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The Spatial Pattern and Spillover Effect of the Eco-Efficiency of Regional Tourism from the Perspective of Green Development: An Empirical Study in China

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Abstract: Scientifically analyzing the spatial pattern and spillover effect of the eco-efficiency of regional tourism embodies the green development theory. In addition, it is also of important significance for realizing the sustainable development of regional tourism and promoting regional ecological civilization. This study incorporates energy consumption and CO_2 emissions of tourism into the efficiency evaluation index system. On this basis, the slacks-based measure–data envelopment analysis (SBM-DEA) with undesirable output, the spatial autocorrelation (SAC) model and the spatial Durbin model (SDM) are used to study the spatial pattern and spillover effect of the eco-efficiency of provincial tourism in China from 2008 to 2017. Results show that the following: (1) The average eco-efficiency of national tourism is 0.534, which is at the medium development level as a whole. Among the decomposed efficiencies of eco-efficiency, the scale efficiency drives the optimal development of eco-efficiency in tourism. (2) The eco-efficiency of tourism shows a spatial differentiation pattern on the regional scale as follows: it is the highest in the central region, moderate in the western region, and lowest in the eastern region. (3) The degree of clustering of the eco-efficiency of tourism first increases and then decreases. The SAC-based cluster pattern is dominated by a low-low (LL) cluster, followed successively by a high-high (HH) cluster and a low-high (LH) outlier, while a high-low (HL) outlier is the least significant (4). Among the influencing factors, the technical level shows spatial spillover effects on both the eco-efficiency and pure technical efficiency of tourism; the economic development level and traffic accessibility mainly have spatial spillover effects on the pure technical efficiency and scale efficiency of tourism; the industrial structure and environmental regulation separately have a spatial spillover effect only on the pure technical efficiency and the scale efficiency of tourism.

Keywords: eco-efficiency of tourism; data envelopment analysis; sustainable development of tourism; spatial autocorrelation; spatial spillover effect

Citation: Li, S.; Ren, T.; Jia, B.; Zhong, Y. The Spatial Pattern and Spillover Effect of the Eco-Efficiency of Regional Tourism from the Perspective of Green Development: An Empirical Study in China. *Forests* **2022**, *13*, 1324. https://doi.org/10.3390/f13081324

Academic Editors: Chi-Ming Hsieh and Wan-Yu Liu

Received: 3 July 2022
Accepted: 16 August 2022
Published: 19 August 2022

1. Introduction

With the improvement of the national consumption level, tourism also bursts and has become a strategic pillar industry of the national economy. The development of tourism not only powerfully drives relevant industries but also promotes the rapid growth of the local social economy. However, large-scale tourist flows and tourist activities exert an obvious negative influence on the local ecological environment when creating economic benefits. Therein, fossil energy consumption and carbon emission incur particularly prominent problems [1,2]. According to data from the United Nations World Tourism Organization and the United Nations Environment Program, tourism contributes to 5% of global carbon emissions [3]. Therefore, tourism has great potential to tackle the energy crisis and mitigate the greenhouse effect. Under the impetus of carbon neutrality, it has become an inevitable choice for the sustainable development of tourism to promote its transition to a low-carbon and resilient tourism economy by developing eco-tourism based on natural resources such as forests and steppe and through carbon sequestration [4]. In such a context, eco-efficiency as a management tool has been proven to be able to improve the capacity of regional sustainable development [5]. Therefore, studying the eco-efficiency of tourism has become a hotspot and focuses on the ecological and environmental influences of tourism nowadays. In view of this, the research evaluates the eco-efficiency of tourism. This provides a theoretical basis for relevant governmental departments to clearly master the state-of-the-art of sustainable development of regional tourism and formulate relevant policies for facilitating the sustainable development of regional tourism. This is also of important practical significance for speeding up regional ecological civilization and co-creating beautiful China.

2. Literature Review

The eco-efficiency was first put forward by Schaltegger et al. [6] in 1990. It refers to bringing the maximum economic and social outputs at the expense of minimum energy consumption and environmental impacts, which is also the internal requirement for the coordinated development of energy, the economy, environment and society. Afterwards, scholars have expanded research on eco-efficiency and applied the eco-efficiency concept to many sectors, including tourism, industry and agriculture. Therefore, existing relevant research on the eco-efficiency of various industries (e.g., tourism and industry) uses basic ideas and methods that inherit the theory and technology of traditional natural eco-efficiency. In research on the eco-efficiency of tourism, scholars not only need to consider the economic and social benefits of tourism but also should take the environmental influences (environmental benefits) of tourism into account. From this, the smaller the environmental influences of tourism are, the higher the eco-efficiency of tourism under the fixed economic and social benefits of tourism. Therefore, the eco-efficiency of tourism can be used as a strategic tool for evaluating the sustainable development of regional tourism. However, most researchers have paid more attention to exploring regional sustainable development from the perspective of eco-efficiency at present [7–9], while rarely using the eco-efficiency of tourism to evaluate the sustainable development of regional tourism.

For example, based on the concept of eco-efficiency, Jing and Wang [10] put forward a theoretical framework for realizing the sustainable development of the social-economic-environment system and constructed an evaluation index system from social harmony, economic development and environmental improvement. Based on this, the evaluation of resource-based cities in China shows that population growth, consumption level improvement and industrial structure adjustment are the key measures to achieving sustainable social development. Stergiou and Kounetas [11] used eco-efficiency to evaluate the sustainable development level of 27 European countries and analyzed the spatial distribution characteristics and laws of sustainable development from the perspective of spatial patterns. The results show that the low eco-efficiency of energy-intensive industries is the main reason for the low level of national sustainable development. Romano and Molinos-Senante [12] used a two-stage network DEA approach to study the impacts of ownership types on the eco-efficiency of municipal solid waste management in different regions. The results show that public companies are more eco-efficient in municipal solid waste management than private companies. Based on a singular fractional differential equation, Ren et al. [13] studied the phenomena and diffusion interactions of the complex ecological-economic-social system to understand its co-evolution process. The results show that the improvement of the orderliness of the ecological subsystem, the economic subsystem and the social subsystem and their mutual co-evolution jointly promote the sustainable development of the region.

In the calculation of evaluation indexes for the efficiency of tourism, scholars mainly use the data envelopment analysis (DEA) method [14–17]. This method considers a variety of inputs and outputs, so the calculation results are relatively accurate. By using the

DEA-Malmquist (DEA-ML) productivity index approach, Joun and Kim [18] measured the productivity of economic activities relating to tourism and culture in South Korea and thus analyzed the capacity and regional characteristics of sustainable development of tourism in cities. The results show that tourism can promote the sustainable development of the local economy by acting on the industrial structure of underdeveloped areas. Lin et al. [19] adopted an evaluation model of SBM-DEA combining new economic with carbon emissions to analyze and optimize energy structures of the sustainable development of tourism in some countries and regions in the world. The results show that the energy efficiency of tourism in European and Oceanian countries is generally higher, while the efficiency value in Asia is the lowest. Li et al. [20] established a framework for measuring green total factor productivity for the sustainable development of tourism and measured and calculated the efficiency and spatial-temporal differences of tourism in China from 2007 to 2018 through the DEA-ML index. The results show that there are spatial differences between the east strong and the west weak in the efficiency of China's tourism industry. By utilizing the DEA method, Chen et al. [21] evaluated the service quality and efficiency of tourism and then evaluated the performance of sustainable development of tourism in Taiwan, attempting to balance the supply of tourism and the demand of tourists. The results show that the inefficiency of providing services to inbound tourists is the main bottleneck restricting the sustainable development of Taiwan's tourism industry. To correctly measure the relationship between the level of economic development of tourism and regional eco-efficiency, Chen et al. [22] evaluated the regional eco-efficiency and the level of economic development of tourism based on the super-efficiency DEA model and grey entropy-weighted method. The results show that tourism economic development and regional ecological efficiency show a significant "Kuznitz curve" effect.

In conclusion, scholars have carried out a series of fruitful research on the efficiency evaluation of tourism. However, existing research seldom considers the influence of the undesirable output when calculating the eco-efficiency of tourism and hardly discusses the spatial spillover effect of the eco-efficiency of regional tourism. This may cause low accuracy of the efficiency evaluation results and also poor implementation effects of relevant policies and suggestions introduced. In view of this, the study took provincial panel data in China as examples. Then, a diachronic study was conducted on the eco-efficiency of tourism from the input-output perspective by building the SBM-DEA model, considering undesirable output and the evaluation index system for the eco-efficiency of tourism. In addition, the spatial pattern and spillover effect of the eco-efficiency of tourism were explored using the spatial autocorrelation model and the spatial econometric model. Two problems need to be solved. One is to measure the eco-efficiency of provincial tourism in China and reveal its spatial pattern, and the other one is to identify the key factors influencing the eco-efficiency of tourism from the perspective of space, so as to promote the sustainable development of tourism.

3. Research Design

3.1. Calculation Models for the Eco-Efficiency of Tourism

The measurement of the eco-efficiency of tourism involves many dimensions, such as tourism resources, economy and society, showing the characteristics of multi-input and multi-output. Therefore, at present, most of the studies on the eco-efficiency of tourism by domestic and foreign scholars have adopted the DEA model [23–25]. Compared with other methods, the DEA model can better judge whether decision-making units (DMUs) with multiple inputs and outputs are effective. Its basic principle is to evaluate the relative efficiency between DMUs by constructing the optimal practical frontier. The traditional DEA model is mainly divided into the Charnes–Cooper–Rhodes (CCR-DEA) model and the Banker–Charnes–Cooper (BCC-DEA) model with different assumptions. The former assumes constant returns to scale, while the latter supposes variable returns to scale [26]. This kind of traditional DEA model is basically radial and angular, failing to calculate influence of slack variables on the efficiency, so the efficiency of DMUs may be overestimated [27]. To solve this problem, Tone [28] proposed a non-radial, non-angular SBM-DEA model, which avoids deviations caused by selection of radial direction and angles and overcomes slack of input and output. This method can more accurately reflect the essence of evaluating the eco-efficiency of tourism. It is specifically described as follows.

Assuming that there are n DMUs, for the jth DMU, namely, DMU_j ($j = 1, \ldots, n$), there are three vectors, that is, an input $X_j = \left(x_{1j}, x_{2j}, \cdots, x_{ij}\right)$, a desirable output $Y_j^g = \left(y_{1j}^g, y_{2j}^g, \cdots, y_{ij}^g\right)$ and an undesirable output $Y_j^b = \left(y_{1j}^b, y_{2j}^b, \cdots, y_{ij}^b\right)$. The production possibility set P containing the undesirable output can be constructed as Formula (1).

$$\mathrm{P} = \left\{ \left(x, y^g, y^b\right) \mid x \geq X\lambda,\ y^g \leq Y^g\lambda,\ y^b \geq Y^b\lambda,\ \lambda \geq 0 \right\} \tag{1}$$

According to the processing method of the SBM-DEA model, the fractional programming form of the SBM-DEA model considering the undesirable output with variable returns to scale is constructed as Formula (2).

$$\rho^* = \min \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{R+L}\left(\sum_{r=1}^{R} \frac{s_r^g}{y_{r0}^g} + \sum_{l=1}^{L} \frac{s_l^b}{y_{l0}^b}\right)} \text{s.t.} \begin{cases} x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-,\ i = 1, \ldots, M \\ y_{r0}^g = \sum_{j=1}^{n} y_{rj}^g\lambda_j - s_r^g,\ r = 1, \ldots, R \\ y_{l0}^b = \sum_{j=1}^{n} y_{lj}^b\lambda_j + s_l^b,\ l = 1, \ldots, L \\ s_i^-,\ s_r^g,\ s_l^b \geq 0, \forall i, \forall r, \forall l \end{cases} \tag{2}$$

In Formula (2), x_{ij}, y_{rj}^g and y_{lj}^b separately represent the variables of input, desirable output and undesirable output of a DMU; s_i^-, s_r^g and s_l^b indicate the slack variables of input, desirable output and undesirable output, respectively; λ denotes the weight vector and the objective function ρ^* stands for the eco-efficiency of tourism. If $\rho^* = 1$, it means that the eco-efficiency of decision-making units (DMUs) is data envelopment analysis (DEA) efficient. Under the condition, values of s_i^-, s_r^g and s_l^b are all 0. If $\rho^* < 1$, then DMUs have an efficiency loss and values of s_i^-, s_r^g and s_l^b are all larger than 0, which indicates that DMUs have input redundancy, desirable output deficiency, or undesirable output redundancy. Therefore, to further explore whether the above situation exists to input and output variables of DMUs, Equations (3)–(5) are used to calculate the relaxation rates (the redundancy rate of inputs, deficiency rate of desirable outputs and redundancy rate of undesirable outputs) of input and output variables.

The redundancy rate of inputs is as follows:

$$\vartheta_{mo}^- = \frac{s_i^-}{x_{i0}} \tag{3}$$

The deficiency rate of desirable outputs is as follows:

$$\vartheta_{ro}^g = \frac{s_r^g}{y_{ro}^g} \tag{4}$$

The redundancy rate of undesirable outputs is as follows:

$$\vartheta_{lo}^b = \frac{s_l^b}{y_{lo}^b} \tag{5}$$

Furthermore, the eco-efficiency of tourism (comprehensive efficiency, TE) is decomposed into two aspects. One is pure technical efficiency (PTE), which refers to the efficiency of resource allocation and utilization and pollutant control. For the specific calculation method, please refer to Zhu et al. [29]. The other is scale efficiency (SE), which implies the efficiency of resource scale aggregation, measuring whether DMUs are produced at the optimal scale. Their value ≤1 and comprehensive efficiency is equal to pure technical efficiency multiplied by scale efficiency.

3.2. Spatial Autocorrelation Model

On the basis of analyzing the longitudinal evolution of eco-efficiency of regional tourism in the time dimension, the research further explores spatial correlation patterns and clustering characteristics of eco-efficiency of provincial tourism in China through spatial autocorrelation (SAC) analysis. SAC analysis, as a spatial analysis method with the recognition function, can be used to explore whether regional factors are spatially correlated in spatial distribution and are divided into global and local SAC. Therein, global SAC describes the correlation degree and significance of all spatial units across the whole study area by calculating the *Global Moran's I*. In the research, global SAC can be used to calculate the *Global Moran's I* of eco-efficiency of tourism in China, so as to verify whether eco-efficiency of tourism has significant spatial correlation patterns and clustering characteristics in China, as expressed below, as follows:

$$Global\ Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - x')(x_j - x')}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{6}$$

$$S^2 = \frac{\sum_{i=1}^{n}(x_i - x')^2}{n} \tag{7}$$

In Formulas (6) and (7), n represents the sample size, that is, the number of provinces; x_i and x' separately denote the eco-efficiency of tourism of the ith province (city) and average overall eco-efficiency of tourism; W_{ij} is the spatial adjacency weight matrix. The value of the *Global Moran's I* is generally between −1 and 1, and a positive value means positive cluster characteristics of regions and a negative indicates negative cluster characteristics. In addition, the larger the absolute value is, the more obvious the corresponding characteristics. When the index is 0, it means that the eco-efficiency of tourism is spatially randomly distributed without spatial autocorrelation [30].

Local SAC is used to judge whether the eco-efficiency of provincial tourism has spatial autocorrelations or not in local regions, and is generally represented by *Local Moran's I* as Formula (8).

$$Local\ Moran's\ I = \frac{(x_i - x') \sum_{j=1} W_{ij}(x_j - x')}{S^2} \tag{8}$$

A positive *Local Moran's I* represent clustering of regions with similar efficiencies, while a negative value indicates clustering of regions with dissimilar efficiencies. The larger the absolute value is, the higher the degree of clustering.

3.3. Spatial Econometric Model

If the eco-efficiency of tourism in China has SAC, then it can be considered that the eco-efficiency of tourism may have a spatial spillover effect with its influencing factors. The spatial spillover effect means that economic and social activities in a specific area have an externality effect on the same activities in surrounding areas. Such an externality effect can drive improvement of the production and technological levels in adjacent areas, thus continuing to strengthen the clustering process. In the research, the spatial econometric model is adopted to explore whether the eco-efficiency of tourism in China and its influencing factors have a spatial spillover effect. The model is represented as follows:

1. The spatial autoregressive model (SAR), indicates that the explained variable in the region is affected by the explained variable in adjacent regions. Therefore, the explained

variable in adjacent region is input into the model as an explanatory variable in the following form:

$$\ln TE_{i,t} = \rho W \ln TE_{i,t} + \beta_i X_i + \alpha_i + \mu_t + \varepsilon_{i,t} \tag{9}$$

In Formula (9), $TE_{i,t}$ represents the explained variable; ρ is the spatial autocorrelation coefficient; W represents a spatial adjacency weight matrix; β_i is the explanatory variable coefficient; α_i and μ_t separately denotes the individual and time fixed effects; X_i is the explanatory variable; $\varepsilon_{i,t}$ is a random disturbance term.

2. The spatial error model (SEM), indicates that the spatial autocorrelation is reflected in the error term with spatial spillover effect. It is displayed as Formulas (10) and (11).

$$\ln TE_{i,t} = \beta_i X_i + \alpha_i + \mu_t + \varphi_{i,t} \tag{10}$$

$$\varphi_{i,t} = \lambda W \varphi_{i,t} + \varepsilon_{i,t} \tag{11}$$

In Formula (11), λ denotes spatial error coefficient and other variables are defined as those above.

3. The spatial Durbin model (SDM), which is the general form of the spatial econometric model. It includes both spatial dependences of explained variables and explanatory variables and can relieve the endogenous bias due to a lack of significant variables, so it is commonly used to analyze the spatial spillover effect of influencing factors. It is expressed as follows:

$$\ln TE_{i,t} = \rho W \ln TE_{i,t} + \beta_i X_i + \gamma W X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t} \tag{12}$$

In Formula (12), γ is the spatial lag coefficient of the explanatory variable, and other variables are defined as those above.

3.4. Variable Selection and Data Source

3.4.1. Selection of Input and Output Variables

A deep understanding of the connotation, characteristics and components of the research objects is the premise of objective and scientific evaluation. Therefore, in the construction of the evaluation index system for eco-efficiency of tourism, it is necessary to deeply analyze its connotation and elements and then obtain the evaluation index system for eco-efficiency of tourism according to the principle of constructing the index system. The specific indexes of input and output are shown in Table 1.

Table 1. The evaluation index system for eco-efficiency of tourism.

Index Category	Index	Serial Number	Unit
Input	Number of employees in tourism	Index 1	Million
	Net fixed assets of tourism	Index 2	Ten thousand yuan
	Energy consumption of tourism	Index 3	Tons of standard coal
	Water consumption of tourism	Index 4	100 million standard cubic meters
Desirable output	Total tourism revenue	Index 5	Ten thousand yuan
	Number of tourists	Index 6	Million
Undesirable output	Tourism CO_2 emissions	Index 7	Ten thousand tons

As mentioned above, the measurement of the eco-efficiency of tourism involves multiple dimensions such as tourism resources, economy and society. Therefore, based on the existing relevant research, the input variables selected in this study include inputs of labor, capital, energy and natural resources [31]. Combined with the availability of data, this study selected the number of employees in tourism in each province and city to represent labor input and the net value of fixed assets as the proxy variable of capital input. The energy input is measured by the total energy consumption of tourism in each region over the years, and the total consumption of water resources of tourism in each region characterizes the input of natural resources. Output variables can be divided into desirable and undesirable outputs. Therein, the desirable outputs include the following two dimensions: economy and society. The research selects the total tourism revenue to characterize the economic benefit; for the social benefit, it is measured by the number of tourist arrivals on the basis of referring to previous relevant research and considering that tourism is a special service industry that has recreational functions of facilitating cultural exchange and relieving life pressure [32]. The undesirable outputs need to consider influences of tourism on the regional ecological environment, so it is represented by CO_2 emissions of tourism [33].

It is notable that Chinese official statistics do not include water consumption, energy consumption and CO_2 emission data for tourism. Therefore, the indicator of water consumption of tourism here is calculated by dividing total tourism revenue in each region by regional GDP and multiplying by total water consumption by referring to previous research [32]. For the indicators of energy consumption and CO_2 emission of tourism, the method proposed by Becken et al. [34] and Patterson et al. [35] to divide tourism into the following three sectors: tourism transportation, tourism accommodation and tourist activities is adopted. The bottom-up method of decomposition first and then summation together is used to calculate total energy consumption and CO_2 emissions of provincial tourism. Besides, to eliminate influences of price volatility, the year 2000 is taken as the base period to deflate the net fixed assets of tourism and total tourism revenue according to the historical consumer price index.

Considering that the DEA method used here is mainly based on the input-output theory, the isotonic assumption needs to be paid attention to when building the evaluation index system for eco-efficiency of tourism. Golany and Roll [36] also further pointed out that correlation analysis has to be performed to verify whether input and output indicators have isotonicity relations (an increase in part of the input causes an increase in part of the output) or not. On this basis, the Pearson correlation tests are conducted to test input and output indicators in Table 1. Results are listed in Table 2.

Table 2. Pearson correlation analysis between input and output.

	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7
Index 1	1						
Index 2	0.737 ***	1					
Index 3	0.695 ***	0.568 ***	1				
Index 4	0.374 ***	0.143 **	0.442 ***	1			
Index 5	0.708 ***	0.550 ***	0.715 ***	0.609 ***	1		
Index 6	0.667 ***	0.423 ***	0.648 ***	0.618 ***	0.922 ***	1	
Index 7	0.683 ***	0.555 ***	0.997 ***	0.438 ***	0.715 ***	0.652 ***	1

Note: ** and *** respectively refer to significance at the 5% and 1% significance levels.

Test results in Table 2 show a significant positive correlation between input and output indicators selected in the research. This indicates that the established evaluation index system for eco-efficiency of tourism meets the isotonic assumption, which further confirms the reasonability of the evaluation index system for eco-efficiency of tourism selected in the research.

3.4.2. Selection of Influencing Factor Variables

Based on the existing studies [23,27,37], the following dependent variables and influencing factor variables are selected by combining with the WSR system method. (1) The TE, PTE and SE in various regions from 2008 to 2017 are selected as dependent variables. (2) The GDP per capita ($X1$) is selected to measure the level of economic development. (3) The proportion of added value of the tertiary industry in local GDP ($X2$) is selected to characterize the industrial structure. (4) The tourism energy consumption per 10,000 Yuan tourism income (*X*3) characterizes the technical level. (5) Transportation accessibility is characterized by the traffic network density (*X*4). (6) The environmental regulation is represented by the proportion of total investment in treatment of environmental pollution in local GDP (*X*5). It is worth explaining that the density of the transportation network = (railway mileage + highway mileage)/regional area. For individual missing data, this study uses interpolation and fitting methods to supplement.

3.4.3. Data Source and Description

Considering the availability and comparability of the data, this study selected the panel data of 30 provinces, autonomous regions and municipalities directly under the central government (Hong Kong, Macao, Taiwan and Tibet are not included due to the lack of relevant index data) in China from 2008 to 2017 as samples. The data are from statistical yearbook of provinces and cities from 2009 to 2018, China Statistical Yearbook, Yearbook of China Tourism Statistics, Yearbook of China Tourism Statistics and China Statistics Yearbook on Environment.

4. Empirical Results and Analysis

4.1. Analysis on Results of the Eco-Efficiency of Tourism

4.1.1. Analysis of Overall Features

By using Matlab R2016b software, the eco-efficiency of provincial tourism in China from 2008 to 2017 was calculated. The corresponding efficiency evaluation results are illustrated in Table 3.

From the perspective of the whole country, the average eco-efficiency of tourism in the whole country over the years has fluctuated around 0.534, but it has not reached the optimal level of development. It is evident that there is still room for progress in the sustainable development of tourism in China, and there is still a certain gap in resource utilization efficiency, quality and benefits, etc., so the transformation and upgrading task should be put on the agenda. From the perspective of regional efficiency differences, the eco-efficiencies of tourism in different provinces and cities increases slowly during the study period. The mean efficiencies in Tianjin City, Henan Province and Guizhou Province are equal to 1 and they become effective DMUs. That is, the sustainable development of tourism in these regions is good. They are directly followed by Shanxi Province, Chongqing City and Beijing City, for which the mean efficiencies over the years are 0.853, 0.848 and 0.802, ranked at the forefront of the country. The most striking is Chongqing City, with an efficiency of only 0.561 in 2008. However, during the study period from 2011 to 2017, they were effective DMUs and the mean efficiency over the years was 0.848. Overall, in the study period, the eco-efficiency of regional tourism showed a decreasing pattern in the central, western and eastern regions.

4.1.2. Analysis of Relaxation Rates of Inputs and Outputs

Efficiency results in Table 3 suggest that the eco-efficiency of tourism remained DEA efficient only in three provinces (or cities) including Tianjin, Henan province and Guizhou province in 2010–2017; the eco-efficiency of tourism in the remaining provinces (or cities) showed efficiency losses to different degrees in different years. The results indicate that most provinces (or cities) have problems including input redundancy, desirable output deficiency, or undesirable output redundancy in the tourism resource allocation process. On this basis, Equations (3)–(5) are used to calculate the redundancy rate of inputs, the deficiency rate of desirable outputs and the redundancy rate of undesirable outputs for input and output indicators. Results are displayed in Table 4 (limited by the length, results are shown as mean values of the eastern, central and western regions of China).

Table 3. The eco-efficiency of provincial tourism in China from 2008 to 2017.

Region	Provinces	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	MEAN
Eastern Region	Beijing	1.000	1.000	1.000	0.584	1.000	0.484	0.420	0.533	1.000	1.000	0.802
	Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Hebei	0.351	0.310	0.460	0.580	0.736	0.551	0.493	0.477	0.480	0.694	0.513
	Shanghai	0.263	0.242	0.320	0.353	0.352	0.298	0.314	0.322	0.284	0.308	0.306
	Jiangsu	0.352	0.349	0.365	0.398	0.413	0.337	0.325	0.340	0.324	0.299	0.350
	Zhejiang	1.000	0.292	0.342	0.385	0.394	0.332	0.320	0.355	1.000	0.388	0.481
	Fujian	0.343	0.319	0.305	0.324	0.321	0.266	0.262	0.301	0.333	0.368	0.314
	Shandong	0.562	0.541	0.496	0.574	0.665	0.525	0.436	0.500	0.479	0.605	0.538
	Guangdong	0.304	0.280	0.303	0.363	0.417	0.368	0.342	0.352	0.356	0.398	0.348
	Hainan	0.124	0.107	0.122	0.143	0.146	0.121	0.136	0.142	0.122	0.132	0.130
	Liaoning	0.431	0.399	1.000	1.000	1.000	0.797	0.542	0.539	0.512	0.512	0.673
	Mean	0.521	0.440	0.519	0.519	0.586	0.462	0.417	0.442	0.535	0.519	0.496
Central Region	Shanxi	0.767	0.503	1.000	0.717	0.837	1.000	0.710	1.000	1.000	1.000	0.853
	Jilin	0.421	0.629	0.478	0.642	1.000	0.628	0.586	0.655	1.000	1.000	0.704
	Heilongjiang	0.572	1.000	1.000	1.000	1.000	1.000	0.272	0.305	0.401	0.318	0.687
	Anhui	0.431	1.000	0.383	0.439	0.464	0.437	0.400	0.410	0.465	0.392	0.482
	Jiangxi	0.263	0.263	0.432	0.450	0.509	0.490	0.459	0.575	1.000	0.655	0.510
	Henan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Hubei	0.364	0.361	0.397	0.534	0.543	0.475	0.416	0.397	0.468	0.391	0.435
	Hunan	0.388	0.303	0.309	0.426	0.428	0.403	0.343	0.357	0.406	0.375	0.374
	Mean	0.526	0.632	0.625	0.651	0.723	0.679	0.523	0.587	0.718	0.641	0.631
Western Region	Guangxi	0.326	0.325	0.383	0.386	0.391	0.378	0.361	0.380	0.556	0.481	0.397
	Inner Mongolia	1.000	1.000	0.415	0.494	0.502	0.415	0.342	0.353	0.491	0.360	0.537
	Chongqing	0.561	0.423	0.495	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.848
	Sichuan	0.501	0.311	0.463	0.523	0.636	0.523	0.522	0.483	0.561	0.441	0.496
	Guizhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Yunnan	0.189	0.222	0.290	0.347	0.357	0.289	0.303	0.310	0.392	0.423	0.312
	Shaanxi	1.000	0.636	0.532	0.550	1.000	1.000	0.616	1.000	0.765	0.755	0.785
	Gansu	0.312	0.403	0.268	0.360	0.362	0.385	0.411	0.503	1.000	0.392	0.440
	Qinghai	0.270	0.239	0.252	0.224	0.323	0.268	0.257	0.233	0.225	0.198	0.249
	Ningxia	0.208	0.169	0.176	0.176	0.170	0.168	0.150	0.149	0.161	0.152	0.168
	Xinjiang	0.223	0.226	0.145	0.169	0.174	0.187	0.177	0.209	0.242	1.000	0.275
	Mean	0.508	0.450	0.402	0.475	0.538	0.510	0.467	0.511	0.581	0.564	0.501
Whole Country	Mean	0.517	0.495	0.504	0.538	0.605	0.538	0.464	0.506	0.601	0.568	0.534

Table 4. The relaxation rates of inputs and outputs.

Region	Input				Desirable Output		Undesirable Output
	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7
Eastern Region	39.442%	44.478%	44.748%	38.205%	31.000%	0.780%	44.198%
Central Region	29.691%	32.295%	34.185%	19.740%	17.539%	3.986%	34.655%
Western Region	42.288%	44.313%	39.447%	33.618%	38.620%	12.234%	36.989%
Whole Country	37.885%	41.169%	39.987%	31.599%	30.204%	5.835%	39.010%

According to the results in Table 4, the following conclusions are obtained: (1) from the input indicators, the redundancy rates of inputs in the eastern and western regions are both larger than those in the central region. Except for the number of tourism employees, the redundancy rates of inputs for other input indicators in the eastern region are larger than those in the western region. It indicates that tourism resources in the eastern region are the most seriously wasted in the sustainable development process of tourism, followed by the western region and finally the central region, which performs relatively better. This is also the same as the undesirable output indicators. The above conclusion further verifies the judgment for the spatial pattern that the eco-efficiency of regional tourism successively reduces in the central, western, the eastern region. (2) From the indicators of desirable outputs, the deficiency rate of desirable outputs is most prominent in the western region; the eastern region is superior to the central region in terms of the deficiency rate of the number of tourist arrivals but inferior to the central region with regard to deficiency rate of total tourism revenue. It is worth noting that the deficiency rate of the number of tourist arrivals is significantly superior to that of the total tourism revenue in all regions. The result indicates that the total tourism revenue is a dominant factor that limits the eco-efficiency of regional tourism from the perspective of desirable outputs. (3) The redundancy rate of the net value of fixed assets of tourism is the most prominent, followed by that of energy consumption, and the deficiency rate of the number of tourist arrivals is the most remarkable on the whole.

4.1.3. Analysis of Decomposition Efficiencies

In order to further explore the overall change characteristics of the eco-efficiency of Chinese tourism, this study decomposed the eco-efficiency of tourism, that is, the comprehensive efficiency, into pure technical efficiency and scale efficiency. The results are displayed in Figure 1.

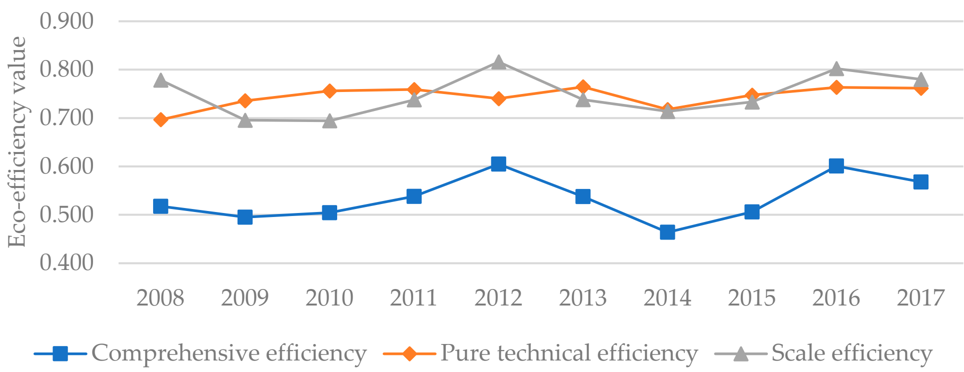

Figure 1. Eco-efficiency of tourism and its decomposition efficiencies in China from 2008 to 2017.

As shown in Figure 1, both the comprehensive efficiency and scale efficiency of Chinese tourism showed W-shaped fluctuation characteristics from 2008 to 2017, while pure technical efficiency was found to have a slow ascent trend. The average comprehensive efficiency over years is mostly lower than 0.6, which still has a large gap with the effective value of 1. Impacted by the 2008 global financial crisis, comprehensive efficiency declined in 2009, which was a result of the international economic depression and, therefore, the decline in economic output in China. The comprehensive efficiency ascended slowly after 2010 and reached a peak (in the study period) of 0.605 in 2012. However, the comprehensive efficiency dropped abruptly and reached the lowest value of 0.464 in 2014, and it did not pick up until 2015. Such a change occurred because the convening of the 18th National Congress of the Communist Party of China and the reiteration of the “two mountains” theory exerted great promotion effects on the sustainable development of tourism; however, the comprehensive efficiency decreased between 2012 and 2015 due to the enlarged industrial scale and resource investment in tourism and the lag of the output effect. Moreover, the steady improvement in pure technical efficiency indicates that tourism has gradually turned to green development with the implementation of the sustainable development strategy. At the same time, energy conservation and emission reduction, optimization of resource allocation and technical progress gradually show their effects. Whereas the changing trend of the scale efficiency suggests that the efficiency has a more powerful explanatory ability and driving action on the comprehensive efficiency. To further verify the result, this study further uses correlation analysis to calculate that the correlation coefficients of the comprehensive efficiency with the pure technical efficiency and scale efficiency are

0.459 and 0.864, respectively. It indicates that the correlation between scale efficiency and comprehensive efficiency is stronger.

4.2. Spatial Autocorrelation Patterns of the Eco-Efficiency of Tourism

The *Global Moran's I* is calculated using Stata.16 software to reveal spatial autocorrelation patterns of the eco-efficiency of provincial tourism in China from 2008 to 2017. The results are given in Table 5.

Table 5. *Global Moran's I* of the eco-efficiency of provincial tourism in China from 2008 to 2017.

Index	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Global Moran's I	0.02	0.086	0.137	0.197	0.296	0.206	0.152	0.16	−0.105	0.094
Z value	0.491	1.073	1.539	2.082	2.927	2.15	1.706	1.748	−0.623	1.14
P value	0.312	0.142	0.062 *	0.019 **	0.002 ***	0.016 **	0.044 **	0.04 **	0.267	0.127

Note: *, ** and *** respectively refer to significance at the 10%, 5% and 1% significance levels.

As shown in Table 5, (1) the eco-efficiency of provincial tourism in China shows obvious positive spatial autocorrelations, which pass the significance test at the 10% significance level in 60% of the years and even pass the test at least at the 5% significance level in 2011–2015. This finding indicates that the eco-efficiency of provincial tourism showed significant spatial autocorrelations in these years. That is, provinces with high (or low) efficiencies are obviously clustered. (2) from the characteristics of sequential variation, the positive spatial autocorrelation of the eco-efficiency of provincial tourism first increases and then decreases, with 2012 as the deflection point. From 2008 to 2012, the *Global Moran's I* was always larger than 0 and increased with fluctuations. This indicates that the positive spatial autocorrelation of the eco-efficiency constantly improved and provincial tourism showed certain cooperativity in terms of sustainable development in the period. The *Global Moran's I*, however, declined substantially after 2012 and it was even lower than 0 in 2016 while failing to pass the significance test. This finding implies that the eco-efficiency of provincial tourism gradually weakened to become unobvious during the period. This is mainly due to the fact that the sustainable development of provincial tourism was effectively driven by resource sharing among provinces, technology transfer and the trickle-down effect before 2012. Thereafter, however, the breakthrough of the previous spatial autocorrelation pattern should be achieved due to the different demands and priorities of various provinces for adjusting the industrial structure, improving management level and intensifying environmental regulation when advancing to high-quality development. As a result, the spatial autocorrelation gradually weakened.

To further study the spatial autocorrelation pattern of the eco-efficiency of provincial tourism in China, data from 2008, 2012 and 2017 were selected as cross-sectional data to calculate the *Local Moran's I* of each province. The results are shown in Figures 2–4. In the figures, the horizontal axis represents the standardized the regional eco-efficiency of tourism in each region and the vertical axis represents the eco-efficiency of tourism in each region by weighting spatially weighted matrixes. Moreover, the first, second, third and fourth quadrants of these figures separately represent the high-high (HH) cluster, low-high (LH) outlier, low-low (LL) cluster and high-low (HL) outlier. The HH cluster means that regions with a high eco-efficiency of tourism are surrounded by regions also with a high eco-efficiency, and others are defined following the same principle.

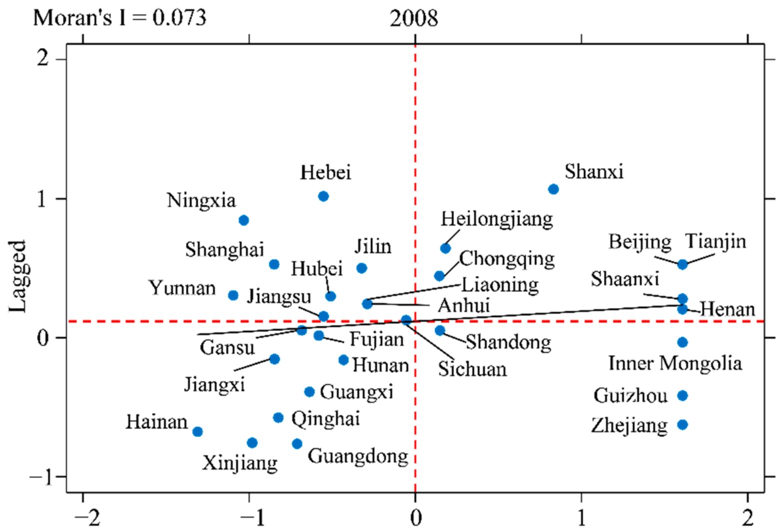

Figure 2. Local scatter plot of the eco-efficiency of tourism in 2008.

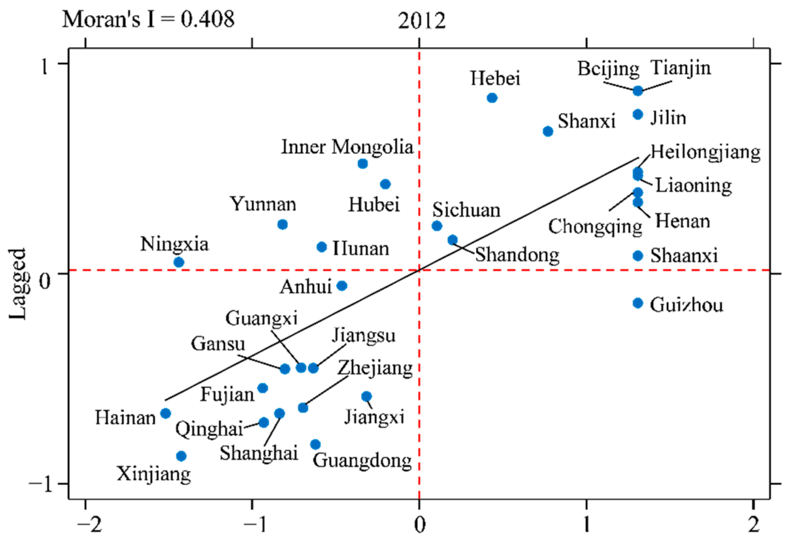

Figure 3. Local scatter plot of the eco-efficiency of tourism in 2012.

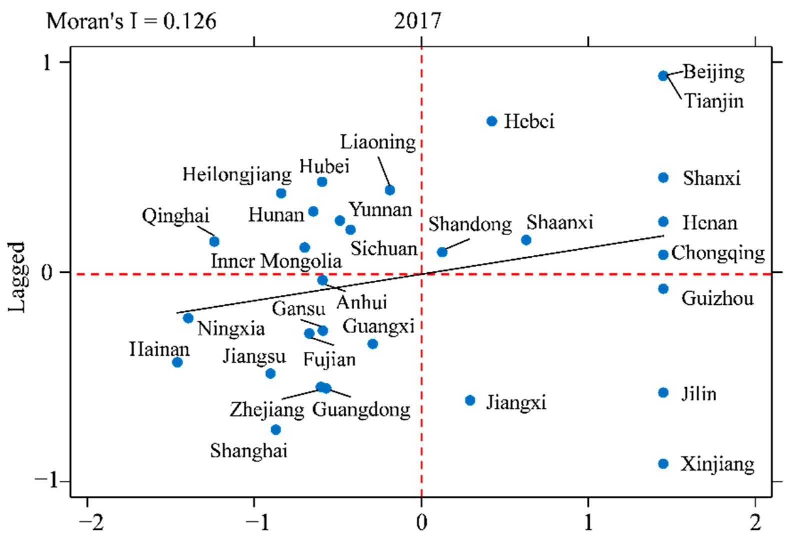

Figure 4. Local scatter plot of the eco-efficiency of tourism in 2017.

It can be seen from Figures 2–4 that the eco-efficiency of provincial tourism in China is mainly clustered in the LL cluster area, followed by the HH cluster and LH outlier areas, while only a few are distributed in the HL outlier area. To be specific, the LL areas mainly include Guangdong, Guangxi, Hainan, Gansu and Fujian, which showed a low degree of clustering in the study period. HH clustering is mainly found in Beijing, Tianjin, Henan, Shanxi, Chongqing and Shaanxi. They play a driving effect on surrounding adjoining provinces during their high-quality development of tourism, thus leading to a pattern of coordinated development of regions. The LH outlier areas mainly cover Hubei and Sichuan, which have lower eco-efficiency in tourism compared with nearby provinces, so they do not coordinate with the surrounding regions in their development. There are few provinces in the HL outlier area. From the evolution trends of clustering characteristics of the eco-efficiency of tourism in various provinces (and cities), Beijing, Tianjin, Henan, Shanxi, Shaanxi, Chongqing, Guangdong, Guangxi, Hainan, Gansu and Fujian always remained in the first and third quadrants throughout the study period. It implies that the eco-efficiency of tourism in these regions was trapped in a dilemma of the Matthew effect as follows: high-efficiency regions further promote their high-quality development of tourism by virtue of the high-efficient management, advanced technologies and resource endowment; while low-efficiency regions find it difficult to reverse the declining tendency of the low efficiency due to inefficiency of management and limitation of ecological bearing capacity. Xinjiang Uygur Autonomous Region, Jiangxi, Jilin, Hebei and Shandong turned from LL cluster and LH outlier to HL outlier and HH cluster; while Heilongjiang, Inner Mongolia Autonomous Region and Zhejiang changed from HH cluster and HL outlier to LH outlier and LL cluster. This finding indicates poor local stability of the eco-efficiency of tourism. To solve the problem, inefficient provinces and cities should take those efficient ones as their benchmark and take measures including factor flow, introducing advanced management technologies and implementing reasonable environmental regulations. By doing so, they are expected to realize an ideal situation of transition from an inefficient region to an efficient one.

4.3. Spatial Spillover Effect of the Eco-Efficiency of Tourism

The above analysis results indicate that the eco-efficiency of Chinese tourism features high spatial autocorrelations, so the spatial factor needs to be considered when studying influencing factors of the eco-efficiency of regional tourism. By using the Stata.16.0 software, the study adopts a spatial panel econometric model to carry out spatial regression analysis (spatial econometrics) on the influencing factors of the comprehensive efficiency, pure technical efficiency and scale efficiency of Chinese tourism. According to results of the Lagrange multiplier (LM) test and likelihood ratio (LR) test, statistics of the robust LM-spatial error and the robust LR-spatial error both pass the significance test at the 1% significance level, and the Hausman test results also reject the null hypothesis at the 5% level. In addition, LR test results demonstrate that the time fixed effect is superior to the spatial fixed effect and the time- and spatial-fixed effect. Therefore, the time-fixed SDM model is used to perform spatial regression analysis on the overall efficiency and decomposed efficiencies of tourism. The results are listed in Table 6.

The following conclusions can be drawn from the regression results in Table 6:

(1) The regression coefficient and spatial lag coefficient of the economic development level ($X1$) with the comprehensive efficiency of tourism are separately -0.023 and -0.126, both of which do not pass the significance test. The regression coefficients of $X1$ with pure technical efficiency and scale efficiency are 0.331 and -0.327, and their spatial lag coefficients are -0.37 and 0.217, respectively, both being significant at the 1% significance level. This indicates that the economic development level mainly has effects on pure technical efficiency and scale efficiency. The development of the social economy promotes the local energy saving and consumption reduction technologies and management level to improve, thus imposing positive effects on the pure technical efficiency of local tourism. However, as shown by Kim et al. [38], the rapid growth of the social economy of a region also leads to the outflow of technology, talent and resource factors from adjoining regions, thereby

inhibiting the pure technical efficiency in the adjoining regions. Moreover, the traditional extensive development mode also causes consumption of huge fossil energy despite its contribution to high-speed growth of the GDP, resulting in a constant rise in the clustering scale of tourism resource input in the region. This alleviates the clustering scale of tourism resource input in adjoining regions while inhibiting improvement of the scale efficiency of tourism in the region, thus promoting the scale efficiencies of adjoining regions.

Table 6. The spatial econometric regression results.

Variable	Comprehensive Efficiency	Pure Technical Efficiency	Scale Efficiency
ln *X*1	−0.023 (0.660)	0.331 *** (0.000)	−0.327 *** (0.000)
*X*2	−0.807 *** (0.001)	−0.580 ** (0.023)	−0.472 ** (0.040)
ln *X*3	−0.209 *** (0.000)	−0.113 *** (0.004)	−0.128 *** (0.000)
ln *X*4	0.252 *** (0.000)	0.252 *** (0.000)	0.025 (0.497)
*X*5	0.031 ** (0.010)	0.019 (0.127)	0.014 (0.210)
W·ln *X*1	−0.126 (0.135)	−0.370 *** (0.000)	0.217 *** (0.006)
W·*X*2	−0.378 (0.452)	−1.057 ** (0.035)	0.457 (0.325)
W·ln *X*3	−0.345 *** (0.000)	−0.332 *** (0.000)	−0.119 (0.129)
W·ln *X*4	−0.024 (0.685)	−0.217 *** (0.000)	0.222 *** (0.000)
W·*X*5	−0.020 (0.304)	0.023 (0.248)	−0.029 * (0.098)
W·ln *TE*	0.197 ** (0.015)	−0.111 (0.184)	0.185 ** (0.021)
R^2-ad	0.130	0.168	0.246
Log-likelihood	−1.3506	−6.6471	23.9062
Number of samples	300	300	300

Note: *, ** and *** respectively refer to significance at the 10%, 5% and 1% significance levels.

(2) The industrial structure (*X*2) shows regression coefficients of −0.807, −0.580 and −0.472 with the comprehensive efficiency, pure technical efficiency and scale efficiency of tourism, which are all significant at the 5% significance level; its spatial lag coefficients with these efficiencies are −0.378, −1.057 and 0.450, and only the SAC coefficient with the pure technical efficiency passes the significance test. The result indicates that the industrial structure exerts an inhibition effect on the improvement of the comprehensive efficiency of tourism. A reasonable industrial structure has a positive effect on the sustainable development of Chinese tourism. In contrast, a single industrial structure may lead to excessive clustering of a single industry and impose heavy pressure on resources and the environment, which is detrimental to the sustainable development of tourism. The gradual increase in the proportion of the tertiary industry in a region also results in the outflow of tourism resources and management technologies in adjoining regions, thus inhibiting the pure technical efficiency of adjoining regions.

(3) The technical level (*X*3) has regression coefficients of −0.209, −0.113 and −0.128 with the comprehensive efficiency, pure technical efficiency and scale efficiency of tourism, which are all significant at the 1% significance level. Its spatial lag coefficients with the comprehensive efficiency, pure technical efficiency and scale efficiency of tourism are −0.345, −0.332 and −0.119, with the former two being significant at the 1% level and the latter failing to pass the significance test. In this study, the energy consumption per ten thousand yuan of tourism revenue is used to characterize the technical level; that is, the larger the figure is, the lower the technical level. The regression coefficients reveal that the technical level exerts adverse effects on both the comprehensive efficiency and decomposed efficiencies of tourism as follows: the higher the technical level is, the lower the energy consumption under the same tourism revenue and the higher the efficiency. From the spatial lag coefficient, the technical level exerts significant spatial spillover effects. That is, improvement of the technical level in a region can drive the sustainable development of tourism in adjoining regions and thus promote comprehensive efficiency and pure technical efficiency to improve.

(4) Traffic accessibility (*X*4) has regression coefficients of 0.252, 0.252 and 0.025 with the comprehensive efficiency, pure technical efficiency and scale efficiency of tourism,

with the former two being significant at the 1% significance level and the latter failing to pass the significance test; its spatial lag coefficients with the comprehensive efficiency, pure technical efficiency and scale efficiency of tourism are −0.024, −0.217 and 0.222, with the former failing to pass the significance test and the latter two being significant at the 1% level. The result indicates that traffic accessibility has a promotion effect on the improvement of the eco-efficiency of tourism. Transportation is an indispensable condition for the development of tourism. Increasing the density of transportation networks can effectively improve the tourist gathering capacity of scenic spots, promote maximum utilization of tourism resources and drive scale development of tourism in adjoining regions. However, the resources and environment of scenic spots are under huge pressure with the continuously passive expansion of the scale of the tourism sector in adjoining regions, thus suppressing improvement of the pure technical efficiency in the adjoining regions.

(5) The regression coefficients of environmental regulation ($X5$) with the comprehensive efficiency, pure technical efficiency and scale efficiency are 0.031, 0.019 and 0.014, and only the coefficient with the comprehensive efficiency passes the significance test at the 5% significance level. The spatial lag coefficients of $X5$ with them are −0.020, 0.023 and −0.029, and only the coefficient with the scale efficiency passes the significance test at the 10% level. These findings indicate that environmental regulation mainly exerts a significant promotion effect on the comprehensive efficiency of a region while it does not significantly influence adjoining regions. Environmental regulation is not only a compulsory measure that forces enterprises to save energy and reduce consumption; it is also an inevitable requirement of green development. Whereas highly strict environmental regulation may lead to the race-to-the-bottom risk. That is, once environmental regulation is so strict that it exceeds the bearing capacity of enterprises, it is highly probable that it will reduce the production efficiency of enterprises and even make enterprises go bankrupt.

5. Conclusions and Suggestions

In this study, the capital, labor, energy and natural resources in tourism were taken as input elements. The total income of tourism and the number of tourists were used as desirable outputs, and the CO_2 emission of tourism was used as an undesirable output. Based on the SBM-DEA model and considering undesired output, this study calculated the eco-efficiency of provincial tourism in 2008~2017. Additionally, with the aid of the spatial autocorrelation model to explore the spatial autocorrelation characteristics. According to the WSR system method, influencing factor variables such as the level of economic development, industrial structure, technical level, traffic accessibility and environmental regulation were selected. The influencing factors for tourism eco-efficiency were empirically analyzed by utilizing the Spatial Durbin model. The results demonstrate that the tourism eco-efficiencies in various regions are significantly different, and the factors have different influences on efficiency. The specific conclusions are made as follows:

(1) Based on comprehensive efficiency, the average eco-efficiency of provincial tourism in 2008~2017 is 0.534, which is at the middle and high levels of development, so there is still room for improvement. Furthermore, a significant difference is found across regions. Based on the results of the ecological efficiency of tourism, the central region shows the optimal efficiency, followed by the western region, while the lowest efficiency is found in the eastern region. The TEs in the eastern and western regions have lowered the overall national level. In the future development of tourism, the eastern region, accounting for large proportions of the economic volume and energy consumption in China, can improve the eco-efficiency of its regional tourism in a series of ways. These include improving innovative tourism technologies, phasing out tourism enterprises with serious environmental pollution and developing a low-carbon and resilient tourism economy. The western region, particularly the Xinjiang Uygur Autonomous Region, Qinghai Province and Gansu Province, is mainly covered by steppe and desert, with a fragile ecological environment. Besides, the region is short on forest resources and has poor carbon sequestration capacity, so it is not suitable for carrying out large-scale tourist activities. Therefore, the eco-efficiency of

tourism in the region can be improved in ways of integrating tourism resources to develop high-quality tourism products, implementing rigorous environmental regulations and controlling tourism pollution emissions. The central region is rich in natural resources for tourism, such as forests and wetlands. For the region, the ecological carbon sequestration capacity can be improved to actively promote the realization of the value of ecotourism products relying on resort areas, forest parks and national cultural parks on the basis of the existing development level. In addition, according to the results of efficiency decomposition, tourism scale efficiency has a stronger ability to explain comprehensive efficiency. Therefore, in the process of sustainable development of the tourism industry in the future, China should reasonably control the scale of tourism resources input and mainly focus on the improvement of quality and benefits of tourism, thus realizing the effective growth of scale in the substantial improvement of quality and efficiency.

(2) From the spatial autocorrelation pattern of efficiencies, the eco-efficiency of provincial tourism in China shows an obvious positive spatial autocorrelation, whose degree first increased and then decreased, and the spatial clustering characteristics persisted throughout the study period. In addition, *Local Moran's I* indicates that clustering of the eco-efficiency of provincial tourism in China mainly occurs in the LL cluster areas, followed by the HH cluster and LH outlier areas, while only a few are in the HL outlier area. This shows a significant Matthew effect. Therefore, the country needs to encourage various provinces to enhance communication and actively carry out inter-governmental cooperation in the future sustainable development of tourism. At the same time, it needs to guide high-efficiency provinces to maximize their spatial spillover effect to drive the sustainable development of tourism in surrounding low-efficiency provinces.

(3) According to the regression results of influencing factors, the level of economic development, industrial structure and technological level inhibit the sustainable development of tourism and have negative spatial spillover effect, but only the spatial spillover effect of technological level passes the significance test. Transportation accessibility and environmental regulation significantly promote the sustainable development of tourism and have negative spatial spillover effects, but they all fail to pass the significance test. It can be seen that different factors have different influential effects on the sustainable development of tourism in different regions of China. To improve the tourism eco-efficiency in China and reduce regional differences, measures such as optimizing and upgrading the industrial structure of tourism, implementing an innovation-driven strategy, increasing the proportion of clean energy consumption and improving the environmental governance mechanism should be taken overall. Each region should take appropriate countermeasures according to the specific influential effects of each factor, so as to effectively enhance the sustainable development ability of regional tourism.

Author Contributions: Conceptualization, S.L. and Y.Z.; methodology, S.L. and B.J.; software, T.R.; validation, S.L. and Y.Z.; formal analysis, S.L. and Y.Z.; investigation, S.L. and B.J.; resources, Y.Z.; data curation, T.R.; writing—original draft preparation, S.L. and Y.Z.; writing—review and editing, T.R.; visualization, S.L.; supervision, B.J.; project administration, Y.Z.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Innovation Program of Hunan Province (2021SK2050), and Program of Hunan Social Science Achievement Review Committee (XSP20YBC127).

Data Availability Statement: The data source have been informed in Section 3.4.3 of the article. The specific link is https://data.cnki.net/ (accessed on 20 August 2021).

Acknowledgments: We thank the editor and anonymous referees, whose remarks have been very constructive and inspiring in preparing the final version of the paper. We are solely responsible for the opinions expressed in this paper.

Conflicts of Interest: The authors declare no conflict of interest.

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