

Retraction

Retracted: Statistical Measurement and Influencing Factors of Green Total Factor Productivity of China's Tourism Industry Based on DEA-EBM Model

Mobile Information Systems

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

Copyright © 2023 Mobile Information Systems. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Z. Xiang, S. Che, and S. Zhou, "Statistical Measurement and Influencing Factors of Green Total Factor Productivity of China's Tourism Industry Based on DEA-EBM Model," *Mobile Information Systems*, vol. 2022, Article ID 4069291, 13 pages, 2022.

Research Article

Statistical Measurement and Influencing Factors of Green Total Factor Productivity of China's Tourism Industry Based on DEA-EBM Model

Zikun Xiang,¹ Shirui Che,² and Sijia Zhou ³

¹School of Economics, Wuhan University of Technology, Wuhan, Hubei 430070, China

²School of Economics, Zhongnan University of Economics and Law, Wuhan, Hubei 430073, China

³School of Economics, Wuhan Donghu University, Wuhan, Hubei 430212, China

Correspondence should be addressed to Sijia Zhou; 2020020019@stu.cdut.edu.cn

Received 20 July 2022; Revised 26 August 2022; Accepted 29 August 2022; Published 12 October 2022

Academic Editor: Chi Lin

Copyright © 2022 Zikun Xiang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to explore the statistical measurement and influencing factors of green total factor productivity in tourism, this paper proposes the use of gray absolute correlation to measure the similarity between input variable sequences. Moreover, this paper obtains the key parameters of the combination of radial and nonradial in the model based on the proximity index of gray correlation and calculates the economic efficiency of the decision-making unit according to the steps. In addition, this paper combines the DEA-EBM model to carry out the statistical measurement of China's tourism industry green total factor productivity and the analysis of influencing factors and verify it through data. Through research, it can be seen that the DEA-EBM model proposed in this paper can play an important role in the statistical measurement and analysis of influencing factors of green total factor production in the tourism industry.

1. Introduction

Tourism is a comprehensive and linked industry. In a society with diverse cultures and ethnic diversity, tourism builds bridges for human communication and promotes mutual understanding between different races and different cultures. At the same time, there are a series of social and economic activities in the process of tourism consumption, which promote the allocation and circulation of people, materials, and funds [1]. According to relevant data from the United Nations World Tourism Organization (UNWTO), currently, tourism accounts for 10% of global GDP, 7% of world exports, and 30% of labor exports. Moreover, modern tourism is a new economy, a comprehensive industry that integrates the primary, secondary, and tertiary industries, which not only promotes the appreciation of agricultural products but also drives the development of industrial products that meet consumer needs [2]. UNWTO's research shows that the contribution of the entire tourism sector to

global warming caused by human factors has reached about 5%–14% [3]. This shows that tourism is closely related to global climate change.

From the macrolevel of the entire economic field, efficiency refers to the rational allocation of resources invested so as to maximize the total surplus value that all members of society can obtain. It is a specific indicator that reflects the research object's ability to use resources and the results obtained. For any economic entity, a high level of efficiency is an important prerequisite for its sustainable development. The issue of efficiency has become the core issue in the current economic development, and it is also a hot spot of domestic research.

This paper combines the EA-EBM model to carry out the statistical measurement and analysis of the influencing factors of the green total factor productivity of China's tourism industry, which provides a theoretical reference for the subsequent development of green tourism.

2. Related Work

Literature [4] studied the main source markets and compared single and multivariable models. From the model research results, it can be seen that the prediction models showed different research results in the main source markets. Literature [5] pointed out that there are many factors that influence tourism demand, and they are a series of factors and not a single factor. Literature [6] pointed out that different countries and regions have differences in prices or income, and their impact on international tourism demand is also different. Literature [7] believes that the economic development of a region or a city is too dependent on the international economic market, which may have a reactionary force on the economic development of the city and affect the development of urban tourism. Literature [8] studied the main reasons that affect rural tourism demand and found that the economic impact was limited and most rural consumers spent their expenditures on food and outdoor activities. Literature [9] conducted an in-depth investigation and exploration of the structural factors of tourism demand after readjusting the gravity model. Literature [10] used hotel overnight tourists as the research object, combined with the tourism demand model and artificial neural network model, carried out a specific analysis of the case, and proposed a prediction model to guide interested tourism suppliers to provide better product supply to meet the needs of tourists. Literature [11] uses a novel evolutionary negative correlation combined with the LSPME model to study tourism demand estimation, compares the LSPME model with other integrated models, and believes that the estimation accuracy of the LSPME model is significantly better than other integrated models. Literature [12] proposes to select a tourism demand model for measurement based on actual conditions. If the independent variable is known, it is best to use a neural network prediction model. When the independent variable is only a fuzzy value, the regression model analysis is more accurate. If the independent variable value is not known, the time series prediction model should be used. Literature [13] believes that there are many influencing factors in the generation of tourism demand, among which the most important factors are the price of tourism products, transportation, and personal disposable income. It also believes that economic growth can stimulate more tourism demand. Literature [14] proposed the concept of tourism compound cost, which included time, income, and other aspects into the model for consideration, and took the travel rate and tourism compound cost as the main measurement indicators so as to establish the tourism demand function for tourism demand and conduct calculation research. At present, domestic scholars have also begun to try to use single or combined forecasting methods to achieve forecasting goals. Literature [15] used the average absolute error and average absolute percentage error to construct multiple mathematical calculation models.

Literature [16] studied the supply of tourism through qualitative and quantitative methods and concluded that the management of water resources should be strengthened in

tourist destinations where water is scarce. From the perspective of supply, literature [17] believes that the tourism supply chain includes not only direct suppliers but also indirect suppliers that provide tourism products and services to meet the needs of tourists; literature [18] puts forward an in-depth analysis of the process of tourism activities. Tourism supply chain is a tourism business network formed by multiple stakeholders, which involves various private enterprises, public departments, large enterprises, and so on. Literature [19] believes that the government should undertake the construction of basic public facilities in tourist destinations. However, the construction of tourism public service system has the characteristics of public welfare, so the profit is too small and may cause some enterprises to provide poor or even unqualified tourism products.

3. DEA-EBM Cross-Efficiency Model for Green Tourism considering Singularity and Competition and Cooperation

In DEA-EBM, due to the quantitative relationship between the input and output of the decision-making unit and the internal correlation in the evaluation to a certain extent, the rationality of the specific efficiency evaluation method has attracted more attention.

We assume that there are n DMUs, and each DMU has m inputs and s outputs. x_{ij} ($i = 1, 2, \dots, m$) represents the i -th input of unit DMU_j ($j = 1, 2, \dots, n$), y_{rj} ($r = 1, 2, \dots, s$) represents the r -th output. For the j -th decision-making unit, its efficiency can be defined as [20]

$$\theta_j = \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \quad (j = 1, 2, \dots, n). \quad (1)$$

Among them, v_i ($i = 1, \dots, m$) and u_r ($r = 1, \dots, s$) represent the weight of input and output.

Considering that the decision-making unit is DMU_d , $d \in \{1, 2, \dots, n\}$, the efficiency of this unit relative to other DMUs is called the CCR model, as shown in

$$\begin{aligned} \max E_{dd} &= \frac{\sum_{r=1}^s u_{rd} y_{rd}}{\sum_{i=1}^m v_{id} x_{id}}, \\ \text{s.t.} &\begin{cases} E_{dd} = \frac{\sum_{r=1}^s u_{rd} y_{rd}}{\sum_{i=1}^m v_{id} x_{id}} \leq 1 \quad j = 1, 2, \dots, n, \\ u_{rd} \geq 0 \quad r = 1, 2, \dots, s, \\ v_{id} \geq 0 \quad i = 1, 2, \dots, m. \end{cases} \quad (2) \end{aligned}$$

The goal of the plan is to find a set of input and output weights that are most beneficial to DMU_d .

By using the Charnes-Cooper transformation, model (2) can be converted into an equivalent linear program to solve, as shown in [21]

TABLE 1: Cross-efficiency matrix for n units.

Target DMU	DMU						Cross-eff 1 (a_1)
	1 (a_1)	2 (a_2)	1 (a_1)	2 (a_2)	1 (a_1)	2 (a_2)	
1	E_{11}	E_{12}	1	E_{11}	E_{12}	1	E_{11}
2	E_{21}	E_{22}	2	E_{21}	E_{22}	2	E_{21}
...
P	E_{1p}	E_{2p}	P	E_{1p}	E_{2p}	P	E_{1p}
...
n	E_{n1}	E_{n2}	n	E_{n1}	E_{n2}	n	E_{n1}

$$\begin{aligned} \max \quad & \sum_{r=1}^s u_r y_{rd} = E_{dd}, \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^m \omega_i x_{ij} - \sum_{r=1}^s u_r y_{rj} \geq 0 \quad j = 1, 2, \dots, n, \\ \sum_{i=1}^m \omega_i x_{ij} = 1, \\ \omega_i \geq 0 \quad i = 1, 2, \dots, m, \\ u_r \geq 0 \quad r = 1, 2, \dots, s. \end{cases} \end{aligned} \quad (3)$$

Among them, E_{dd} is the CCR efficiency of the decision-making unit U_d ; that is, the optimal efficiency that the unit can achieve, reflecting the self-evaluation of the unit. The optimal weight coefficient of each decision unit DMU_d , ($d = 1, 2, \dots, n$) is $\omega_d^* = (\omega_{1d}^*, \dots, \omega_{md}^*, \mu_{1d}^*, \dots, \mu_{sd}^*)$. Since each unit can get its own set of ω_d^* , the efficiency of other units can be calculated according to co, which is called cross efficiency. Sexton et al. defined the crossover efficiency obtained by DMU_p using U_d 's weight as

$$E_{dp} = \frac{\sum_{r=1}^s u_r y_{rp}}{\sum_{i=1}^m \omega_i^* x_{ip}} \leq 1, \quad d, p = 1, 2, \dots, n, \quad d \neq p. \quad (4)$$

This model reflects the evaluation results of DMU_d on DMU_p . Model (3) needs to be run n times to solve the efficiency of each DMU. Therefore, for n DMUs, n sets of input-output weights will be obtained, forming $n-1$ sets of cross efficiency and a CCR efficiency, thereby forming a cross-efficiency matrix (CEM), as shown in Table 1 [22].

Model (3) may have multiple sets of optimal solutions; that is, the nonuniqueness of input and output weights will destroy the use of cross-efficiency evaluation. In order to solve this problem, Sexton proposed a set of quadratic goals to optimize the input and output weights while ensuring the efficiency of model (3). It uses an aggressive strategy to calculate the cross efficiency. The aggressive cross efficiency of the decision-making unit p based on d is shown in model (5), and the efficiency value is \underline{E}_{dp} . The benevolent cross efficiency of decision-making unit p based on d is shown in model (6), and the efficiency value is \underline{E}_{dp} .

$$\begin{aligned} \text{Minimize} \quad & \sum_{r=1}^s u_r d \left(\sum_{p=1, p \neq d}^n y_{rp} \right), \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^m v_{id} \left(\sum_{p=1, p \neq d}^n x_{rp} \right) = 1, \\ \sum_{r=1}^s u_r d y_{rp} - E_{dd} \sum_{i=1}^m v_{id} x_{rp} = 0, \\ \sum_{r=1}^s u_r d y_{rp} - \sum_{i=1}^m v_{id} x_{rp} \leq 0 \quad p = 1, 2, \dots, n, \\ v_{id} \geq 0 \quad i = 1, 2, \dots, m, \\ u_r d \geq 0 \quad r = 1, 2, \dots, s. \end{cases} \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Maximize} \quad & \sum_{r=1}^s u_r d \left(\sum_{p=1, p \neq d}^n y_{rp} \right), \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^m v_{id} \left(\sum_{p=1, p \neq d}^n x_{rp} \right) = 1, \\ \sum_{r=1}^s u_r d y_{rp} - E_{dd} \sum_{i=1}^m v_{id} x_{rp} = 0, \\ \sum_{r=1}^s u_r d y_{rp} - \sum_{i=1}^m v_{id} x_{rp} \leq 0 \quad p = 1, 2, \dots, n, \\ v_{id} \geq 0 \quad i = 1, 2, \dots, m, \\ u_r d \geq 0 \quad r = 1, 2, \dots, s. \end{cases} \end{aligned}$$

The above two models ensure the worst and the best overall efficiency of other units while maintaining the DMU_d efficiency score.

In addition, DEA-EBM also includes some other common secondary target models:

- Minimize $\sum_{r=1}^s u_r d \left(\sum_{j=1, j \neq d}^n y_{rk} \right) - \sum_{i=1}^m v_{id} \left(\sum_{j=1, j \neq d}^n x_{ij} \right)$.
- It replaces $\text{Minimize } 1/n \sum |\alpha'_j - \bar{\alpha}'|$ with $\sum_{r=1}^s u_r d y_{rj} - \alpha_d \sum_{i=1}^m v_{id} x_{rj} \geq 0$ in model (5). Among them, $\alpha_d \in (\min_{1 \leq j \leq n} E_{jj}, 1)$ is a parameter that controls the range of DMU_d efficiency scores.

(c) *MinMaximize* α'_j or *Minimize* $1/n \sum_{j=1}^n |\alpha'_j - \bar{\alpha}'|$

$$s.t. \begin{cases} \sum_{i=1}^m v_{id} x_{id} = 1, \\ E_{dd} = \sum_{r=1}^s u_{rd} y_{rd}, \\ \sum_{r=1}^s u_{rd} y_{rd} - \sum_{i=1}^m v_{id} x_{id} + \alpha'_j = 0 \quad j = 1, 2, \dots, n. \end{cases} \quad (6)$$

Among them, $\bar{\alpha}' = 1/n \sum_{j=1}^n \alpha'_j$.

Models (4) to (6) give the general DEA cross-efficiency calculation method, and model (5) treats all decision-making units as hostile situations. However, model (6) regards all decision-making units as Allies. They simply regard all decision-making units as alliance or hostile relations.

The mutual information of discrete and continuous variables can be expressed as follows:

Continuous type: $I(X, Y) = \iint p(x, y) \log_2 p(x, y) / p(x)p(y) dx dy$.

Discrete type: $I(X, Y) = \sum \sum p(x, y) \log_2 p(x, y) / p(x)p(y)$.

Among them, $p(x, y)$ represents the joint probability distribution of random variable X and random variable Y . It can be seen from the above two forms that when the random variable X and the random variable Y are independent of each other, the mutual information $I(X, Y) = 0$.

We set a sample set $U = \{x_1, x_2, \dots, x_n\}$, $x_i \in R^N$. Δ is the distance function defined on U , satisfying $\Delta(x_i, x_j) \geq 0$. In applications, 2-norm distance (also known as Euclidean distance) is often used: $(\sum_{k=1}^N |x_{ik} - x_{jk}|^2)^{1/2}$. We assume that $\delta \geq 0$, and the neighborhood of labeled sample x_i is $\delta(x) = \{x_j | \Delta(x_i, x_j) \leq \delta\}$. At the same time, we are given two feature spaces R and S , and $\delta_R(x)$ and $\delta_S(x)$ are, respectively, the neighborhood of X calculated based on the distance in these feature spaces. The neighborhood has the following attributes: $\delta_{R \cap S}(x) = \delta_R(x) \cap \delta_S(x)$. In addition to the distance function given above, there are many ways to measure the distance between heterogeneous features and missing data. Definition 1 and Definition 2 refer to Huetal's description.

Definition 1. We are given a sample set $U = \{x_1, x_2, \dots, x_n\}$, which is described by a numerical or discrete $R, S \subseteq F$ attribute subset. The neighborhood of sample x_i on attribute S can be denoted as $\delta_S(x_i)$. The neighborhood uncertainty of the sample can be defined as

$$NH_\delta^{x_i}(S) = -\log \frac{\|\delta_S(x_i)\|}{n}. \quad (7)$$

Moreover, the average uncertainty of the sample set can be defined as

$$NH_\delta(S) = -\frac{1}{n} \sum_{i=1}^n \log \frac{\|\delta_S(x_i)\|}{n}. \quad (8)$$

Definition 2. $R, S \subseteq F$ is two attribute subsets, and the neighborhood mutual information defined based on R and S is

$$NMI_\delta(R; S) = -\frac{1}{n} \sum_{i=1}^n \log \frac{\|\delta_R(x_i)\| \cdot \|\delta_S(x_i)\|}{n \|\delta_{S \cup R}(x_i)\|}. \quad (9)$$

If we give two attribute subsets R and S and $NMI_\delta(R; S)$ is the mutual information between these two attribute subsets, then the following equation holds:

- (1) $NMI_\delta(R; S) = NMI_\delta(S; R)$
- (2) $NMI_\delta(R; S) = NH_\delta(R) + NH_\delta(S) - NH_\delta(R, S)$
- (3) $NMI_\delta(R; S) = NH_\delta(R) + NH_\delta(S) - NH_\delta(R, S)$

We assume that there are n decision-making units to be evaluated, and each decision-making unit has m inputs and s outputs. Moreover, we use x_{ij} and y_{rj} to represent the i ($i = 1, 2, \dots, m$) input and r ($r = 1, 2, \dots, s$) output of the j -th decision-making unit, respectively.

e_j represents the average other-evaluation efficiency score of decision-making unit j , and h_{jj} represents the self-evaluation optimal efficiency score of the model. h_{kj} represents the evaluation value of the decision unit j when the decision unit k is optimized; that is, the decision unit j is evaluated with the optimal weight of the decision unit k . M_j represents the singularity index. Then, the formula for calculating the singular index is

$$M_j = \frac{h_{jj} - e_j}{e_j}, e_j = \frac{\sum_{k \neq j} h_{kj}}{n-1}. \quad (10)$$

What M_j expresses is the difference and changes in the efficiency of the decision-making unit between other- and self-evaluation. The larger h_{jj} , the smaller e_j . The larger M_j is, the easier the decision-making unit j is to be regarded as a singular person; that is, the decision-making unit j is pseudoeffective. The smaller M_j is, the closer the self-evaluation value is to his evaluation value, and the easier the final evaluation value of decision-making unit j is to be accepted.

Under the optimistic (optimal) frontier, the DEA-EBM model pursues the maximization of efficiency to determine the input and output weights. The optimistic efficiency of the k -th decision unit can be obtained by solving

$$\theta_{kk} = \max \sum_{r=1}^s u_{rk} y_{rk}, \quad s.t. \begin{cases} \sum_{i=1}^m v_{ik} x_{ik} = 1, \\ E_{dd} = \sum_{r=1}^s u_{rd} y_{rd}, \\ \sum_{r=1}^s u_{rd} y_{rd} - \sum_{i=1}^m v_{id} x_{id} + \alpha'_j = 0 \quad j = 1, 2, \dots, n. \end{cases} \quad (11)$$

Among them, v_{ik} and u_{rk} represent the weights of the i -th input and r -th output of the k -th ($k = 1, 2, \dots, n$) decision-making unit, and the optimistic efficiency value of the k -th

decision-making unit is within $\theta \in [0, 1]$. If $\theta_{kk} = 1$, the k -th decision-making unit is called optimistic and effective; otherwise, the decision-making unit is called optimistic and noneffective.

Under the pessimistic (worst) frontier, the DEA-EBM model pursues the minimization of efficiency to determine the input-output weight. The pessimistic efficiency of the k -th decision unit can be obtained by solving

$$\begin{aligned} \phi_{kk} = \min & \sum_{r=1}^s u_{rk} y_{rk}, \\ \text{s.t.} & \begin{cases} \sum_{i=1}^m v_{ik} x_{ik} = 1, \\ \sum_{r=1}^s u_{rk} y_{rj} - \sum_{i=1}^m v_{ik} x_{ij} \geq 0, j = 1, 2, \dots, n, \\ u_{rk} \geq 0, v_{ik} \geq 0, r = 1, 2, \dots, s, i = 1, 2, \dots, m. \end{cases} \end{aligned} \quad (12)$$

In the above formula, the pessimistic efficiency of the k -th decision-making unit is $\phi_{kk} \geq 1$. If the force >1 , the decision-making unit k is called pessimistic and invalid; otherwise, the decision-making unit is called pessimistic noninvalid.

Decision-making units are each other's Allies, and each unit between classes is each other's opponents. Then, we assume that the k -th decision-making unit is in the Tt category, that is, $k \in Tt$, and use the decision-making unit k ($k = 1, 2, \dots, n$) to evaluate other decision-making units separately, so that we try to make the efficiency of the units belonging to the Tt category as high as possible, and vice versa, as low as possible. Finally, we use the arithmetic average method to fuse self-evaluation and other-evaluation efficiency to obtain the overall crossover efficiency of competition and cooperation. The model is shown in

$$\begin{aligned} \min & \sum_{j \neq k, j \in T_i} s_{kj}^{CP} - \sum_{j \in T_i} s_{kj}^{CP}, \\ \text{s.t.} & \begin{cases} \sum_{r=1}^s u_{rk} y_{rj} - \sum_{i=1}^m v_{ik} x_{ij} + s_{kj}^{CP} = 0, j = 1, 2, \dots, n, j \neq k, \\ \sum_{r=1}^s u_{rk} y_{rk} - \theta_{kk}^* \sum_{i=1}^m v_{ik} x_{ik} = 0, \\ s_{kj}^{CP} \geq 0, j = 1, 2, \dots, m, j \neq k, \\ u_{rk} \geq 0, v_{ik} \geq 0, r = 1, 2, \dots, s, i = 1, 2, \dots, m. \end{cases} \end{aligned} \quad (13)$$

Model (13) embodies the competitive and cooperative relationship between decision-making units, enabling the decision-making unit to establish a competitive or cooperative relationship with other units based on personal preference.

This paper first uses the bounded DEA-EBM model to provide an efficiency interval for each decision-making unit. The model is shown in

$$\begin{aligned} \psi_{kk} = \frac{\max}{\min} & \sum_{r=1}^s u_{rk} y_{rk}, \\ \text{s.t.} & \begin{cases} \sum_{i=1}^m v_{ik} x_{ik} = 1, \\ \sum_{r=1}^s u_{rk} y_{rj} - \sum_{i=1}^m v_{ik} x_{ij} \leq 0, j = 1, 2, \dots, n, \\ \sum_{r=1}^s u_{rk} y_{rj} - \alpha \sum_{i=1}^m v_{ik} x_{ij} \geq 0, j = 1, 2, \dots, n, \\ u_{rk} \geq 0, v_{ik} \geq 0, r = 1, 2, \dots, s, i = 1, 2, \dots, m. \end{cases} \end{aligned} \quad (14)$$

Among them, $\alpha = \max \theta^* / \min \varphi^*$ ($0 < \alpha \leq 1$) represents the adjustment coefficient of pessimistic efficiency, and θ^* and φ^* are obtained by models (11) and (12), respectively. Due to the inconsistency of the two efficiency scores, the values of optimistic efficiency and pessimistic efficiency can be adjusted to be within the interval $[\alpha, 1]$. We use model (14) to evaluate the k -th decision-making unit, and the maximum value of the objective function is $\psi_{kk}^{U^*}$, which shows the best relative efficiency of the decision-making unit. The minimum value of the objective function is $\psi_{kk}^{L^*}$, which represents the worst relative efficiency of the decision-making unit. The two together constitute the efficiency interval $[\psi_{kk}^{L^*}, \psi_{kk}^{U^*}]$ of the k -th decision-making unit.

Based on model (13), we construct a new cross-efficiency model (15). By ensuring that the evaluation efficiency of the evaluated decision-making unit is not lower than its worst relative efficiency $\psi_{kk}^{L^*}$, we enable the decision-making unit to adopt different evaluation strategies for other units according to the degree of association.

$$\begin{aligned} \min & \left[z_1 \left(\theta_{dd} - \sum_{r=1}^s u_{rk} y_{rd} \right) - z_2 \left(\theta_{dd} - \sum_{r=1}^s u_{rk} y_{rd} \right) \right], \\ \text{s.t.} & \begin{cases} \sum_{i=1}^m v_{ik} x_{id} = 1, \\ \sum_{r=1}^s u_{rk} y_{rk} - \psi_{kk}^{U^*} \sum_{i=1}^m v_{ik} x_{ik} = 0, \\ \psi_{kk}^{L^*} \sum_{i=1}^m v_{ik} x_{id} - \sum_{r=1}^s u_{rk} y_{rd} \leq 0, \\ \sum_{r=1}^s u_{rk} y_{rj} - \sum_{i=1}^m v_{ik} x_{ij} \leq 0, j = 1, 2, \dots, n, \\ u_{rk} \geq 0, v_{ik} \geq 0, r = 1, 2, \dots, s, i = 1, 2, \dots, m, \\ z_1 = 1, z_2 = 0, \{k, d\} \subset H; z_1 = 0, z_2 = 1, \{k, d\} \notin H. \end{cases} \end{aligned} \quad (15)$$

We first use model (14) to calculate the optimal relative efficiency of each decision unit $\psi_{kk}^{U^*}$ and the worst relative efficiency of $\psi_{kk}^{L^*}$ and then evaluate decision unit d under the condition that the optimal relative efficiency of decision unit k keeps $\psi_{kk}^{U^*}$ unchanged. At the same time, we ensure that the

other-evaluation efficiency of unit d is not less than its worst relative efficiency ψ_{kk}^* . As a singular index, $\theta_{dd} - \sum_{r=1}^s u_{rk} - y_{rd}$ indicates the difference between self-evaluation and other evaluations. If the decision-making units k and d are in the same set, then $z_1 = 1, z_2 = 0$, which means that the decision-making unit d 's other-evaluation efficiency is as large as possible. On the contrary, it is necessary to make the decision-making unit d 's other-evaluation efficiency as small as possible. In addition, model (15) ensures that the other-evaluation efficiency of the decision-making unit d is not lower than its worst relative efficiency and can improve the acceptability of the evaluation results.

The same DEA-EBM model has many expressions. For example, model (3) is called a multiplier model of CCR. By solving this model n times, the efficiency score of each unit from DMU to DMU can be obtained. Although model (3) is

$$T = \left\{ (x, y): \sum_{j=1}^n z_j x_{ij} \leq x_i, \sum_{j=1}^n z_j y_{rj} \geq y_r, r = 1, 2, \dots, s, z_j \geq 0 \quad j = 1, 2, \dots, n \right\}. \quad (17)$$

Among them, $x = (x_1, x_2, \dots, x_n)$ and $y = (y_1, y_2, \dots, y_n)$ are input and output vectors, respectively. T is the reference technology set containing all possible input-output combinations.

linear, the calculation of efficiency scores often needs to be transformed into a dual form, as shown in

$$\begin{aligned} \max \quad & \theta, \\ \text{s.t.} \quad & \begin{cases} \sum_{i=1}^m \lambda_j x_{ij} \leq \theta x_{ro}, j = 1, 2, \dots, n, \\ \sum_{r=1}^s \lambda_j y_{rj} \geq y_{x_{ro}}, \\ \lambda_j \geq 0, j = 1, 2, \dots, n. \end{cases} \end{aligned} \quad (16)$$

Model (16) is the envelope form of the input-oriented CCR model (Farrell model). It means that the input to the DMU shrinks as much as possible without reducing the current output level. Both inputs and outputs are highly disposable:

In the traditional DEA-EBM model as shown in Figure 1, if $(x, y) \in T$ and $x' \geq x$ (or $y' \leq y$), then $(x', y) \in T$ or $(x, y') \in T$.

Under the DEA-EBM framework, the weakly disposable reference technology is also called the environmental DEA-EBM technology, which can be expressed as model (18):

$$T_e = \left\{ (x, y, u): \sum_{j=1}^n z_j x_{ij} \leq x_i, i = 1, 2, \dots, m, \sum_{j=1}^n z_j y_{rj} \geq y_r, r = 1, 2, \dots, s, \sum_{j=1}^n z_j u_{kj} = u_k, k = 1, 2, \dots, t, z_j \geq 0 \quad j = 1, 2, \dots, n \right\}. \quad (18)$$

Among them, $u = (u_1, u_2, \dots, u_t)$ represents the undesired output vector, and the difference between T and T_e is that, in T_e , it is not feasible to reduce only the undesired output, but it is feasible to reduce the expected output and the undesired output proportionally.

We assume that there are n homogeneous units as $DMU_j (j = 1, 2, \dots, n)$, and the input vector, expected output vector, and undesired output vector of each decision-making unit are expressed as $x = (x_1, x_2, \dots, x_m)$, $y = (y_1, y_2, \dots, y_s)$, and $z = (z_1, z_2, \dots, z_t)$, respectively, which consumes m types of inputs and produces s types of expected output and t kinds of undesired output.

In order to properly describe the production process with expected output and undesired output, the following two assumptions need to be added to the production technology set T proposed by Fare:

- (1) Weak disposability of output. That is, if $(x, y, b) \in T$ and $0 \leq \theta \leq 1$, then $(x, \theta y, \theta b) \in T$.
- (2) Zero combination of undesired output and expected output. That is, if $(x, y, b) \in T$ and $b = 0$, then $y = 0$. These two assumptions show that it is not feasible to reduce only undesired output, and the reduction of undesired output must be accompanied by the reduction of expected output.

There are many models that DEA-EBM technology uses to measure environmental performance in an environment with constant returns to scale. Among these models, the model only allows adjustments to undesired output.

$$PEI_1 = \min \lambda$$

$$\text{s.t.} \begin{cases} \sum_{k=1}^K z_k x_{nk} \leq x_{n0} & n = 1, \dots, N \\ \sum_{k=1}^K z_k y_{mk} \geq y_{m0} & m = 1, \dots, M \\ \sum_{k=1}^K z_k u_{jk} = \lambda u_{j0} & j = 1, \dots, J \\ z_k \geq 0 & k = 1, 2, \dots, K \end{cases} \quad (19)$$

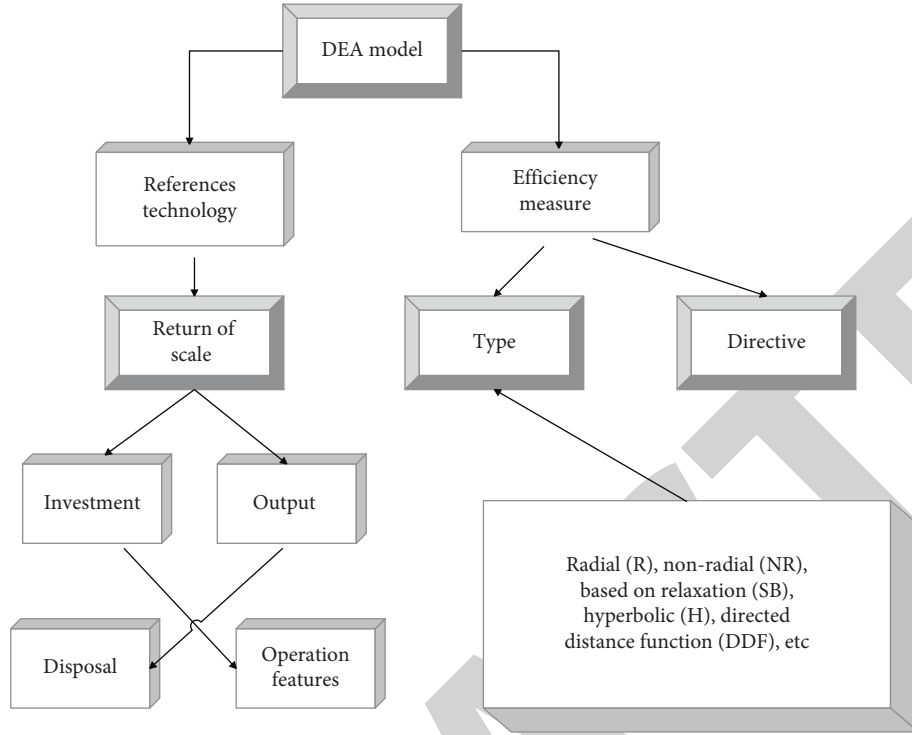


FIGURE 1: The general structure of the DEA-EBM model.

This paper proposes the following input-oriented EBM-GR-U model framework. The economic and ecological efficiency of n units can be obtained by solving the model n times. This paper assumes weak disposability of pollutants that play an important role in environmental impact, such as

$$\gamma^* = \min \beta - \varepsilon \sum_{i=1}^m \frac{w_i^- s_{i0}^-}{x_{i0}}$$

$$\text{s.t.} \begin{cases} \beta x_{i0} - \sum_{j=1}^n x_{ij} \lambda_j - s_{i0}^- & i = 1, \dots, m, \\ \sum_{j=1}^n y_{rj} \lambda_j \geq y_{r0} & r = 1, \dots, s, \\ \sum_{j=1}^n b_{pj} \lambda_j = pb_{p0} & p = 1, \dots, t, \\ \lambda_j \geq 0, s_{ij}^- \geq 0 & i = 1, \dots, m \quad j = 1, \dots, n. \end{cases} \quad (20)$$

θ in the above formula is the fraction of radial efficiency, which represents the degree of radial efficiency. $\sum_{i=1}^m w_i^- s_{i0}^- / x_{i0}$ represents the nonradial relaxation term. ε is a key parameter that combines the radial efficiency score and nonradial relaxation. w_i^- represents the weight of the i -th input and satisfies $\sum_{i=1}^m w_i^- = 1 (\forall i, w_i^- \geq 0)$. In this formula, the values of ε and $w_i^- (i = 1, \dots, m)$ need to be obtained in advance. ρ represents the environmental efficiency level of DMU_o . Therefore, the eco-economic efficiency of DMU_o can

be integrated through economic efficiency and environmental efficiency; that is, economic eco-efficiency = $\gamma^* \cdot \rho$.

Definition 3 (EBM-GR-U input-oriented efficiency). DMU_o is called EBM-GR-U input valid $\Leftrightarrow \gamma^* = 1$.

Definition 4. The optimal solution of model (19) is expressed as $(\theta^*, \lambda^*, s^{*-})$.

The projection of $DMU_o(x_o, y_o)$ can be defined as follows:

$$\begin{cases} x_o^* = X\lambda^* = \theta^* x_o - s^{*-}, \\ y_o^* = Y\lambda^*, \\ z_o^* = Z\lambda^*, \end{cases} \quad (21)$$

As shown in model (19), the values of two types of important parameters ε and $w = (w_i, i = 1, \dots, m)$ need to be obtained in advance, as shown in Table 2.

In addition, since the information expressed by the two types of input data overlaps to a certain extent, the eigenvalues and eigenvectors of the proximity matrix can be solved based on the idea of principal component analysis. When the closeness between the input indicators is higher, the characteristic roots compressed by principal components will be larger. According to the functional relationship between ε and the characteristic root, ε is reduced at this time, and the nonradial features of the model are reduced; that is, the radial compression is more suitable for input at this time. Conversely, when the input index is closer, the data is more scattered, the characteristic root will be smaller, and ε will increase. At this time, it is more suitable for projection based on nonradial relaxation.

TABLE 2: Input sequence used in correlation construction.

	$x_1(X_1)$...	$x_i(X_i)$...	$x_i(X_i)$...	$x_m(X_m)$
DMU ₁	x_{11}	...	x_{i1}	...	x_{j1}	...	x_{m1}
...
DMU _k	x_{1k}	...	x_{ik}	...	x_{jk}	...	x_{mk}
...
DMU _n	x_{1n}	...	x_{in}	...	x_{jn}	...	x_{mn}

Proposition 1. We set the behavior column of the system $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ and mark the broken line $x_i(1) - x_t(1), x_i(2) - x_t(1), \dots, x_i(n) - x_t(1)$ as $X_i(1) - x_t(1)$ and $s_i = \int_1^n (X_i - x_t(1)) ds$.

Then,

- (1) When X_i is an increasing sequence, $s_i \geq 0$
- (2) When X_i is the attenuation sequence, $s_i \leq 0$
- (3) When X_i is an oscillating sequence, the symbol of s_i is uncertain

Proposition 2. We set the behavior sequence of the system as $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ and $X_j = (x_j(1), x_j(2), \dots, x_j(n))$. The two sequences have the same length. By operating $x_i^0 = x_i(k) - x_i(1), k = 1, 2, \dots, n$ on the elements in the sequence, the zeroized images of the starting point of the two sequences can be obtained as

$$X_i^0 = (x_i^0(1), x_i^0(2), \dots, x_i^0(n)), X_j^0 = (x_j^0(1), x_j^0(2), \dots, x_j^0(n)). \quad (22)$$

Moreover, we set $s_i - s_j = \int_1^n (X_i^0 - X_j^0) ds$.

Then,

- (1) When X_i^0 is above X_j^0 , $s_i - s_j \geq 0$.
- (2) When X_i^0 is below X_j^0 , $s_i - s_j \leq 0$.
- (3) When X_i^0 intersects at X_j^0 , the sign of $s_i - s_j$ is uncertain.

Definition 5. We assume that the sequences X_i and X_j have the same length and the definitions of s_i and s_j are as shown in Proposition 1, and then we call

$$s_{ij} = \varepsilon_{ij} = \frac{1 + |s_i| + |s_j|}{1 + |s_i| + |s_j| + |s_j - s_i|}. \quad (23)$$

It is the gray absolute correlation degree of X_i and X_j , the similarity index s_{ij} of these two sequences can be defined as $s_{ij} = \varepsilon_{ij}$.

Definition 6. We assume that the two sequences X_i and X_j have the same length, and the definitions of s_i and s_j are shown in Proposition 1. Then, the similarity index $s(i, j)$ of these two sequences can be defined as follows:

TABLE 3: Proximity matrix based on proximity index.

	...	X_i	...	X_j
X_1	...	ε_{1i}	...	$\varepsilon_{1j}(S_{ij})$
...
X_j	...	ε_{ji}	...	ε_{jj}

$$s_{ij} = \varepsilon_{ij} = \frac{\sqrt{|s_j s_i|} + |s_i| + |s_j|}{\sqrt{|s_j s_i|} + |s_i| + |s_j| + |s_j - s_i|}, \quad (24)$$

$$s_{ij} = \varepsilon_{ij} = \frac{1 + \sqrt{|s_j s_i|} + |s_i| + |s_j|}{1 + \sqrt{|s_j s_i|} + |s_i| + |s_j| + |s_j - s_i|}.$$

Formulas (22) and (23) have the following four properties:

- (1) Reflexivity, $\forall i, s(i, j) = 1$
- (2) Symmetry, $\forall i, j, s(i, j) = s(j, i)$
- (3) Normative, $\forall i, j, 0 \leq s(i, j) \leq 1$
- (4) Proximity.

Proof 1

- (1) Reflexivity: $|s_j - s_i| = 0, \forall i, s(i, j) = 1$.
- (2) Symmetry: $|s_i - s_j| = |s_j - s_i|$ and $\min 1 - 1/m \sum s_i^- / x / 1/m \sum s_i^- / x$

$$s.t. \begin{cases} \beta x_{i0} - \sum_{j=1}^n x_{ij} \lambda_j - s_{i0}^- & i = 1, \dots, m \\ \sum_{j=1}^n y_{rj} \lambda_j \geq y_{r0} & r = 1, \dots, s \\ \sum_{j=1}^n b_{pj} \lambda_j = p b_{p0} & p = 1, \dots, t \\ \lambda_j \geq 0, s_{ij}^- \geq 0 & i = 1, \dots, m \quad j = 1, \dots, n \end{cases}.$$

- (3) Normative: Obviously, $s_{ij} = \varepsilon_{ij} > 0$, and $|s_j - s_i| \geq 0$, so $s_{ij} = \varepsilon_{ij} \leq 1$.

- (4) Proximity: Obviously, it is established. \square

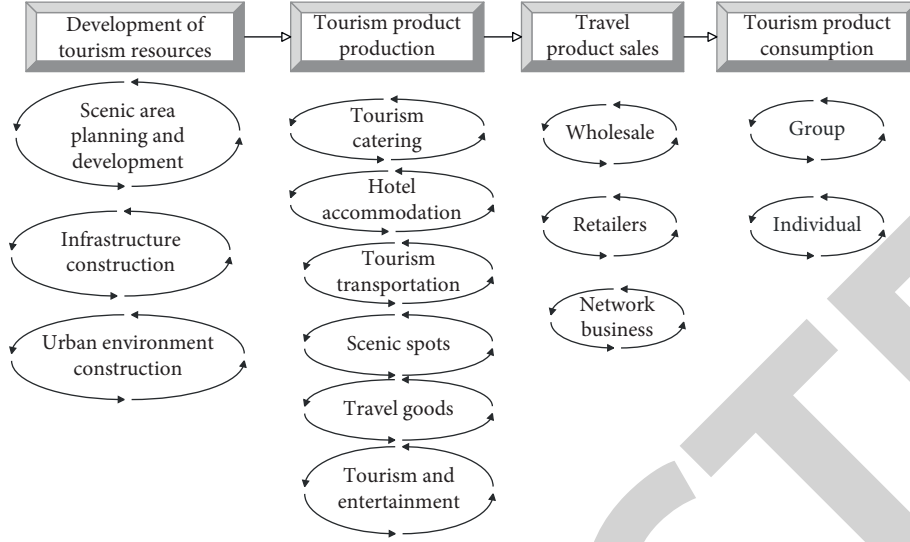


FIGURE 2: The core tourism industry chain.

Step 1. The algorithm projects all DMUs onto the front surface of the VRS.

$$\min \frac{1 - 1/m \sum_{i=1}^m s_i^- / x_{io}}{1 + 1/s \sum_{r=1}^s s_r^+ / y_{ro}}$$

$$\begin{aligned} & x_{io} = \sum_{j=1}^n x_{ij} \lambda_j + s_i^- \quad i = 1, \dots, m, \\ & y_{ro} = \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ \quad r = 1, \dots, s, \\ \text{s.t.} & \quad b_{p0} = \sum_{j=1}^n b_{pj} \lambda_j \quad p = 1, \dots, t, \\ & \quad \sum_{j=1}^n \lambda_j = 1, \\ & \quad \lambda_j \geq 0, s_i^- \geq 0 \quad s_r^+ \geq 0, \forall i, j, r. \end{aligned} \quad (25)$$

The algorithm can improve the accuracy of estimation by projecting all DMUs onto the frontier under the assumption of variable returns to scale. The projection model is shown in model (24).

The projection using slack input and output can be defined as $\tilde{x}_{io} = x_{io} - s_i^-$ ($i = 1, \dots, m$) and $\tilde{y}_{ro} = y_{ro} - s_r^+$ ($r = 1, \dots, s$).

DMUS for N effective VRS units can be expressed as $\bar{X} = \bar{x}_1, \dots, \bar{x}_m$, $\bar{Y} = \bar{y}_1, \dots, \bar{y}_s$, and all DMUs with valid CRS and VRS are also included in this set.

Step 2. Because Step 1 uses different projection models to get different projection results, you can also replace the projection based on the actual data observed.

That is, the algorithm uses $X = \begin{pmatrix} x_1 \\ \dots \\ x_m \end{pmatrix} = \begin{pmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{pmatrix}$ and $Y = \begin{pmatrix} y_1 \\ \dots \\ y_m \end{pmatrix} = \begin{pmatrix} y_{11} & \dots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{s1} & \dots & y_{sn} \end{pmatrix}$

instead of \bar{X} and \bar{Y} . According to formula (19), we only consider the proximity of the input sequence, and the proximity matrix $S = [s_{ij}] \in R^{m \times m}$ is composed of elements $s_{ij} = s(\bar{x}_i, \bar{x}_j)$ or $s_{ij} = s(\bar{x}_i, \bar{x}_j)$. As shown in Table 2, x_i, x_j is the sequence of the i -th and j -th input actual data of all units, where $i, j = 1, 2, \dots, m$. $s_{ij} = \varepsilon_{ij} = s(x_i, x_j)$ is the closeness index between the two input sequences obtained according to the actual input data and the definition of formula (21) or (22), and the final closeness matrix is shown in Table 3. According to the relevant properties of the formula, all elements in the matrix are obtained: $0 \leq s_{ij} = \varepsilon_{ij} \leq 1$.

Step 3. The algorithm solves the maximum eigenvalue of the similarity matrix and its corresponding eigenvector.

The matrix S is a nonnegative symmetric matrix, and the diagonal elements are all 1. According to the Peron–Frobenius theorem, S has the largest characteristic root ρ_x and its corresponding nonnegative characteristic vector w_x . The nonnegative vector w_x corresponds to the weight of each input element. According to the P–F theorem, $m \geq \rho_x \geq 1$.

In Step 4, the algorithm uses the largest feature root and feature vector model in Step 3 to calculate the values of ε and w^- . If $m > 1$, then $\varepsilon = m - \rho_x / m - 1$; and if $m = 1$, then $\varepsilon = 0$, and $w^- = w_x / \sum_{i=1}^m w_x$.

Step 4. The algorithm uses the obtained values of ε and w^- to use model (19) to calculate EBM-GR-U.

In summary, model (19) reasonably combines radial and nonradial models under the weak disposability of

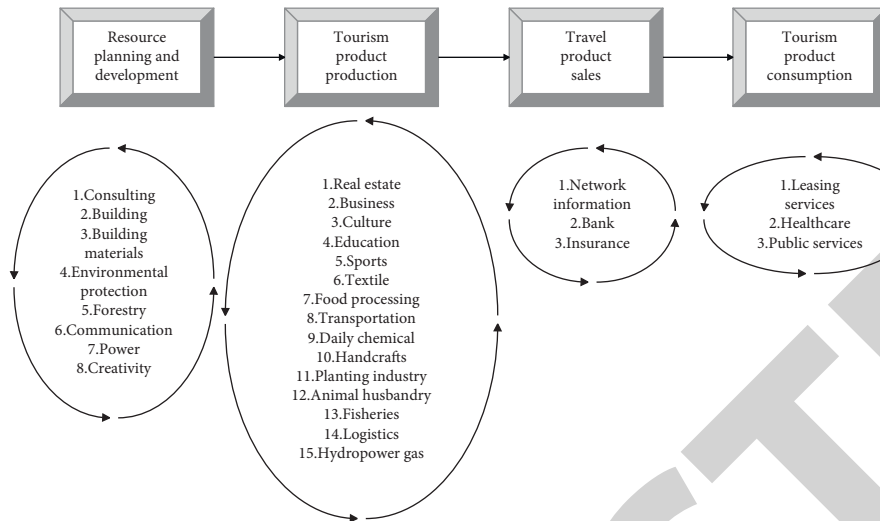


FIGURE 3: The tourism-related industry chain.

TABLE 4: Indicators in the study of tourism efficiency and tourism total factor productivity.

Investment indicators	Output indicators
Average price problem	
Service level	Customer satisfaction
Number of hotels	
Number of rooms	
Number of employees	Accommodation income
Number of rooms	Hotel income (dining and beverage)
Hotel occupancy rate	Other incomes
Operating expenses	
Number of employees	Operating income
The number of wages and wealth	Customer volume
Operating cost	Number of overnight stays
Other costs	
Number of employees	Operating income
Capital	Added value, profit
Number of employees in the tertiary industry	
Fixed asset investment	Star-rated hotel operating income
Actual use of foreign capital	
Number of employees in the tourism industry	Total tourism revenue
Tourism net fixed assets	
Tourism fixed assets	Total operating income of tourism enterprises
Number of employees in the tourism industry	
Number of employees in the tertiary industry	
Fixed capital stock	Total tourism revenue
Comment on the number of scenic spots	Total number of tourists
Number of star hotels	
Number of travel agencies	Operating income
Number of employees in the tertiary industry	Number of tourists served by travel agencies
Fixed asset investment	Total tourism revenue
Tourism net fixed assets	CO2 emissions from tourism
Number of employees in the tourism industry	

undesired output. Moreover, its proximity index based on gray correlation obtains the key parameters of the combination of radial and nonradial in the model and

measures the economic efficiency of the decision-making unit according to the steps. Similarly, it can be calculated by building an output-oriented model.

TABLE 5: Total factor productivity evaluation indicator system.

Category	Indicator name	Specific indicators
Investment indicators	Labor force	Number of employees in the tertiary industry/10,000 people
	Capital	Urban investment in fixed assets/100 million yuan
Output indicators	Output value	Total tourism revenue/100 million yuan
	Scale	Total number of tourists/10,000 people

TABLE 6: Productivity and decomposition of tourism total factors.

Time	Effch	Techch	Pech	Sech	Tfpch
2012-2013	1.135	0.924	1.104	1.039	1.039
2013-2014	1.067	1.138	1.045	1.030	1.203
2014-2015	0.995	1.122	1.000	1.005	1.106
2015-2016	0.993	1.188	0.999	1.003	1.167
2016-2017	0.896	1.343	1.048	0.863	1.192
2017-2018	1.057	0.990	1.061	1.007	1.037
2018-2019	0.969	1.150	0.974	1.005	1.103
2019-2020	0.941	1.196	0.911	1.043	1.114
2020-2021	1.024	1.129	0.988	1.046	1.144
Average value	1.006	1.125	1.013	1.003	1.121

TABLE 7: Analysis table of the total factor productivity indicator of urban tourism.

Years	<1 city/count	City/a below average	Variance	Max	Minimum	Average value
2011-2012	64	76	0.031	1.722	0.364	1.039
2012-2013	14	87	0.022	1.736	0.717	1.203
2013-2014	27	97	0.014	1.468	0.830	1.106
2014-2015	12	96	0.014	1.717	0.932	1.167
2015-2016	7	80	0.019	1.206	0.554	1.192
2016-2017	58	71	0.022	1.919	0.514	1.037
2017-2018	22	77	0.012	1.436	0.540	1.103
2018-2019	19	68	0.017	1.627	0.581	1.114
2019-2020	19	96	0.028	1.892	0.464	1.144
2020-2021	8	80	0.004	1.314	0.906	1.121

TABLE 8: Analysis table of urban tourism technical efficiency indicator.

Years	<1 city/count	City/a below average	Variance	Max	Minimum	Average value
2012-2013	45	84	0.041	1.939	0.458	1.135
2013-2014	51	81	0.016	1.586	0.655	1.067
2014-2015	101	92	0.008	1.258	0.795	0.995
2015-2016	102	96	0.010	1.388	0.789	0.993
2016-2017	141	82	0.013	1.264	0.464	0.896
2017-2018	48	69	0.019	1.385	0.504	1.057
2018-2019	125	81	0.008	1.353	0.472	0.969
2019-2020	128	76	0.013	1.335	0.467	0.941
2020-2021	78	86	0.024	1.699	0.399	1.024
Average value	87	83	0.003	1.176	0.876	1.006

4. Statistical Measurement and Influencing Factors of Green Total Factor Productivity of China’s Tourism Industry

The tourism industry chain is an input-output system of material, capital, technology, and information completed by different enterprises in the whole process from the development of tourism resources to the consumption of tourism products. We summarize the tourism industry

chain into the core tourism industry chain (shown in Figure 2) and the tourism-related industry chain (shown in Figure 3).

When evaluating the total factor productivity of the tourism industry and its subsectors, due to the availability of data or different research purposes, a unified evaluation index system has not been formed. Researchers make diversified choices of indicators and variables according to different specific research goals. Moreover, even in the face

TABLE 9: Analysis table of urban tourism technology progress indicator.

Years	<1 city/count	City/a below average	Variance	Max	Minimum	Average value
2012-2013	123	100	0.016	1.178	0.708	0.924
2013-2014	9	158	0.008	1.469	0.895	1.138
2014-2015	7	111	0.008	1.287	0.946	1.122
2015-2016	0	74	0.001	1.252	1.094	1.188
2016-2017	0	81	0.016	1.599	1.079	1.343
2017-2018	142	139	0.002	1.134	0.815	0.990
2018-2019	3	65	0.002	1.221	0.962	1.150
2019-2020	0	83	0.003	1.312	1.052	1.196
2020-2021	0	87	0.003	1.202	1.050	1.129
Average value	1	78	0.001	1.198	0.983	1.125

of the same research object, scholars will construct different evaluation index systems (see Table 4).

The total number of tourists includes the number of domestic tourists and the number of international tourists. The total number of tourists reflects the city's tourism reception volume and directly reflects the tourism benefits of a city's tourism. Therefore, the total number of tourists in this paper reflects the tourism scale of the tourist city. Total tourism revenue includes domestic tourism revenue and international tourism revenue, which is the most direct economic benefit of a city's tourism development. Moreover, it is also the tourism output value of the region and an important indicator to measure the level and quality of urban tourism development. The total factor productivity evaluation index system is shown in Table 5.

The model proposed in this paper should be used to calculate the total factor productivity of tourism in tourist cities. From Table 6, it can be seen that the total factor productivity of tourism is showing a general upward trend.

Through data sorting (Table 7), it is found that the total factor productivity of the tourist city research sample during the study period fluctuates greatly.

The technical efficiency change index is the product of pure technical efficiency and scale efficiency. The specific performance is output maximization and input minimization; that is, the maximum output is achieved when the input elements are fixed or the input element items are minimized under the given conditions of output, as shown in Table 8.

In terms of technological progress in tourism, the overall variance of the various years fluctuates relatively small and relatively stable, indicating that the technological progress of each city is different but small, as shown in Table 9.

It can be seen from the above research that the DEA-EBM model proposed in this paper can play an important role in the statistical measurement and analysis of influencing factors of green total factor production in the tourism industry.

5. Conclusion

Tourism efficiency relates to the inclusive growth and sustainable development of the tourism industry. It is a comparison between input and output in the process of tourism development within a certain area. Moreover, it is an important indicator used to measure the ability of the entire

tourism industry to achieve effective competition, the ability to use resources, the ability to achieve sustainable development, the ability of the tourism industry to compete in the market, the ability of input and output, and the ability of sustainable development. The level of tourism efficiency will directly determine the position of a region in the competitive environment. In addition, better industrial operation efficiency can effectively reduce production costs and increase economic returns, which plays an important role in the development of tourism. This paper combines the EA-EBM model to carry out the statistical measurement of China's tourism industry green total factor productivity and the analysis of influencing factors and verify it through data. Through research, it can be seen that the DEA-EBM model proposed in this paper can play an important role in the statistical speed measurement and influencing factor analysis of green total factor production in the tourism industry.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] T. A. Bhutto, R. Farooq, S. Talwar, U. Awan, and A. Dhir, "Green inclusive leadership and green creativity in the tourism and hospitality sector: serial mediation of green psychological climate and work engagement," *Journal of Sustainable Tourism*, vol. 29, no. 10, pp. 1716–1737, 2021.
- [2] C. H. Chin, C. L. Chin, and W. P. M. Wong, "The implementation of green marketing tools in rural tourism: the readiness of tourists?" *Journal of Hospitality Marketing & Management*, vol. 27, no. 3, pp. 261–280, 2018.
- [3] L. T. Tuan, "Environmentally-specific servant leadership and green creativity among tourism employees: dual mediation paths," *Journal of Sustainable Tourism*, vol. 28, no. 1, pp. 86–109, 2020.
- [4] Y. Yusof, Z. Awang, K. Jusoff, and Y. Ibrahim, "The influence of green practices by non-green hotels on customer satisfaction and loyalty in hotel and tourism industry," *International Journal of Green Economics*, vol. 11, no. 1, pp. 1–14, 2017.

- [5] I. Andersson and L. James, "Altruism or entrepreneurialism? The co-evolution of green place branding and policy tourism in Växjö, Sweden," *Urban Studies*, vol. 55, no. 15, pp. 3437–3453, 2018.
- [6] C. Irazábal, "Coastal urban planning in the 'Green Republic': tourism development and the nature–infrastructure paradox in Costa Rica," *International Journal of Urban and Regional Research*, vol. 42, no. 5, pp. 882–913, 2018.
- [7] H. Wee, N. A. Mustapha, and M. S. Anas, "Characteristic of green event practices in mice tourism: a systematic literature review," *International Journal of Academic Research in Business and Social Sciences*, vol. 11, no. 16, pp. 271–291, 2021.
- [8] A. D. Do, Q. V. Nguyen, D. U. Nguyen, Q. H. Le, and D. U. Trinh, "Green supply chain management practices and destination image: evidence from Vietnam tourism industry," *Uncertain Supply Chain Management*, vol. 8, no. 2, pp. 371–378, 2020.
- [9] I. Mykola, A. Vadym, P. Anatoliy, H. Yurii, and R. Nataliia, "Features of the content and implementation of innovation and investment projects for the development of enterprises in the field of rural green tourism," *International Journal of Management*, vol. 11, no. 3, pp. 304–315, 2020.
- [10] M. Simanjuntak and A. Rumondang Banjarnahor, "Re-investigating the roles of green service-scape to improve tourism performance marketing service dominant logic perspective: a literature review," *Quantitative Economics and Management Studies*, vol. 2, no. 4, pp. 214–232, 2021.
- [11] Z. Lili, "Retracted article: prediction of air pollutants and rural green tourism factors based on dynamic migration," *Arabian Journal of Geosciences*, vol. 14, no. 17, pp. 1777–7, 2021.
- [12] H. L. T. Trang, J. S. Lee, and H. Han, "How do green attributes elicit pro-environmental behaviors in guests? The case of green hotels in Vietnam," *Journal of Travel & Tourism Marketing*, vol. 36, no. 1, pp. 14–28, 2019.
- [13] N. Kongbuamai, Q. Bui, H. M. A. U. Yousaf, and Y. Liu, "The impact of tourism and natural resources on the ecological footprint: a case study of ASEAN countries," *Environmental Science and Pollution Research*, vol. 27, no. 16, pp. 19251–19264, 2020.
- [14] R. Kisiel, J. Zielińska-Szczepkowska, and D. Taradejna, "Natural and cultural resources of Green Kurpie as drivers of tourism development," *Ekonomia i Środowisko-Economics and Environment*, vol. 65, no. 2, p. 15, 2018.
- [15] R. Rahmawati, A. R. Suprpti, S. R. H. Pinta, and P. Sudira, "Green entrepreneurship: a study for developing eco-tourism in Indonesia," *The Journal of Asian Finance, Economics and Business*, vol. 8, no. 5, pp. 143–150, 2021.
- [16] V. Milla, A. Villalobos, L. Wallbott, and M. Lederer, "Green and social beyond a postcard scene? Sustainable tourism in Costa Rica and vietnam," *Sociology*, vol. 8, no. 2, pp. 50–67, 2020.
- [17] S. R. A. R. S. Rum Handayani Putu Sudira, A. R. Suprpti, R. Handayani, and P. Sudira, "Green entrepreneurship development strategy based on local characteristic to support eco-tourism continuous," *Jurnal Manajemen*, vol. 23, no. 2, pp. 257–273, 2019.
- [18] S. V. Kalchenko, A. O. Hutorov, L. S. Bezuhla, O. A. Leushina, T. V. Popova, and O. V. Dorokhov, "Managing the SOCIO-economic development of small forms of green tourism," *Series II: Forestry Wood Industry Agricultural Food Engineering*, vol. 14(63), no. 1, pp. 141–152, 2021.
- [19] N. W. S. Dewi, I. K. Sutarna, and N. G. N. S. Murni, "Belimbing tourism village: a green marketing strategy," *International Journal of Glocal Tourism*, vol. 2, no. 3, pp. 160–169, 2021.
- [20] E. A. Dzhandzhugazova, E. L. Iljina, A. N. Latkin, A. R. Davydovich, and V. V. Siganova, "Problems of development of ecological tourism on the territory of national parks of Russia," *Ekoloji*, vol. 28, no. 107, pp. 4913–4917, 2019.
- [21] O. Adamchyk, "Innovative sources of increasing the competitiveness of rural green tourism enterprises," *University Economic Bulletin*, no. 46, pp. 38–45, 2020.
- [22] D. Cvijanović, D. Sekulić, and D. Pavlović, "Are green hotels suitable for the development of entrepreneurship in tourism?" *Ekonomika preduzeća*, vol. 66, no. 7-8, pp. 424–432, 2018.