiang et al., 2022; Liu et al., 2021; Wang & Wang, 2021). These five aspects include industrial structure (IS), the degree of transportation convenience (DTC), the level of economic development (LE), the degree of opening to the outside world (DOW), and the level of scientific and technological development (LST).

1. Industrial structure. From the perspective of IS, the proportion of an industry is an indicator that directly reflects the importance of the industry to the development of the local economy. Industries with a large scale of output value or an increasing proportion of output value can often get the government's attention and more capital or policy support, thereby affecting industrial efficiency. The impact of this situation on the input and output of the industry is often in the same direction, so to find out what kind of impact on industrial efficiency needs data analysis. This paper uses the proportion of GDP of the tertiary industry to reflect the IS to verify the impacts of IS on the efficiency of the tourism industry.
2. The degree of transportation convenience. Whether transportation is convenient or not directly affects the tourist's travel experience. Decent transportation conditions can reduce the time cost of tourists and attract more visitors to tourist destinations. Within reasonable limits, it has the potential to have a significant impact on the size and efficiency of the tourism industry. Therefore, it is also one of the essential factors affecting the efficiency of the tourism industry to be studied in this part. In this paper, the density of the road network is used to reflect the convenience of transportation, and the influence of DTC on the efficiency of the tourism industry is explored.
3. The level of economic development. Tourism development requires consumers to have sufficient spending power and developers to have sufficient funds for destination development. At the same time, it also requires that the area where the tourism destination is located has sufficient financial support to invest in the construction of service facilities. The level of local economic development is somewhat correlated with the points above. Without considering additional variables, the input and output of the tourism industry increase as LE increases, suggesting that LE may significantly impact how efficiently the industry operates. Therefore, to understand the factors that affect the effectiveness of the tourism

Table 2 Selection of influencing factors of tourism efficiency

Influencing factors	Specific indicators	Symbols
Industrial structure	The proportion of GDP of the tertiary industry	IS
The degree of transportation convenience	The density of the road network	DTC
The level of economic development	Per capita GDP	LE
The degree of opening to the outside world	Foreign investment	DOW
The level of scientific and technological development	Energy consumption per 100 million yuan of tourism revenue	LST

industry, LE is crucial. This study uses per capita GDP as a particular indicator of LE.

4. The degree of opening to the outside world. On the one hand, increasing DOW can increase the scale and income of the tourism industry by attracting additional tourists. On the other hand, more foreign capital can be attracted to invest in its construction, and foreign advanced technology and even management experiences will be introduced. DOW can affect the input and output of the tourism industry from the above aspects and then has an impact on the efficiency of the tourism industry. Therefore, DOW is also an essential aspect in analyzing the factors affecting the efficiency of the tourism industry. This article uses the amount of foreign investment to reflect DOW.
5. The level of scientific and technological development. Improving technology is one of the basic ways to improve industrial efficiency, so the level of scientific and technological development will also affect tourism development. Tourism is a highly comprehensive industry, so when LST increases the efficiency of some tourism-related industries, the efficiency of tourism will also increase. Energy-saving technologies are key to improving energy efficiency in various industries under carbon emissions constraints. However, the quantitative criteria for LST are not clear. Considering that this paper studies tourism efficiency under the constraint of carbon emissions, selecting the indicators related to tourism and energy consumption is more appropriate. This paper uses the energy consumption per 100 million yuan of tourism revenue as a specific indicator to measure LST and analyzes its impact on the tourism industry efficiency.

Data sources and processing

Data sources

The dataset of this study contains data related to the tourism industry of 31 provincial administrative regions in the mainland China from 2000 to 2019. The data used to calculate the carbon emissions from the tourism industry and tourism efficiency come from the China Statistical Yearbook, the China Energy Statistical Yearbook, the Yearbook of

China Tourism Statistics, the China Cultural Heritage and Tourism Statistical Yearbook, and statistical yearbooks of provincial administrative regions. The data of fixed asset investment and the number of employees in this study are a summary of the data of three industries closely related to tourism: transportation, wholesale and retail, and hotels. Relevant data for it come from the Statistical Yearbook of the Chinese Investment in Fixed Assets. In addition, data on impact factors were obtained from the statistical yearbooks of provincial administrative regions and the corresponding national economic and social development bulletin. Missing data are supplemented by the interpolation method.

Data processing and tests

This paper used the data envelopment analysis software DEAP2.1 to calculate the DEA model and MI, and Stata16 was used to complete the Tobit regression analysis. In the analysis of influencing factors, logarithmic processing is adopted for the data corresponding to DTC, LE, and DOW to eliminate the influence of heteroscedasticity. In order to avoid spurious regression in data processing, the unit root test is performed on the data to verify the stationarity of the data before performing Tobit regression analysis. Then, the cointegration test is performed to verify whether there is a cointegration relationship between the variables. The results of LLC and Fisher-ADF unit root tests for each variable using Stata16.0 are shown in Table 3. Each variable has passed two unit root tests, indicating that each variable has a certain degree of stationarity. Then, perform the Kao test, Pedroni test, and Westerlund test for each variable, and the results are shown in Table 4. The test results performed well except for the Kao test. Therefore, it is believed that there is a cointegration relationship between the CE, TE, and SE of the tourism industry and various influencing factors. So the regression analysis can be further conducted.

Results

Tourism efficiency under carbon emission constraints

The CE of tourism under the carbon emissions constraints has only a relatively small fluctuation in other

Table 3 Unit root test of tourism efficiency and influencing factors data

	\mathcal{Y}_{OE}	\mathcal{Y}_{TE}	\mathcal{Y}_{SE}	\mathcal{X}_1	$\ln \mathcal{X}_2$	$\ln \mathcal{X}_3$	$\ln \mathcal{X}_4$	\mathcal{X}_5
LLC	-4.5733 0.0000	-4.0806 0.0000	-1.7228 0.0425	-2.4523 0.0071	-2.3879 0.0085	-3.2008 0.0007	-4.1399 0.0000	-9.2729 0.0000
Fisher-ADF	134.4528 0.0000	156.4660 0.0000	121.3231 0.0000	206.7533 0.0000	207.6458 0.0000	120.4428 0.0000	161.3447 0.0000	325.0150 0.0000
Conclusion	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary

years except for a relatively large increase in 2003. As shown in Fig. 1, from 59.87% in 2003 to 62.79% in 2019, the total growth rate in 16 years is only 4.88%, while there is still much room for improvement in CE. And it is noteworthy that the CE of the tourism industry in China has shown a downward trend since 2017.

From the perspective of spatial differences (Table 5), 12 regions have a CE of tourism that exceeds the national average. Among them, Tibet, Ningxia, Tianjin, Beijing, and Shanghai rank in the top five. And among the 19 regions whose CE of tourism is lower than the national average, Hebei Province has the lowest efficiency value, which is only 38.44%, and the rest are above 40%.

The results of TE and SE are shown in Fig. 2 and Table 6. As shown in Fig. 2, SE has been at a high level overall from 2000 to 2019, but there is a downward trend after 2016. TE rose overall between 2000 and 2016, with the largest increase in 2003. Since 2017, however, there has been a downward trend in

TE. Table 6 shows the average value of TE and the average value of SE of the tourism industry from 2000 to 2019 in various regions. TE is relatively high in Tibet (1.000), Ningxia (0.955), Tianjin (0.920), and Beijing (0.902), with values more than 0.9. And TE is relatively low in Henan (0.496), Hunan (0.488), Gansu (0.470), Xinjiang (0.439), Shaanxi (0.436), Hubei (0.421), Heilongjiang (0.409), and Hebei (0.388), and values are less than 0.5. The SE of each region is high, and only the values of Jiangsu (0.899), Shandong (0.891), and Guangdong (0.707) are less than 0.9.

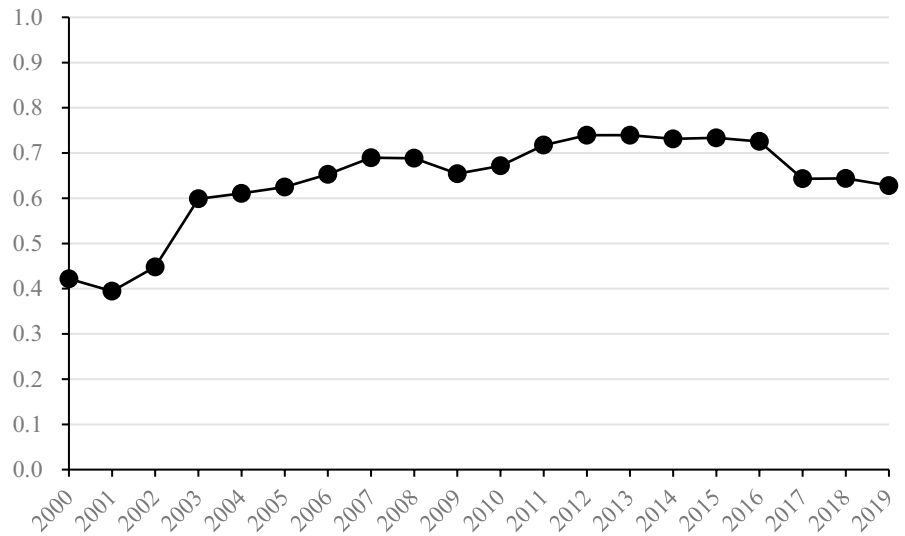
Tourism TFP under carbon emission constraints

From Table 7, it can be found that from 2000 to 2019, the MI of the tourism industry under the carbon emission constraints exceeded 1.0 in most cases, and the MI of a few periods less than 1.0 also remained above 0.9. The average value of MI is 1.075, indicating that

Table 4 Cointegration test of three types of tourism efficiency and influencing factors data

	Kao test		Pedroni test		Westerlund test		Conclusion
Equation (3)	-1.0726	0.1417	5.6066	0.0000	21.0245	0.0000	There is a cointegration relationship
	-1.2237	0.1105	-4.6346	0.0000			
	-1.7433	0.0406	-4.3772	0.0000			
	-2.3262	0.0100					
	-1.9632	0.0248					
Equation (4)	-1.3994	0.0809	5.3555	0.0000	20.7252	0.0000	There is a cointegration relationship
	-1.6938	0.0451	-5.4024	0.0000			
	-2.316	0.0103	-5.0227	0.0000			
	-2.4013	0.0082					
	-2.2609	0.0119					
Equation (5)	0.1863	0.4261	5.3592	0.0000	19.5464	0.0000	There is a cointegration relationship
	0.6284	0.2649	-11.1409	0.0000			
	-2.2922	0.0109	-11.0724	0.0000			
	-0.5997	0.2743					
	0.0533	0.4787					

Fig. 1 CE of the tourism industry under carbon emission constraints



the productivity of the tourism industry under carbon emission constraints has grown at an average annual rate of 7.5% from 2000 to 2019.

Figure 3 compares the dynamic changes of the efficiency decomposition components of the tourism industry under the constraints of carbon emissions. The change in technical progress (TPch) and the pure TE (PEch) performed better overall. The mean values were 1.048 and 1.027, respectively. The change in SE (SEch) was the most stable, with the index value consistently staying between 0.95 and 1.05, but the overall mean was 0.998, which was less than 1.0. It shows that technical progress significantly improves the tourism TFP under emission constraints, and pure TE also plays a positive role in promoting it. Although the change of SE is not obvious, it generally limits the improvements in the tourism TFP.

Table 8 is the decomposition result and variation coefficient of the MI of tourism industry efficiency under carbon emission constraints in various regions. There are 24 regions where the MI is greater than 1.0, indicating that the tourism TFP is increasing under the constraints of carbon emissions in most regions. Among them, the MI of 13 regions, including Liaoning, Zhejiang, Yunnan, Hebei, Jiangsu, Sichuan, Shandong, Fujian, Hunan, Inner Mongolia, Jiangxi, Guangxi, and Henan, are all above 1.1, indicating that the tourism industry under the carbon emission constraints in these regions has a TFP growing at more than 10% a year. Seven regions, including Heilongjiang, Hainan, Gansu, Beijing, Tibet, Ningxia, and Qinghai, had a MI of less than 1.0, indicating that the tourism TFP under the carbon emissions constraints in these regions has declined as a whole. From the

Table 5 Measured value of the average CE of tourism in 31 regions

Beijing	Tianjin	Hebei	Shanxi	Inner Mongolia	Liaoning	Jilin	Heilongjiang	Shanghai
0.8973	0.9163	0.3844	0.7291	0.5987	0.7068	0.5850	0.4002	0.8483
Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong	Henan	Hubei	Hunan
0.7919	0.8292	0.5631	0.5865	0.5911	0.5834	0.4857	0.4157	0.4799
Guangdong	Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan	Tibet	Shaanxi
0.5999	0.5577	0.6760	0.5145	0.5656	0.8046	0.6053	1.0000	0.4304
Gansu	Qinghai	Ningxia	Xinjiang	(Nationwide)				
0.4610	0.7861	0.9528	0.4268	0.6378				

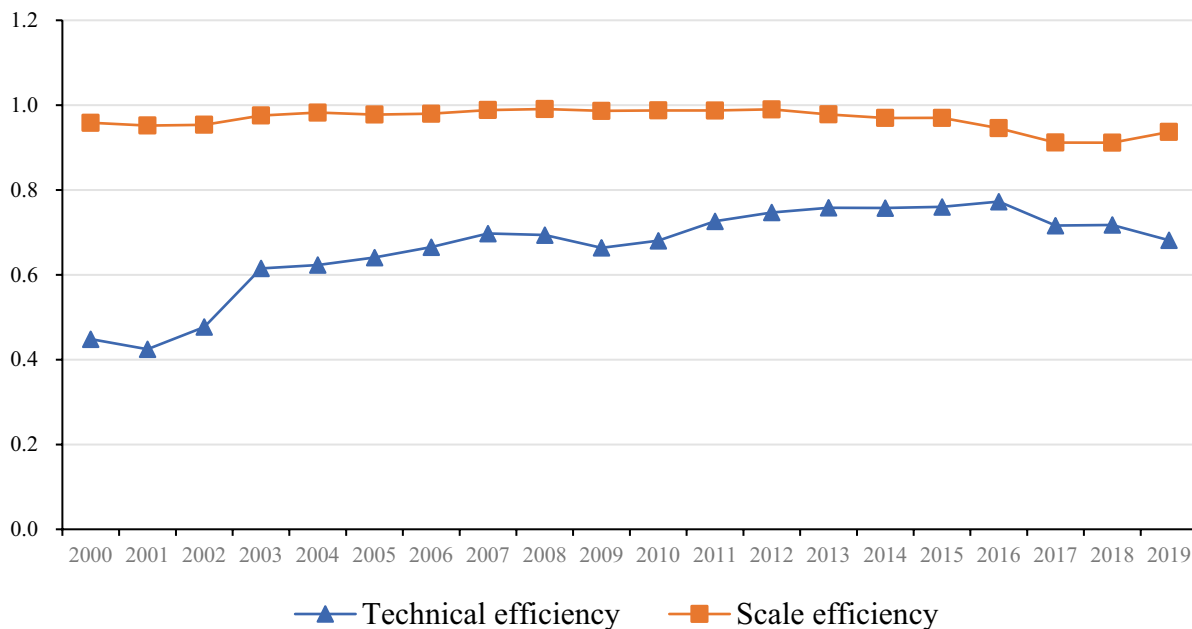


Fig. 2 The TE and SE of the tourism industry under carbon emission constraints

results of the variation coefficient of each part after the decomposition of the MI in each region, changes in technical progress (TPch) are the main factors contributing to changes in TFP in various regions. This finding is consistent with the conclusion obtained by analyzing the temporal variation characteristics of the MI of the tourism industry. Therefore, attention should be paid to improving the technological capabilities of regions with poor TFP growth in the

tourism industry to promote the balanced development of tourism in different regions.

Analysis of influencing factors of tourism efficiency under carbon emission constraints

Using Stata16 to perform Tobit regression on the data of the CE of the tourism industry and various influencing factors, the results are shown in Table 9. From

Table 6 The TE and SE of tourism industry under carbon emission constraints in various regions

	Beijing	Tianjin	Hebei	Shanxi	Inner Mongolia	Liaoning	Jilin	Heilongjiang	Shanghai
TE	0.902	0.920	0.388	0.732	0.601	0.738	0.588	0.409	0.864
SE	0.990	0.995	0.986	0.994	0.994	0.964	0.994	0.977	0.973
	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong	Henan	Hubei	Hunan
TE	0.887	0.871	0.573	0.590	0.600	0.674	0.496	0.421	0.488
SE	0.899	0.949	0.978	0.992	0.986	0.891	0.977	0.986	0.979
	Guangdong	Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan	Tibet	Shaanxi
TE	0.890	0.566	0.713	0.522	0.616	0.808	0.618	1.000	0.436
SE	0.707	0.980	0.945	0.985	0.933	0.993	0.985	1.000	0.986
	Gansu	Qinghai	Ningxia	Xinjiang	(Nationwide)				
TE	0.470	0.788	0.955	0.439	0.663				
SE	0.981	0.997	0.997	0.973	0.967				

Table 7 MI decomposition of the tourism industry from 2000 to 2019

	TEch	TPch	PEch	SEch	MI
2000–2001	0.930	1.009	0.937	0.992	0.938
2001–2002	1.165	0.837	1.163	1.002	0.975
2002–2003	1.392	1.122	1.346	1.034	1.561
2003–2004	1.012	0.924	1.005	1.007	0.935
2004–2005	1.037	1.021	1.042	0.995	1.059
2005–2006	1.059	1.005	1.055	1.003	1.064
2006–2007	1.074	1.004	1.064	1.009	1.078
2007–2008	1.002	0.971	0.999	1.003	0.973
2008–2009	0.935	1.014	0.940	0.995	0.948
2009–2010	1.042	1.057	1.041	1.001	1.101
2010–2011	1.073	1.082	1.074	1.000	1.161
2011–2012	1.040	1.028	1.037	1.003	1.069
2012–2013	0.999	1.031	1.012	0.987	1.031
2013–2014	0.984	1.048	0.993	0.990	1.031
2014–2015	1.009	1.046	1.009	1.000	1.056
2015–2016	0.989	1.152	1.018	0.972	1.139
2016–2017	0.865	1.334	0.906	0.954	1.153
2017–2018	0.996	1.180	1.000	0.996	1.175
2018–2019	0.973	1.146	0.949	1.026	1.116
Mean	1.025	1.048	1.027	0.998	1.075

the regression results, it can be seen that except for DOW, which passed the 10% significant level, the rest of the influencing factors passed the 1% significant

level test. Among them, the regression coefficients of \mathcal{X}_1 , $\ln\mathcal{X}_4$, and \mathcal{X}_5 to \mathcal{Y}_{OE} are negative, and the regression coefficients of $\ln\mathcal{X}_2$ and $\ln\mathcal{X}_3$ are positive. Considering that \mathcal{X}_5 (energy consumption per 100 million yuan of tourism revenue) is negatively correlated with LST, the impacts of IS and DOW on the CE of tourism are negative. And the degree of traffic convenience, LE, and LST positively impacts the CE of tourism. In terms of the degree of influence, the CE of the tourism industry can be increased by 8.79% only by increasing LST by 0.1 percentage points, and its influence on the CE of the tourism industry is far greater than the other influencing factors. The impact of economic development level on the CE of the tourism industry ranks second, and every one percentage point increase in economic development level can increase the CE of the tourism industry by 10.86%. The impact of traffic convenience on CE of tourism ranks third, and every one percentage point increase in traffic convenience can promote CE of tourism by 9.0%. The influence of DOW on the CE of the tourism industry ranks fourth among the five influencing factors and is a negative effect. Each one percentage point increase in the level of opening up will reduce the CE of the tourism industry by 4.26%. The IS is the smallest factor affecting the CE of the tourism industry, and it is a negative effect. When the proportion of GDP in the tertiary industry increases by one percentage point, the CE of the tourism industry only decreases by 0.83%.

Fig. 3 Dynamic changes of tourism TFP under carbon emission constraints (2000–2019)

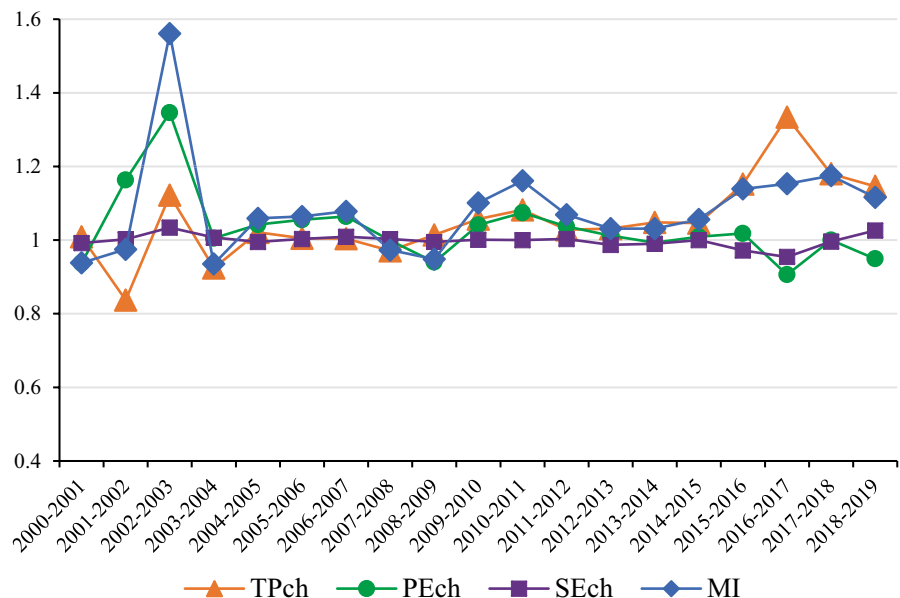


Table 8 MI decomposition of the regional tourism industry

	TEch	TPch	PEch	SEch	MI
Beijing	0.955	1.023	0.955	1.000	0.977
Tianjin	0.966	1.073	0.966	0.999	1.036
Hebei	1.073	1.092	1.071	1.002	1.171
Shanxi	1.058	1.018	1.057	1.001	1.077
Inner Mongolia	1.044	1.088	1.044	1.000	1.136
Liaoning	1.070	1.125	1.069	1.001	1.203
Jilin	1.050	1.009	1.049	1.001	1.060
Heilongjiang	1.016	0.983	1.017	0.999	0.999
Shanghai	0.955	1.075	0.958	0.997	1.027
Jiangsu	1.024	1.139	1.059	0.967	1.166
Zhejiang	1.051	1.134	1.056	0.995	1.191
Anhui	1.040	1.056	1.037	1.002	1.097
Fujian	1.006	1.135	1.006	1.000	1.141
Jiangxi	1.034	1.092	1.032	1.001	1.129
Shandong	1.040	1.118	1.047	0.994	1.162
Henan	1.031	1.071	1.030	1.001	1.104
Hubei	1.018	1.060	1.018	1.000	1.079
Hunan	1.058	1.074	1.056	1.002	1.137
Guangdong	0.986	1.101	1.000	0.986	1.085
Guangxi	1.059	1.046	1.057	1.003	1.108
Hainan	1.002	0.984	1.009	0.993	0.987
Chongqing	0.983	1.059	0.983	1.000	1.041
Sichuan	1.044	1.114	1.043	1.001	1.163
Guizhou	1.042	1.041	1.041	1.001	1.085
Yunnan	1.064	1.111	1.066	0.999	1.182
Tibet	1.000	0.973	1.000	1.000	0.973
Shaanxi	1.034	1.044	1.034	1.000	1.079
Gansu	1.024	0.957	1.023	1.000	0.980
Qinghai	1.024	0.881	1.024	1.000	0.902
Ningxia	1.019	0.899	1.019	1.000	0.917
Xinjiang	1.033	0.993	1.032	1.001	1.025
Coefficient of variation	0.031	0.063	0.031	0.007	0.075

Using Stata16 to perform Tobit regression on the data of the TE of the tourism industry and various influencing factors, the results are shown in Table 10. It can be seen from the regression results that all the other influencing factors have passed the

Table 9 Tobit regression results of CE (\mathcal{V}_{OE})

Independent variable	Regression coefficients	Standard error	Z value	P value
\mathcal{X}_1	-0.0083	0.0017	-4.7500	0.0000
$\ln\mathcal{X}_2$	0.0900	0.0306	2.9500	0.0030
$\ln\mathcal{X}_3$	0.1086	0.0292	3.7200	0.0000
$\ln\mathcal{X}_4$	-0.0426	0.0228	-1.8700	0.0610
\mathcal{X}_5	-0.8786	0.2444	-3.6000	0.0000

Table 10 Tobit regression results of TE (\mathcal{V}_{TE})

Independent variable	Regression coefficients	Standard error	Z value	P value
\mathcal{X}_1	-0.0062	0.0018	-3.3700	0.0010
$\ln\mathcal{X}_2$	0.0638	0.0322	1.9800	0.0470
$\ln\mathcal{X}_3$	0.1108	0.0304	3.6500	0.0000
$\ln\mathcal{X}_4$	-0.0176	0.0235	-0.7500	0.4540
\mathcal{X}_5	-0.8245	0.2602	-3.1700	0.0020

5% significant level test except for the result of DOW. Among them, the regression coefficients of \mathcal{X}_1 and \mathcal{X}_5 to \mathcal{V}_{TE} are negative, and the regression coefficients of $\ln\mathcal{X}_2$ and $\ln\mathcal{X}_3$ are positive. Therefore, the influence of IS on TE is negative, and the degree of traffic convenience and economic development level has a positive impact on TE. Considering that \mathcal{X}_5 (energy consumption per 100 million yuan of tourism revenue) is negatively correlated with LST, LST positively impacts the TE of the tourism industry. This part does not consider DOW because the significance test is not passed. Regarding the degree of influence, LST has the greatest impact on the TE of tourism. For every 0.1 percentage point increase in LST, the TE of the tourism industry will increase by 8.24%. The second is LE. An increase of 1 percentage point will drive the TE of the tourism industry to increase by 11.08%. The third place is DTC. Whenever DTC increases by one percentage point, the TE of the tourism industry will increase by 6.38%. The last one is the IS. When the proportion of GDP in the tertiary industry increases by one percentage point, the TE of the tourism industry decreases by 0.62%. From the regression results, the impact of various factors on the TE of the tourism industry is generally similar to the impact on CE. The main difference is that the DOW significantly impacts the CE, but the impact on the TE is not significant.

Similarly, Stata16 is used to perform Tobit regression on the data of the tourism industry SE, and various

Table 11 Tobit regression results of SE (\mathcal{V}_{SE})

Independent variable	Regression coefficients	Standard error	Z value	P value
\mathcal{X}_1	-0.0019	0.0007	-2.6600	0.0080
$\ln\mathcal{X}_2$	0.0247	0.0108	2.2900	0.0220
$\ln\mathcal{X}_3$	0.0189	0.0100	1.8900	0.0590
$\ln\mathcal{X}_4$	-0.0377	0.0079	-4.7700	0.0000
\mathcal{X}_5	-0.1486	0.1018	-1.4600	0.1450

influencing factors, and the results are shown in Table 11. From the regression results, it can be seen that the influence of LST on the SE of the tourism industry is not significant, LE is significant within the 10% level, and the rest of the influencing factors have passed the test at the 5% significant level. LST is not significant, so its impact on the SE of the tourism industry is not considered. Among the variables corresponding to the four indicators of other indicators, the regression coefficients of \mathcal{X}_1 and $\ln\mathcal{X}_4$ are negative, and the regression coefficients of $\ln\mathcal{X}_2$ and $\ln\mathcal{X}_3$ are positive, so the impacts of IS and openness on the SE of the tourism industry are negative. And the impacts of transportation convenience and economic development level on the SE of tourism are positive. From the perspective of the degree of influence, DOW has the greatest and negative impact on the SE of the tourism industry. Every time DOW increases by one percentage point, the SE of the tourism industry will decrease by 3.77%. The second is the influence of traffic convenience on the SE of the tourism industry. When traffic convenience increases by one percentage point, the SE of the tourism industry will increase by 2.47%. LE has the third largest influence on the SE of the tourism industry. When LE increases by one percentage point, the SE of the tourism industry will increase by 1.89%. The industry structure has the least impact on the SE of the tourism industry. When the proportion of GDP of the tertiary industry increases by one percentage point, the SE of the tourism industry will decrease by 0.19%. Compared with the regression results of Tables 3, 4, and 5 and Tables 3, 4, 5, and 6, the influence of various factors on the SE of the tourism industry shown in Table 11 is quite different from the influence of various factors on the CE and TE of the tourism industry.

Summarize the regression coefficients and influence directions of various factors on the CE, TE, and SE of the tourism industry and get Table 12. After comparison, it is found that the influence of IS and DOW on the TE and SE of the tourism industry is negative, so the degree of negative influence reflected in the CE is further strengthened. But at the same time, the influence of these two factors on tourism efficiency

is the smallest among the five factors. DTC, LE, and LST have a relatively obvious positive role in promoting tourism efficiency. Among them, LST has the most obvious role in promoting tourism efficiency. Every time LST increases by one percentage point, it can drive the TE of the tourism industry to achieve an increase of 82.45%. The influence of LE on tourism efficiency is second only to the influence of LST on tourism efficiency. Every one percentage point increase in LE can drive the TE and SE of the tourism industry to achieve an increase of 11.08% and 1.89%, and the growth rate reflected in the CE is 10.86%. DTC has a relatively obvious role in promoting the TE and SE of the tourism industry. Whenever DTC increases by one percentage point, the TE and SE of the tourism industry will increase by 6.38% and 2.47%, respectively, and the CE will increase by 9.00%.

In the influencing factors analysis results, IS and DOW negatively affect tourism efficiency improvement. However, the degree of the negative impact of the two (0.0083 and 0.0426) is less than half of the positive impact of transportation convenience (0.0900) and LE (0.1086) and far less than the positive impact of the level of scientific and technological development (0.8786). In addition, the increase in the proportion of tertiary industries in GDP and the degree of opening up may lead to the development of transportation convenience, economic development level, and scientific and technological development level, which will significantly positively impact tourism efficiency. Therefore, it cannot be concluded that reducing the proportion of GDP in the tertiary industry and reducing the degree of opening up can improve the efficiency of the tourism industry. LST has a strong driving force on the CE of the tourism industry. Since the impact on the SE of the tourism industry is insignificant, it mainly affects the CE of the tourism industry by affecting the TE of the tourism industry. However, considering that the index selected for LST in this paper is the energy consumption per 100 million yuan of tourism revenue (photo focus/100 million yuan), increasing tourism efficiency by improving LST is not easy.

Table 12 Influence degree and influence direction of various factors on tourism industry efficiency

	IS		DTC		LE		DOW		LST	
CE	0.0083	-	0.0900	+	0.1086	+	0.0426	-	0.8786	+
TE	0.0062	-	0.0638	+	0.1108	+	/	/	0.8245	+
SE	0.0019	-	0.0247	+	0.0189	+	0.0377	-	/	/

In addition, the growth rate of the CE of the tourism industry driven by LE is 10.86%, which is still lower than the growth of TE when the driving effect on SE is positive. The specific reasons for this situation call for a more detailed study. The positive and significant effect of economic development on tourism efficiency indicates that high-quality tourism consumers are the basic driving force for developing the tourism market and the key to promoting tourism efficiency. And adequate tourism consumption can not only increase the scale of the tourism market but also promote the further improvement of the CE of the tourism industry by improving the utilization efficiency of tourism resources. DTC has a significant role to play in promoting tourism efficiency. The index reflecting DTC in this paper is the density of the road network. The analysis results prove that improving transport infrastructure services can improve tourism efficiency by enhancing transportation convenience.

Discussion

High-quality low-carbon development in the tourism sector pursues both economic growth and decarbonization degree. Therefore, tourism industry efficiency under carbon emission constraints has become one of the key issues in China's tourism development, and it reflects the effectiveness of China's low-carbon development policies in the tourism industry. Based on the DEA model, MI model, and Tobit regression, this paper analyzes the tourism industry efficiency under carbon emission constraints and the influencing factors in 31 provincial administrative regions in mainland China. The findings of this paper provide a more comprehensive picture of the state of China's tourism industry in the context of low-carbon development than studies conducted in local areas of China (Xue et al., 2022; Zha et al., 2019).

In this paper, some existing findings are demonstrated, while some new conclusions are identified. In previous studies of China's tourism industry, various factors, such as poor infrastructure, have led to the fact that the less economically developed western regions tend to perform worse than the economically developed eastern regions in the tourism industry (He et al., 2023). The results of this paper show that the top-ranked regions in terms of tourism efficiency

include regions with better economic development, such as Tianjin, Beijing, and Shanghai, as well as regions with relatively poor economic development, such as Tibet and Ningxia. This is also inconsistent with the findings of Jiang et al. (2022) on tourism carbon emission efficiency, who found that five of the six provinces that reached the efficient frontier of tourism carbon dioxide emission efficiency were economically developed regions such as Beijing and Tianjin and that the eastern region was far superior to the central and western regions. In the context of sustainable and high-quality development, the tourism industry is no longer obsessed with increasing tourism revenue. With a significant low-carbon transition, it may be a good state of development even if economic growth is mediocre. Therefore, the evaluation method of this paper may be more equitable in terms of the results.

The results of MI show that technological progress contributed the most to improving TFP in the Chinese tourism industry under the carbon emission constraints from 2000 to 2019. This is consistent with the findings of Sun et al. (2015), who found an increasing trend in the TFP of China's tourism industry from 2001 to 2009 and that technological progress was the dominant factor influencing the change in TFP.

The results of the analysis of the influencing factors in this paper show that transportation, economy, and LST have a significant contribution to tourism efficiency, while the tertiary sector and the DOW have a negative impact. This is also not exactly the same as the findings of previous studies. The findings of Liu et al. (2021) show that the economy, transportation, and openness can significantly contribute to the efficiency of tourism. Gao et al. (2022) found that the economy, the tertiary sector, and urbanization are the main factors driving tourism efficiency. Differences in the selection of indicators may account for the large differences between the study results, and more detailed research is needed to sort out this issue.

Based on the results, the following policy suggestions can be made. First, to promote the low-carbon development of the tourism economy, an evaluation system should be established, and the governance mechanism should be improved. The low-carbon development level should be considered as one indicator of the quality of the tourism industry, and tax relief and policy support should be provided to guide the low-carbon development of the tourism industry.

When regions with better development of low-carbon tourism obtain more tourism policy support, it will lead to more tourists flowing from regions with lower levels of low-carbon tourism to regions with higher levels of low-carbon tourism. On the one hand, transferring tourists can reduce per capita carbon emissions and improve the overall level of low-carbon tourism. On the other hand, the shift of tourists can motivate regions to pursue higher levels of low-carbon tourism in order to obtain policy support. Second, balance regional differences by strengthening inter-regional tourism cooperation. The exchange and cooperation of information, technology, and talents in tourism development between regions should be promoted to improve tourism efficiency under the constraint of carbon emissions. More efficient regions provide technology and management experience to less efficient regions which can lead to an overall increase in total factor productivity of the tourism industry. Third, technological innovation and industrial upgrading should be utilized to improve the efficiency of low-carbon tourism. Promoting low-carbon tourism technologies and accelerating the progress and application of low-carbon technologies in transportation, accommodation, and other tourism segments are necessary. Transportation and technological innovation contribute significantly to tourism efficiency and are relatively easy to control and plan for, and gradually increasing investment in them may be effective in improving tourism efficiency as low-carbon tourism develops. Finally, economic development plays a significant role in promoting tourism efficiency under the constraint of carbon emissions. The process of new type urbanization construction should be accelerated, the construction of tourism infrastructure and related facilities should be improved, the optimization and upgrading of the tourism industry structure should be accelerated, and the improvement of tourism industry efficiency under the constraint of carbon emissions should be further promoted.

Conclusion

By measuring tourism efficiency under the carbon emission constraints and analyzing its influencing factors, this study identified the following findings. Firstly, there are obvious regional differences in the CE of the Chinese tourism industry under the carbon

emissions constraints, and it faces the risk of decline due to the simultaneous decline of TE and SE. Secondly, the TFP of the Chinese tourism industry under the constraint of carbon emissions has achieved significant growth. Technological progress is the key to enhancing tourism TFP under carbon emission constraints. The results of the MI analysis show that technological progress has the greatest contribution to improving the tourism TFP under emission constraints, and TE also plays a positive role in promoting it. The overall change in the SE is not evident, which limits further progress in improving the tourism TFP. Thirdly, all factors impact tourism efficiency, and positive factors play a greater role. Except that DOW has no significant impact on the TE and LST does not significantly impact the SE of the tourism industry, different factors have varying degrees of influence on the TE and SE of tourism. Therefore, they have different effects on the CE of tourism. Among them, the degree of traffic convenience, LE, and LST positively affect tourism efficiency, and the impacts are strong. The IS and the degree of openness have inhibitory effects on tourism efficiency, but the impacts are weak. Based on these findings, it can be concluded that China's demand for low-carbon development has not limited the progress of its tourism industry. However, at the same time, shortcomings such as regional differences and insufficient development drivers still exist.

This study measures the efficiency of the Chinese tourism industry from the perspective of carbon emission constraints and attempts to select more representative indicators from a wide range of complex tourism-related indicators as influencing factors for analysis. Under the background of sustainable development and high-quality development, this paper enriches the content and direction of tourism efficiency theory research and provides a new theoretical reference for related research on ecotourism, sustainable industrial development, and industrial efficiency under carbon emission constraints. Due to the strong comprehensiveness of the tourism industry and the lack of relevant data, the research process is not smooth. There is still room for improvement in the data analysis part. And this is also a common problem in studying the tourism industry in developing countries. To make the results more accurate and reliable, this study's calculation results are obtained by calculating the basic statistical data. The deficiency

of this paper is the lack of discussion and conclusions relating to practice, and these issues will be carried out in the follow-up research based on this paper.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Zi Tang and Xiaopeng Si. The first draft of the manuscript was written by Xiaopeng Si and Weili Wang. All authors commented on previous versions of the manuscript, and the revision was completed by Xiaopeng Si and Yan Liang. All authors read and approved the final manuscript.

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Data availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Competing interests The authors declare no competing interests.

Ethics declarations All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

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