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Understanding the Evolution of Regional Tourism Efficiency: Through the Lens of Evolutionary Economic Geography

Songsong Zhao [1], Tai Huang [1,*] and Jianchao Xi [2]

[1] Department of Tourism Management, Soochow University, Suzhou 215123, China
[2] Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
* Correspondence: huangtai@suda.edu.cn

Abstract: To further understand the evolution of regional tourism efficiency, a more systematic and theoretical analysis is required. Taking the urban agglomeration in the middle reaches of the Yangtze River as a case, this study applied evolutionary economic geography to analyze the evolutionary process of regional tourism efficiency. Data envelopment analysis (DEA) and the Malmquist index were used to measure the regional tourism efficiency and total factors productivity changes. Moreover, this paper employed the semi-variogram, Kriging interpolation, and Markov chain to explore the spatiotemporal evolution and transition characteristics of regional tourism efficiency. Finally, based on the test results of Geo-detector, the driving mechanism of the spatiotemporal evolution of regional tourism efficiency was constructed. The results show that the overall tourism development was inefficient, and the leading sources of inefficiency were primarily embedded in pure technology inefficiency, while the main contributor to the growth of total factor productivity was the positive technical change. Over time, the spatial spillover effect of regional tourism continued to increase, and the spatial pattern changed from divergence to convergence, resulting in co-evolution. The inertial trajectory of the evolution of regional tourism efficiency reveals a significant path dependence. Factors such as traffic accessibility, tourism resource endowments, tourism specialization, industrial structure, informatization, and openness can reasonably explain the evolution of regional tourism efficiency.

Keywords: evolutionary economic geography; regional tourism efficiency; spatiotemporal evolution; driving mechanism; urban agglomeration in the middle reaches of the Yangtze River

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Citation: Zhao, S.; Huang, T.; Xi, J. Understanding the Evolution of Regional Tourism Efficiency: Through the Lens of Evolutionary Economic Geography. *Sustainability* **2022**, *14*, 11042. https://doi.org/10.3390/su141711042

Academic Editors: Lóránt Dénes Dávid, Laszlo VASA and Setiawan Priatmoko

Received: 5 July 2022
Accepted: 1 September 2022
Published: 4 September 2022

1. Introduction

The analysis of efficiency is key to assessing the sustainability of tourism and reshaping the tourism economy [1]. At the regional level, tourism efficiency is influenced by broader socioeconomic factors in addition to location, resources, life cycle, management, and technology [2]. Therefore, spatial heterogeneity is one of the prominent manifestations of regional tourism efficiency. Likewise, the imbalance in tourism efficiency constrains the sustainable development of China's tourism industry [3]. Therefore, the Chinese government has emphasized that regional tourism should improve efficiency and synergy. Among the open challenges in this field, it is crucial to understand the evolution of regional tourism efficiency.

In the extensive existing literature, hotels, travel agencies, airports, and destinations are the main objects of tourism efficiency research [4]. However, in addition to the traditional sectors, the tourism industry also involves labor, capital, land, and other inputs [5]. Productivity measures for a single sector do not ideally project onto the tourism industry as a whole. As a result, the assessment of multi-factor productivity for the regional tourism industry has become a new area of academic interest. The study of regional tourism efficiency covered cross-sectional comparisons [6,7], temporal changes [8], spatial variation [9,10], and influencing factors [11,12]. Furthermore, the evolution of tourism efficiency reflects the changes in the tourism development model [13]. As a complex system, the regional tourism industry is not only affected by endogenous factors such as resource endowments, management, and technology, but also by broader socioeconomic factors [2]. However, our understanding of the evolution and influencing factors of regional tourism efficiency is still limited. Therefore, to further develop our knowledge on the evolution of regional tourism efficiency, a more systemic and theoretical analysis is required. In addition, a new empirical paradigm should be developed to be better conceptualize the evolutionary paths of regional tourism efficiency and the conditions required for change. Evolutionary economic geography (EEG), which studies the change and reconstruction of uneven spatial economies over time [14], seems to be a better way to attain this goal.

EEG is an emerging framework that seeks to better understand long-term economic changes and differences across regions [15]. It advocates an evolutionary perspective to track the spatial activities of economic changes [16]. On the one hand, based on the theory of evolution and complex systems, EEG emphasizes the role of historical processes and spatial heterogeneity [17]. On the other hand, tourism is highly dependent on local resources and has a strong regional and historical nature. Thus, there is a natural coupling between tourism research and EEG that emphasizes regional experience [18,19]. As a new theoretical framework for tourism economics research, tourism scholars are increasingly interested in EEG. In recent decades, EEG has been widely applied to study the development of tourism areas [20–22], the governance of tourist destinations [17,23,24], and the path creation of tourism industry [25,26]. In particular, the concepts of path dependence and co-evolution have greatly contributed to the theorizing of tourism economics research [19]. Additionally, with the development of EEG in tourism studies, a "structure–process" perspective has emerged. However, although tourism scholars have consciously specified a more systematic and rigorous framework for the application of EEG in tourism research, there is still no coherent empirical paradigm and methodology. Moreover, EEG rarely pays attention to the influencing factors and driving mechanisms behind the changes of tourism economy in tourism research.

To deepen the application of EEG in the study of regional tourism efficiency evolution, this paper aims to establish a rigorous paradigm and a coherent methodological framework. To this end, this paper took the urban agglomeration in the middle reaches of the Yangtze River (UAMRYR) as a case to investigate the evolution and driving mechanism of regional tourism efficiency through the lens of EEG. First, this paper introduced the core concepts and epistemological principles of EEG. Second, following the framework of "structure–process–mechanism", this paper used data envelopment analysis (DEA) to measure the relative tourism efficiency. Furthermore, using the Malmquist index (MI), semi-variogram, Kriging interpolation, and Markov chain, the spatiotemporal dynamics and transition characteristics of regional tourism efficiency were analyzed respectively in this study. Finally, the Geo-detector model was utilized to explore the influencing factors and driving mechanisms of regional tourism efficiency evolution.

This study may have three potential contributions to tourism scholarship. First, this paper deepens the application and adaptability of EEG in tourism efficiency research by refining the "structure–process" perspective. Second, this study provides a non-linear narrative for depicting the evolution of tourism efficiency by placing tourism within broader, dynamic, and regional development frames. Third, the methodology used in this study is interdisciplinary, coherent, and replicable, allowing for a comprehensive quantitative description of the spatiotemporal evolution of tourism efficiency at the regional level.

The paper will proceed as follows: The next section presents the literature review on tourism efficiency and EEG in tourism studies. Section 3 recommends the research methodology. Section 4 accounts for the data. Section 5 reports and discusses the empirical results through the lens of EEG. Finally, Section 6 summarizes the conclusions and policy implications.

2. Literature Review

2.1. Tourism Efficiency at the Regional Level

Traditional tourism sectors have been the primary focus of tourism efficiency research [27–30]. However, to more precisely identify the gaps in existing literature, we mainly reviewed the empirical studies on regional tourism efficiency.

With the increasing availability of statistical data and advancement of methodology, the study of tourism efficiency at the regional level has received extensive academic attention [3,31–33]. Moreover, the development of pluralistic and interdisciplinary approaches has led to a more accurate and comprehensive assessment of regional tourism efficiency. Therefore, the research on regional tourism efficiency is diverse, including analysis of temporal trends, spatiotemporal dynamics, and influencing factors. Among them, Lionetti [34] used the stochastic frontier approach (SFA) to analyze the tourism efficiency of 208 countries and regions globally and examined the impact of structural characteristics on spatial differences. Hadad et al. [35] incorporated the entire tourism industry into the measure of tourism efficiency, rather than being limited to the micro tourism sector. Using the input-oriented DEA model with constant returns to scale, Kurt [7] evaluated the tourism efficiency of 29 European countries based on the input factors that affect the tourism economy. Wang et al. [33] found that the spatial spillover effects and spatial dependence of urban tourism efficiency in China were not significant. Furthermore, there are differences in the development paths of tourism efficiency in different regions [36]. However, few studies have provided a comprehensive description of the evolution of regional tourism efficiency.

Exploring the determinants of tourism efficiency is critical to improving tourism performance [2]. Thus, it is necessary to examine the factors that affect regional tourism efficiency. Among the studies in this topic, Mamatzakis et al. [37] examined the effect of labor market regulations on tourism performance in Greece. Corne and Peypoch [2] implemented a two-stage DEA model to analyze the influencing factors of tourism efficiency. Cao et al. [38] found that economic policies, the pursuit of economic benefits in tourist destinations, and tourism demand can contribute to the growth of tourism efficiency in the Pan-Yangtze River Delta of China. According to Li et al. [39], the comparative advantages of location, resource conditions, economic development, technological progress, and policy implementation were the determinants of the significant increase in tourism efficiency. Furthermore, Li and Liu [40] found that tourism industry agglomeration has a significant impact on tourism efficiency at the provincial level in China. Tang [41] confirmed that trade facilitation can improve the efficiency of Japan's inbound tourism. Nevertheless, most scholars have failed to propose a driving mechanism for the evolution of regional tourism efficiency.

2.2. EEG and Tourism Studies

Over the past decade, EEG has been applied to various research fields, such as regional science, tourism geography, and industrial economics [42,43]. Many papers on the theoretical framework and applications of EEG have also been published in mainstream tourism journals.

Path dependence is one of the core concepts of EEG, which refers to the likelihood that previous events affect future events [44]. Earlier studies applied the concepts of path dependence and co-evolution to the governance of tourist resorts [45,46]. In particular, Brouder [42] emphasized the link between these two concepts and tourism research, arguing that EEG can provide a non-linear perspective for the study of tourism evolution. Moreover, by introducing the basic principles of EEG, a new way of incorporating EEG into tourism research has been developed [47]. In general, previous studies have provided many ideas for the extension of EEG in tourism research.

Tourism is a dynamic system that needs to remain competitive. Therefore, tourism scholars are concerned not only with changes in the tourism economic pattern over time, but also with the driving mechanisms behind these changes [48]. The study of tourism evolution is an established reflective lens that can be used to validate, develop, and challenge

EEG in tourism studies [42]. However, most of these studies are theoretical and qualitative, and the research areas were relatively limited and have not been extended to larger urban agglomerations.

Scholars synthesize their findings, resulting in a more prescriptive EEG paradigm in tourism research. These achievements suggest that fields such as rural tourism, sustainable tourism, destination governance, and the evolution of tourism areas could be studied through the lens of EEG [23–25,49]. For instance, Ma and Hassink [46] provided an alternative path-dependent model to explain the evolution of tourist areas. The research confirmed that the evolution of tourist areas depends on the original location and resources, that it will be affected by history, and that it has path dependence. However, interactions and linkages make the tourism economy malleable, and path dependence is not immutable [24]. Tourist areas will be forced to adapt or create new paths in order to remain competitive [45]. Therefore, the derived concept of "path creation" is applicable in tourism research [21]. Additionally, the complex system theory of EEG provides a narrative for the study of tourism geography and highlights a focus on broader integrated regional elements [50]. In conclusion, these studies confirmed the applicability of EEG in explaining the evolutionary process of tourist destinations. However, in tourism research, EEG has rarely been applied to depict the evolution of tourism efficiency at the regional level. In addition, EEG is less persuasive because it lacks solid empirical method support.

A review of the existing literature reveals three gaps that have yet to be addressed. Firstly, most of the existing studies stay on the simple evaluation and lack in-depth analysis of the evolutionary process of regional tourism efficiency. Second, although previous studies have examined the influencing factors of regional tourism efficiency, they have failed to comprehensively explore the driving mechanisms from the perspective of dynamics and heterogeneity. Thirdly, although EEG has been applied to tourism research, studies on regional tourism efficiency are rare and lack rigorous empirical frameworks and methods.

3. Methodology

3.1. Data Envelopment Analysis

DEA is an effective method for accessing efficiency by using the actual economic distance to the production frontier [51]. It is a non-parametric estimation method that calculates the input–output ratio of the tourism industry by taking the region as the decision-making unit (DMU). Returns to scale in the tourism economy change frequently and are not always optimal. Therefore, this study used the variable returns to scale model proposed by Banker, Charnes, and Cooper [52] (DEA-BCC model). The DEA-BCC model can decompose comprehensive efficiency (CE) into pure technical efficiency (TE) and scale efficiency (SE). TE is the production efficiency influenced by technology and management. SE represents the production efficiency at the optimal production scale. This model has been widely used to evaluate tourism efficiency, and the detailed formula can be found in Baker and Riley [53].

3.2. Malmquist Index

As DEA is unable to measure changes in economic performance over time, MI was developed [54]. MI is the change of total factor productivity (TFPC), which reflects the growth rate of tourism efficiency from time t to time t + 1 [1]. MI is calculated as follows:

$$MI(y_{t+1}, x_{t+1}) = \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d^t(x_t, y_t)}{d^{t+1}(x_t, y_t)} \right]^{1/2} \quad (1)$$

In Equation (1), MI > 1, MI = 1, and MI < 1 indicate the increase, constant, and decrease of efficiency, respectively. x_t, y_t and x_{t+1}, y_{t+1} denote the inputs (x) and outputs at time t and t + 1.

$$MI(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d^t(x_{t+1}, y_{t+1})}{d^t(x_t, y_t)} \times \frac{d^{t+1}(x_{t+1}, y_{t+1})}{d^{t+1}(x_t, y_t)} \right] \quad (2)$$

MI can be decomposed into technical change (TC) and efficiency change (EC), with EC situated on the right side of Equation (2), preceded by TC. Furthermore, EC can be decomposed into pure efficiency change (PEC) and scale efficiency change (SEC). These decompositions represent their contributions to TFPC.

3.3. Semi-Variogram

The semi-variogram is one of the most effective methods for analyzing the spatial variation of regionalized variables [55]. In this paper, it is mainly used to reveal and observe the spatial correlation and spatial variation characteristics of regional tourism efficiency. The functional estimator of $\gamma(h)$ is called the semi-variogram. The semi-variogram between two locations, $Z(x_i)$ and $Z(x_i + h)$, separated by a distance h, is defined by Equation (3):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{3}$$

where $\gamma(h)$ is the semivariance for the lag distance h, and $Z(x_i)$ and $Z(x_i + h)$ are the observed values located in x_i and $x_i + h$, respectively. Among the parameters of the model, C_0 is the nugget variance, indicating that the regionalized variable is not continuously variable when it is smaller than the sampling scale. C is the structured variance. C_0 + C is the sill, indicating that when the variation function $\gamma(h)$ increases with the interval distance h, it reaches a relatively stable constant from a non-zero value, which is the largest variation in the system. Proportion [$C/(C_0 + C)$]: this statistic provides a measure of the proportion of sample variance (C_0 + C) that is explained by spatially structured variance C, which reflects the degree of spatial variation. Range (A_0) is the separation distance over which spatial dependence is apparent. The fractal dimension D represents the curvature of the semi-variogram. The closer it is to 2, the more balanced the spatial distribution is. Finally, R^2 indicates how well the model fits the variogram data.

3.4. Markov Chain

The Markov chain is an effective method to portray the evolution of geographical things. It can use a matrix to represent the transition of tourism efficiency state. Specifically, Markov processes assume that the state of an event at a particular time depends on its previous condition [56]. Based on this assumption, it is possible to measure the transition probabilities of the different states of regional tourism efficiency. In this paper, the method is employed to analyze the path dependence of regional tourism efficiency. The method divides regional tourism efficiency data into w state before calculating the transition probability. The transition probabilities between different categories of regional tourism efficiency are represented by a $w \times w$ probability matrix (M). The matrix element m_{ij} represents the transition probability from state i to state j, where $m_{ij} = n_{ij}/n_i$, n_{ij} is the number of units transitioning from state i to state j, and n_i is the number of units belonging to state i.

3.5. Geo-Detector

Geo-detector is a new statistical method for detecting drivers of spatial heterogeneity without assumptions of linearity [57]. The main idea is that if an independent variable has a significant impact on the dependent variable, their spatial distributions should be similar. The Geo-detector approach can effectively identify the core influencing factors of regional tourism efficiency. This paper used Geo-detector to identify the influencing factors of regional tourism efficiency and observe the changes. The formula is as follows:

$$q_{d,u} = 1 - \frac{1}{n\delta^2 u} \sum_{i=1}^{m} n_i \delta^2 u_i \tag{4}$$

4. Data Description

4.1. Inputs and Outputs

Multiple inputs and outputs are used to evaluate tourism efficiency at the regional level. Land, labor, and capital are commonly used indicators to measure economic efficiency [58]. However, due to the ambiguity of tourism land, it is often not included in the measurement of tourism efficiency [3]. Therefore, this study selects two inputs of labor and capital to measure regional tourism efficiency. The resources required for tourism production are referred to as tourism capital. The primary sectors of tourism industry include travel agencies, star-rated hotels, and A-class tourist scenic spots [59]. Thus, the number of tourism sectors was defined as the input of capital, as Wang et al. [3] suggested. In addition, we defined the number of employees in the tertiary industry as labor input because of the comprehensiveness of the tourism industry at the regional level [60]. If tourism is effective, there will be more tourists and revenue [12,51]. Therefore, tourist arrivals and tourist receipts were defined as outputs.

4.2. Study Area

UAMRYR is a large urban agglomeration in the Yangtze River Basin of China, consisting of the Wuhan metropolitan circle, the Chang-Zhu-Tan urban agglomeration, and the Poyang Lake urban agglomeration (Figure 1). It is one of the three major cross-regional urban agglomerations in the Yangtze River Economic Belt. To promote the coordinated development of tourism in urban agglomeration, the "Development Plan for Urban Agglomerations in the Middle Reaches of the Yangtze River" puts forward the goal of building an integrated tourist area. In 2017, UAMRYR accounted for more than 1/3 of the number of visitors and tourism revenue from China. However, there is significant spatial heterogeneity in the tourism efficiency of UAMRYR. Therefore, it is representative to study the evolution of regional tourism efficiency by taking UAMRYR as a case.

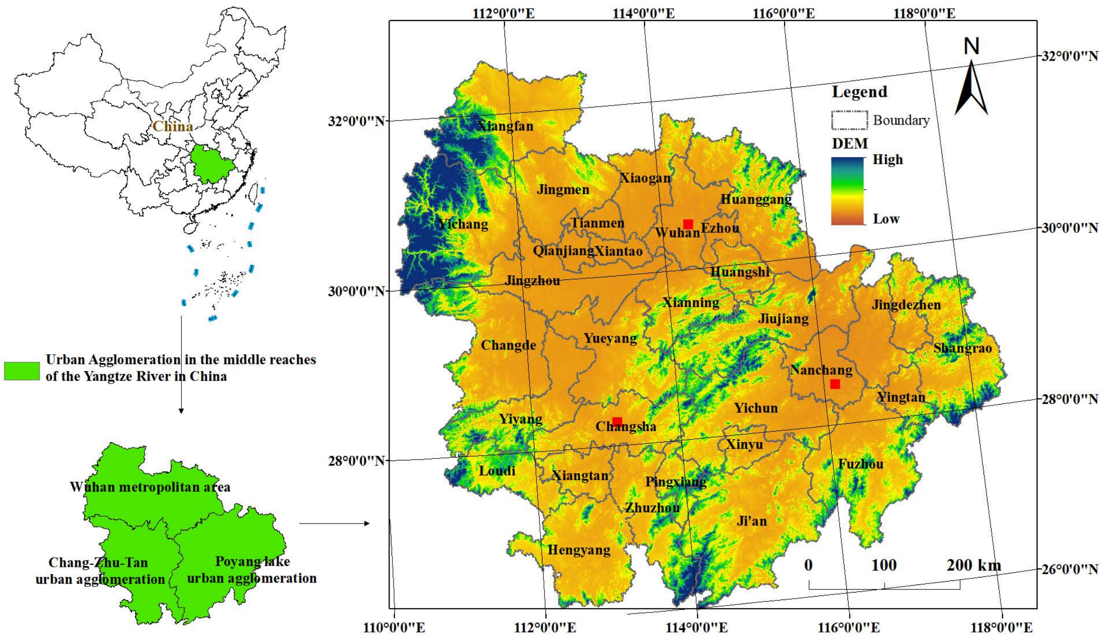


Figure 1. Location of the study area.

4.3. Data Collection

In this study, the 31 cities of UAMRYR are used as spatial units to explore the evolution of regional tourism efficiency. The data of the number of employees in the tertiary industry, tourism arrivals, tourism receipts, and the influencing factors are obtained from "The Hubei Statistical Yearbook", "The Hunan Statistical Yearbook", "The Jiangxi Statistical

Yearbook", "The Regional Economic Statistical Yearbook", "The China City Statistical Yearbook" for the years 2002 to 2018, and "The Statistical Bulletin on National Economy and Social Development (SBNESD)" for all cities from 2001 to 2017. The data of the number of tourism sectors are obtained from the website of the Ministry of Culture and Tourism of China (www.mct.gov.cn, accessed on 23 November 2019). Very few missing data are supplemented by interpolation. The data of administrative division, geographic boundary, government site, and elevation come from the 1:1 million vector database of the National Geomatics Center of China (www.ngcc.cn/ngcc/, accessed on 23 November 2019).

5. Results and Discussion

5.1. General Characteristics of Regional Tourism Efficiency

According to the DEA-BCC model, the tourism efficiency of UAMRYR from 2001 to 2017 was calculated. Based on the results, a heat map was drawn to describe the overall characteristics of regional tourism efficiency. As shown in Figure 2, the average tourism efficiency in UAMRYR from 2001 to 2017 was 0.569, indicating that it is possible to reduce overall inputs by 46.1% while keeping tourism outputs constant. There was a significant distance between the actual tourism efficiency and the optimal production frontier. Thus, the tourism development in UAMRYR was relatively inefficient. Moreover, Figure 2 reveals the differences in tourism efficiency among different cities. The comprehensive efficiency (CE) of Wuhan was the highest at 0.972, while that of Xiantao was the lowest at 0.209. By comparison, 77.4% of the cities in UAMRYR had higher scale efficiency (SE) than pure technical efficiency (TE). This suggests that the tourism efficiency in UAMRYR was scale-oriented.

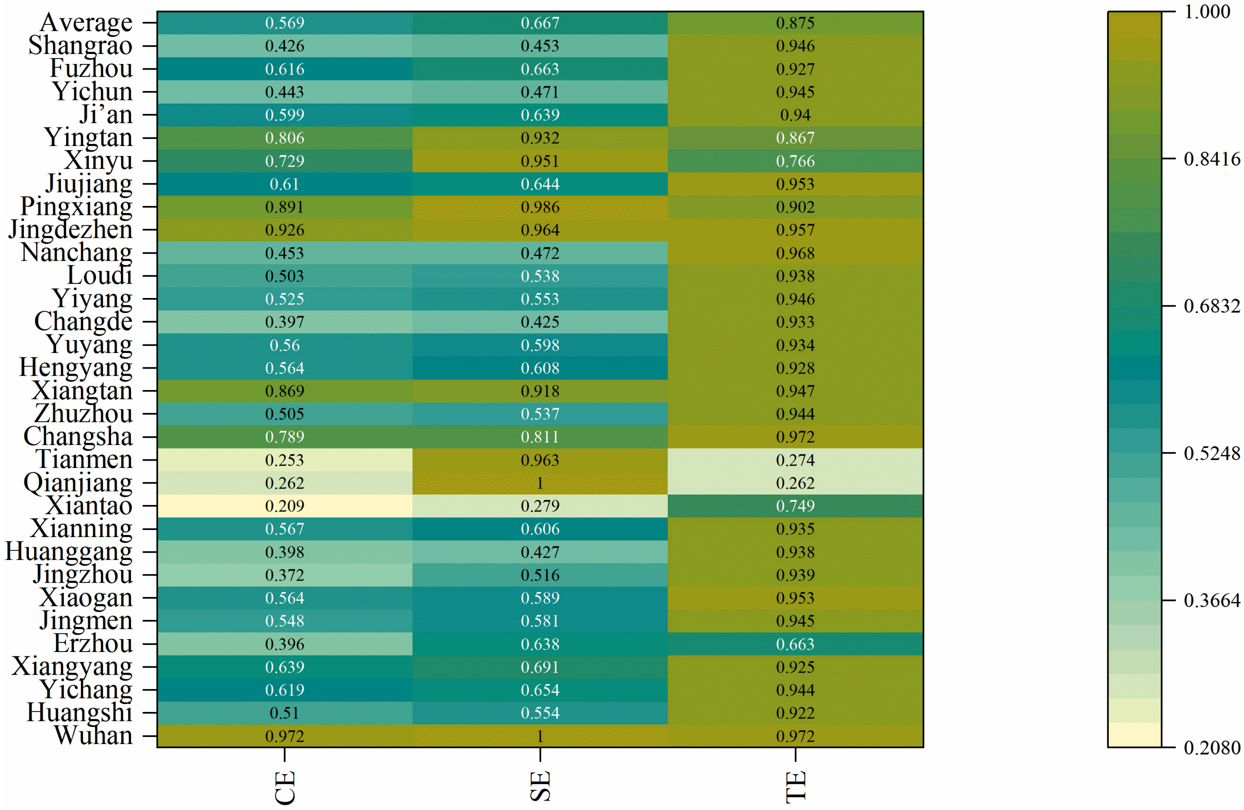


Figure 2. The average tourism efficiency in UAMRYR.

5.2. Spatiotemporal Evolution of Regional Tourism Efficiency

5.2.1. Changes and Decomposition of Total Factors Productivity

Tourism efficiency measured by DEA cannot account for changes in regional tourism efficiency. To further reveal the changes in regional tourism efficiency, based on the formula of MI, TFPC was calculated and decomposed. The mean value of TFPC is 1.134, as shown in Table 1, indicating that the tourism efficiency of UAMRYR was steadily improving at a rate of 13.4% per year. There are 30 cities with a TFPC greater than 1, showing a significant increase in tourism efficiency from 2001 to 2017. During the study period, TC grew by 12.6% per year, PEC increased by 1.6% per year, and SEC decreased by 0.9% per year. Furthermore, TCs were higher than ECs in all cities, and 18 cities (58.1%) had an SEC below 1, suggesting that the main contributor to total factor productivity growth is the positive technical change, but scaling up reduces productivity.

Table 1. Total factor productivity changes and its decomposition.

Region	City	EC	TC	PEC	SEC	TFPC
Wuhan metropolitan area	Wuhan	0.989	1.150	1.000	0.989	1.138
	Huangshi	1.072	1.104	1.067	1.005	1.183
	Xiangyang	1.025	1.114	1.028	0.997	1.142
	Ezhou	0.918	1.146	1.000	0.918	1.052
	Jingmen	0.987	1.113	0.982	1.005	1.099
	Xiaogan	0.978	1.084	0.975	1.003	1.060
	Jingzhou	1.004	1.123	1.006	0.998	1.127
	Huanggang	0.978	1.090	0.982	0.997	1.066
	Xianning	1.046	1.110	1.046	1.000	1.161
	Xiantao	1.002	1.118	1.006	0.996	1.120
	Qianjiang	0.875	1.119	1.000	0.875	0.979
	Tianmen	0.926	1.098	1.000	0.926	1.018
	Yichang	0.974	1.162	0.989	0.985	1.132
	Average	0.983	1.118	1.006	0.976	1.098
Chang-Zhu-Tan urban agglomeration	Changsha	0.988	1.148	0.997	0.991	1.134
	Zhuzhou	1.027	1.138	1.025	1.002	1.169
	Xiangtan	1.025	1.156	1.019	1.006	1.184
	Hengyang	0.983	1.100	0.986	0.996	1.081
	Yueyang	1.001	1.112	1.004	0.997	1.113
	Changde	1.010	1.130	1.014	0.997	1.142
	Yiyang	1.049	1.098	1.047	1.002	1.152
	Loudi	1.003	1.109	0.994	1.010	1.113
	Average	1.011	1.124	1.011	1.000	1.136
Urban agglomeration around Poyang Lake	Nanchang	1.045	1.142	1.052	0.994	1.193
	Jingdezhen	1.040	1.152	1.029	1.011	1.199
	Pingxiang	1.034	1.121	1.006	1.028	1.159
	Jiujiang	1.029	1.168	1.034	0.995	1.202
	Xinyu	1.048	1.165	1.017	1.031	1.221
	Yingtan	0.998	1.161	0.987	1.011	1.159
	Jian	1.049	1.129	1.054	0.995	1.184
	Yichun	1.060	1.115	1.064	0.996	1.182
	Fuzhou	1.019	1.101	1.017	1.002	1.123
	Shangrao	1.059	1.138	1.068	0.992	1.205
	Average	1.038	1.139	1.033	1.005	1.183
	Average (all cities)	1.007	1.126	1.016	0.991	1.134

5.2.2. Spatiotemporal Evolution of Regional Tourism Efficiency

EEG believes that the evolution of regional tourism economy is reflected in two dimensions of time and space. Further analysis of the evolutionary process of the spatial pattern of regional tourism efficiency is indispensable. Therefore, the tourism efficiency data of UAMRYR in 2001, 2010, and 2017 were fitted with semi-variograms under incremental steps in this paper, and the results were presented in Tables 2 and 3.

Table 2 shows that C_0, as fitted by the semi-variogram model, continued to rise, but $C_0 + C$ rose and then declined during the study period. Meanwhile, $C/C_0 + C$ decreased, indicating that the spatial difference of tourism efficiency in UAMRYR was gradually weakening and the sample variance caused by spatially structured variance lessened over time. Furthermore, the significant increase in A_0 from 2001 to 2017 suggests that the range of the spatial dependence and spatial correlation of regional tourism efficiency in UAMRYR was expanding. In 2001, 2009, and 2017, the fitting models were spherical function, Gaussian function, and linear function, demonstrating that there are significant differences and variations in the spatial structure of regional tourism efficiency. Moreover, the fitting coefficients were low for all time, showing a significant gap between the actual state and the ideal trend of regional tourism efficiency, and showing that the regional tourism efficiency in UAMRYR has not yet formed an orderly self-organizing evolution.

Table 2. Fitting parameters of the semi-variogram.

Year	Range, A_0	Nugget, C_0	Sill, C_0 + C	Proportion, C/(C_0 + C)	Model	Fitting Coefficient, R^2
2001	77.08 km	0.0001	0.0717	0.9990	Gaussian	0.405
2010	259.00 km	0.0103	0.0826	0.8750	Spherical	0.774
2017	317.45 km	0.0413	0.0611	0.3240	Linear	0.380

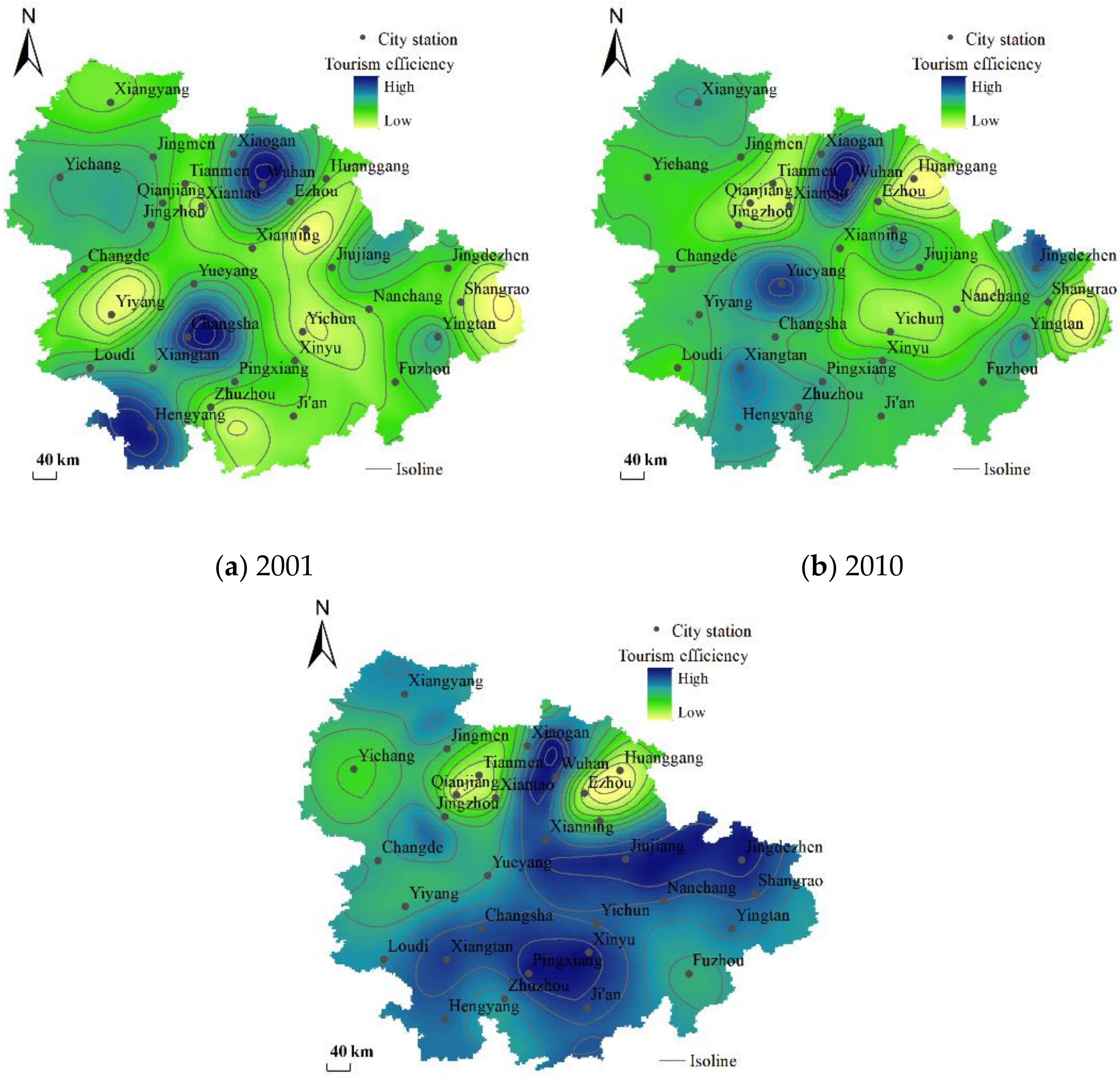
Table 3. The results of fractal analysis.

Year	Isotropic		South–North (0°)		Northeast–Southwest (45°)		East–West (90°)		Southeast–Northwest (135°)	
	D	R^2	*D*	R^2	*D*	R^2	*D*	R^2	*D*	R^2
2001	1.859	0.240	1.667	0.384	1.856	0.140	1.891	0.085	1.953	0.022
2010	1.637	0.689	1.722	0.494	1.475	0.768	0.811	0.528	1.890	0.101
2017	1.941	0.189	1.948	0.010	1.901	0.070	1.375	0.376	1.828	0.452

As shown in Table 3, the isotropic fractional dimension rose from 1.859 to 1.941, which is closer to the ideal value 2, indicating that the spatial pattern of tourism efficiency in UAMRYR shifted to relative equilibrium. From 2001 to 2017, except for the east-west direction, the fractional dimensions in other directions all increased, suggesting that the overall spatial difference in regional tourism efficiency is narrowing. Specifically, the fractal dimension in the south–north direction was closest to 2, indicating that the spatial balance in this direction is optimal. However, the worst spatial equilibrium was observed in the east–west direction. In 2017, the fractional dimension of isotropy reached a maximum of 1.941. At this time, the spatial pattern of regional tourism efficiency was the most balanced.

To more intuitively depict the evolutionary process of the tourism efficiency in UAMRYR, this paper performed Kriging interpolation (Figure 3) based on the fitting results of semi-variogram model. The results highlight three characteristics of the evolution of regional tourism efficiency. First, the spatial pattern of regional tourism efficiency was spatially dependent, which is embodied in the fixity and correlation of locations of the hot and cold spots. The second is that the spatial evolution of tourism efficiency was asymmetric, and the core-periphery of the spatial pattern was the most direct manifestation of spatial competition. However, spatial spillover effects can promote co-evolution between different geographical units, resulting in the third trend: the spatial pattern of regional tourism efficiency has changed from divergence to convergence. This is primarily reflected in the enhancement of spatial diffusion and the reduction of spatial differences.

The evolutionary process of regional tourism efficiency is roughly as follows: First, nodes appeared, but were scattered and few. This is the period of path emergence. After that, although the number of cold spots has decreased, their locations have remained relatively fixed. The spatial structure of regional tourism efficiency also has not changed significantly, which implies path dependence. Over time, the increasing spatial spillover has caused the original hot spots to shift from a scattered distribution to cross-regional clusters, resulting in co-evolution. Accordingly, neighboring regions became hot spots, which is referred to as a regional branch or a path of innovation. There has been a shift in the spatial pattern of regional tourism efficiency from divergence to convergence. Path dependence and path innovation jointly promote the spatiotemporal evolution of regional tourism efficiency.



(**a**) 2001 (**b**) 2010

(**c**) 2017

Figure 3. Kriging interpolation of the tourism efficiency in UAMRYR. (**a**) Kriging simulation in 2001; (**b**) Kriging simulation in 2010; (**c**) Kriging simulation in 2017.

5.2.3. Transition Characteristics of Regional Tourism Efficiency

To further clarify the stability and dependence of the spatiotemporal evolution of regional tourism efficiency, a Markov chain was used to calculate the transition probability in this paper. The tourism efficiency of the 31 cities in UAMRYR was first divided into four states using natural breaks (Jenks), and then the matrixes of transition probability (Table 4) were measured for 2001–2010, 2010–2017, and 2001–2017 by the Markov chain method.

Table 4. Markov transition probability matrix.

t/t + 1	2001–2010				2010–2017				2001–2017			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	0.7234	0.2128	0.0426	0.0213	0.7742	0.2258	0.0000	0.0000	0.7436	0.2178	0.0256	0.0128
2	0.1383	0.7234	0.1170	0.0213	0.0649	0.7273	0.1948	0.0130	0.1053	0.7251	0.1520	0.0175
3	0.0115	0.1724	0.6667	0.1494	0.0000	0.2031	0.6875	0.1094	0.0066	0.1854	0.6755	0.1325
4	0.0196	0.0196	0.2353	0.7255	0.0000	0.0000	0.1739	0.8261	0.0103	0.0103	0.2062	0.7732

The results show that the transition probabilities on the main diagonal is significantly higher than that on the off-diagonal, indicating that the regional tourism efficiency will maintain its initial state with a high probability. The maximum probability of the initial high level remaining unchanged is 77.32%, and the probability of a downward shift will not be greater than 21.78%, which suggests that the transition of high-level tourism efficiency is inertial. Moreover, the maximum probability of shifting from a low level to a high level is 21.78%. Therefore, it can be judged that the evolution of regional tourism efficiency may also fall into the "poverty trap". In summary, the "history", such as the original level and structure, has profoundly affected the evolutionary path of regional tourism efficiency [16]. In other words, the inertial trajectory of the evolution of regional tourism efficiency reveals significant path dependence.

5.3. Driving Mechanism of Regional Tourism Efficiency Evolution

5.3.1. Geo-Detector Measurements and Interpretation

Based on previous literature [2,3,12,61–64], this paper selected eight explanatory variables to explore the influencing factors and driving mechanism of the evolution of regional tourism efficiency. Using the Geo-detector model, the effects of each influencing factor were calculated. The variables are as follows: The tourism endowments (TRE) were calculated based on the weighted scores of various tourism attractions. The ratio of tertiary industry added value to GDP was used to represent industrial structure (IS). Per capita GDP was used to measure the state of the regional economy (SRE). Tourism specialization (TS) was expressed in terms of location entropy. Trade openness (TO) was measured by foreign direct investment. The level of informatization (IL) was stated as the total volume of postal and telecom business. The total retail sales of consumer goods were used to calculate the consumer market (SCM). The traffic network density was used to represent traffic accessibility (TA). The tourism efficiency in UAMRYR was used as the dependent variable. The independent variables in the Geo-detector cannot be numerical data; this paper used K-means clustering algorithm to discretize the original data of the influencing factors.

The results in Table 5 show that there were significant differences in the effects of the influencing factors on regional tourism efficiency. From 2001 to 2017, the q-values of each influencing factor showed a general upward trend, and there was an increase in the number of key influencing factors. Specifically, the statistically significant influencing factor in 2001 was TA, with a q-value of 0.2977. In 2010, the q-values of different influencing factors were ranked as follows: TS (0.3982) > TRE (0.3291). The ranking of the q-values in 2017 was as follows: TS (0.6656) > IL (0.5811) > TRE (0.4636) > IS (0.4298) > TO (0.4185). In 2017, the q-values of all significant influencing factors exceeded 0.4.

5.3.2. Discussion of the Driving Mechanism

According to EEG, the evolution of regional tourism is a complex and dynamic process [46]. It is possible to better understand how regional tourism efficiency changes over time by analyzing the driving mechanism. Therefore, this study discussed the driving mechanism behind the evolution of regional tourism efficiency based on the detection of the influencing factors.

Table 5. Results of the Geo-detector analysis.

Year	IS	SRE	TO	SCM	IL	TA	TRE	TS
2001	0.3579 (0.5427)	0.4322 (0.2818)	0.2043 (0.9449)	0.4449 (0.2582)	0.1827 (0.6647)	0.2977 (0.0931) *	0.1645 (0.6274)	0.3243 (0.6420)
2010	0.1615 (0.9731)	0.2207 (0.3876)	0.3048 (0.1134)	0.1157 (0.8517)	0.3031 (0.7811)	0.0427 (0.9115)	0.3291 (0.0224) **	0.3982 (0.0500) **
2017	0.4298 (0.0330) **	0.0656 (0.9098)	0.4185 (0.0477) **	0.1222 (0.7499)	0.5811 (0.0023) ***	0.1100 (0.6787)	0.4636 (0.0059) ***	0.6656 (0.0031) ***

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Supported by many scholars, location is considered to be one of the most influential factors on tourism performance [65]. EEG also points out that location is a fundamental condition that profoundly influences the emergence and evolution of tourist areas [16]. Geographical advantages represented by transportation accessibility are one of the prerequisites for the development of tourism destinations [66]. Accessibility to traffic may reduce the time-space lag in the allocation of tourism resources and enhance tourism outputs [21]. As a result, tourist areas with better accessibility became hot spots, and the initial spatial pattern of regional tourism efficiency was formed.

With the advent of the nodes of regional tourism efficiency, geographical advantages have become less important. Instead, tourism resource endowments and tourism specialization emerged as critical influencing factors in this period. This is because tourism resource endowment and tourism specialization can contribute to the establishment of brand advantages and capital accumulation in tourism destinations [22]. The asymmetry of the spatial pattern of regional tourism efficiency becomes more pronounced because of the large differences in tourism resource endowment and specialization in different regions [67]. Furthermore, the location and number of hotspots of regional tourism efficiency did not change significantly, so the evolutionary path was further fixed and strengthened [68].

To avoid being locked into a stagnant path, tourism regions need to adapt [46]. More extensive socio-economic factors played a leading role in the evolution of regional tourism efficiency during this time. Specifically, industrial structure, informatization, and openness contributed to the spatial spillover of capital, manpower, and knowledge. Through the spatial spillover effects, liquidity improvement and technological imitation, the neighboring regions of the original hotspots established late-developing advantages and became new hotspots. In addition, the spatial pattern of regional tourism efficiency shifted from divergence to convergence. Therefore, regional tourism efficiency entered the stage of path innovation and co-evolution [47,69]. The overall path dependence of the evolution of regional tourism efficiency was still significant, nevertheless, as path innovation depended on "history" or "legacy", such as tourism specialization and resource endowment [67,70].

6. Conclusions and Implications

6.1. Main Conclusions

Although EEG focuses on the changes in uneven economic landscapes over time, it is still novel in the study of regional tourism efficiency. This paper developed a "structure–process–mechanism" empirical framework for understanding the evolution of regional tourism efficiency. The main theoretical contribution of this paper is to provide a coherent and rigorous paradigm for deepening EEG in the study of tourism economy. Furthermore, this study provides a complete methodology and implementation procedure, which is reproducible. Therefore, this study served to overcome the shortcomings of previous literature that are mostly limited to characterization. The focus on the driving mechanism of the evolution of regional tourism efficiency provides insights for policymakers who are committed to realizing the co-evolution and sustainable development of regional tourism efficiency.

The main results of this study are as follows: First, the leading sources of inefficiency were primarily embedded in pure technology inefficiency. The positive technical change was the main contributor of total factor productivity growth. Second, the sample variance of tourism efficiency in UAMRYR caused by spatially structured variance lessened over time. Moreover, the overall spatial pattern of regional tourism efficiency changed from divergence to convergence. The inertial trajectory of the evolution of regional tourism efficiency reveals significant path dependence. Third, traffic accessibility, tourism endowments, tourism specialization, industrial structure, informatization, and trade openness jointly drove the evolution of regional tourism efficiency.

6.2. Practical Implications

The empirical results confirm that the evolution of regional tourism efficiency is open, asymmetrical, and dynamic. Therefore, to promote the co-evolution and sustainable development of regional tourism industry, this paper provides some implications for policy-makers, local governments, regulators, and other stakeholders. First, tourism destinations should optimize the allocation of resources and promote technological innovation and realize the transformation from extensive growth to intensive development.

Second, the peripheral regions should formulate strategic planning according to local conditions for tourism development and take the initiative to learn from developed regions to form a late-mover advantage. Furthermore, policymakers should pay attention to the spatial dependence and spatial correlation of regional tourism efficiency and enhance the knowledge and human capital spillovers of the core regions.

Third, governments at all levels should establish and improve the mechanisms for regional tourism cooperation, such as joint development, collaborative governance, and information sharing. Within the region, it is necessary to eliminate the barriers to the flow of tourism resources and elements, and to promote the sharing of the inputs and outputs of tourism industry, so as to reduce the imbalance of space and achieve the goal of coordinated development.

Fourth, in the evolution of regional tourism efficiency, special attention should be paid to the role of socioeconomic factors such as regional industrial structure, informatization, and openness, as well as local factors such as tourism specialization and resource endowments, in order to promote path innovation and narrow spatial differences.

Inevitably, some limitations in this study require further exploration. First, since the research framework of EEG has not yet been completely established, there may be a certain degree of bias in the interpretation of some issues. Therefore, more empirical case studies are needed to apply and test the framework of EEG in future tourism research. Second, the selected influencing factors may not fully describe the driving mechanism of the evolution of regional tourism efficiency. Accordingly, a broader model is needed to incorporate more influencing factors and their interactions.

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

Funding: This research was funded by the National Social Science Foundation of China (No. 17BGL123). It is also supported by the National Nature Science Foundation of China (No. 41771162).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

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