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Efficiency Evaluation of a Forestry Green Economy under a Multi-Dimensional Output Benefit in China—Based on Evidential Reasoning and the Cross Efficiency Model

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Abstract: The efficiency evaluation of forestry green economy development is related to the direction of forestry development and plays an important role in balancing the economic and environmental issues within that forestry development. The existing research faces three challenges: first, the output indicator is singular; second, the perspective of a self-assessment is extremely limited; and third, the multi perspective fusion method is not in line with the mechanism of the cross efficiency evaluation model. To address these challenges and the characteristics of forestry development output, we constructed multi-level output indicators from four aspects: ecology, economy, society, and sustainability and used evidence reasoning to combine the output indicators. Based on the perspective of a cross evaluation among peers, four different cross efficiency values are defined from the evaluation relationship between the different decision-making units to obtain economic–aggressive, social–neutral, ecological–benevolent, sustainable–neutral, and comprehensive–neutral cross efficiencies. According to the relationship between self- and cross evaluation, an order conditional entropy cross efficiency aggregation model has been proposed and used to analyze the development efficiency of the forestry green economy in 31 Chinese provinces in 2019. Considering the uneven distribution of the forestry resources in China, the development in the 31 provinces and cities is divided into four types by discussing the relationship between the output indicators and efficiency, while the reasons for the unbalanced development and the poor comprehensive development are discussed according to five cross efficiencies.

Keywords: forestry green economy; cross efficiency evaluation; conditional entropy; information fusion

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Citation: Huang, Y.; He, X.; He, S.; Dai, Y. Efficiency Evaluation of a Forestry Green Economy under a Multi-Dimensional Output Benefit in China—Based on Evidential Reasoning and the Cross Efficiency Model. *Sustainability* **2022**, *14*, 13881. https://doi.org/10.3390/su142113881

Academic Editor: Luigi Aldieri

Received: 21 September 2022
Accepted: 23 October 2022
Published: 26 October 2022

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1. Introduction

A green economy, as defined by the International Energy Agency (IEA) (2012), is the "decoupling of unsustainable resource use and environmental impact from economic growth." The green economy has gradually become a consensus solution to the reduction in available resources, environmental degradation, and the financial crisis, and is also a measure to better prevent the occurrence of accidents and reduce losses [1]. Many countries have formulated strategic green development plans, such as the United States focusing on clean energy [2], and the European Union building green industries for green development [3]. Forestry development is closely related to climate change, economic development, and ecological and environmental protection, and is one of the most effective means by which the green economy theory can be applied to forestry development. In the context of the green economy, the investment in and management of forest resources can achieve various benefits. First, forestry improves human well-being by providing rich products and forest tourism services. Second, forestry promotes green employment, increases the income of local farmers, and reduces poverty. Third, unique ecological functions such as

windbreaks, sand fixation, and biodiversity conservation play important roles in tackling climate change and reducing environmental risk. A forestry-based green economy is a sustainable development model for forest resources that includes the cultivation and planting of trees, wood cutting, transportation, processing, and manufacturing. The biggest difference between the previous economic development model and a forestry-based green economy is that a forestry-based green economy pays direct attention to social benefits such as green employment and poverty reduction. An efficient forestry green economy model can, thus, improve the environment, achieve social equity, reduce environmental risks, and is recognized as a stable model in the field of economic development.

Forestry input–output efficiency has been regarded as one of the most important indicators for measuring the level of forestry development. With the application of a green economy in forestry input–output efficiency, the development of a forestry green economy can be measured. Research that includes an efficiency evaluation of forest management based on data envelopment analysis (DEA) has attracted considerable attention. At present, the evaluation of forestry management in terms of efficiency is focused mainly on factors such as the space–time efficiency, production indicators, and efficiency improvements (See Section 2.1 for details).

However, several challenges remain regarding the existing efficiency evaluation research of forest management: (i) The number of indicators used in the DEA model is restricted, and the current output indicators are often singular and lack comprehensive consideration; however, forestry development is associated with economic, social, and ecological benefits (see Section 2.2 for details). Therefore, the application of the DEA method in evaluating the efficiency of a forestry green economy needs further discussion so that improvements can be made in the output indicators used. (ii) Evaluation of a green economy is diversified and complex [3]. Previous evaluations were based on self-efficiency, meaning that effective suggestions for coordination and win–win goals for the development of the forest green economy are not generated. (iii) A means to reasonably aggregate the overall and multi-directional efficiency evaluation results to obtain the final efficiency evaluation results remains unidentified.

To overcome these challenges, this study included the following: (i) To address the first challenge, a multi-level output indicator system based on the evidence reasoning (ER) model was constructed from four dimensions. (ii) To address the second challenge, a cross efficiency evaluation model was constructed using a peer evaluation. A modern green economy is beneficial in terms of sustainability, the economy, social aspects, and the ecology of an area; thus, the four generated cross efficiency matrixes are defined as "Economic–Aggressive", "Ecology–Benevolent", "Social–Neutral", and "Sustainability–Neutral". Moreover, the multi-dimensional output benefit is considered and a comprehensive cross efficiency matrix calculated. (iii) To address the third challenge, an order conditional entropy (OCE) cross aggregation method is proposed to aggregate the above cross efficiency matrixes. (iv) To demonstrate the effectiveness of the OCE cross efficiency model, forestry green economy data from 2013–2018 were adopted in an empirical study of 31 mainland-China provinces.

The contributions of this paper are as follows:

(i) The contribution of an efficiency evaluation. Compared with the use of a single output, the integration of multi-level output indicators means that the efficiency evaluation of a forestry green economy can include sustainable development, the economy, ecology, and societal benefits, so that the evaluation results can comprehensively reflect the current situation in terms of forestry green development. Compared with the self-efficiency model that is generally used in the existing literature, the cross efficiency model can ensure an overall evaluation. According to the results of cross efficiency, empirical analysis is used to consider the reasons for the unbalanced development of the existing green economy from four output dimensions, as well as providing direction in improving the comprehensive efficiency. The evaluation results provide information from multiple perspectives that can be utilized in decision-making.

(ii) The contribution of cross efficiency aggregation. The developed method fully describes the mechanism by which the cross evaluation model functions in the aggregation process for the first time. By considering the optimal weight information that is used for self-evaluation in the cross model, the OCE cross efficiency aggregation method considers the self-evaluation results as a conditional attribute set and the cross evaluation results as decision attributes in defining the cross efficiency conditional entropy. The order relationship of self-efficiency is considered when using cross efficiency, hence, the evaluation differences can also be taken into account to give a reasonable weight distribution when the cross evaluation results are similar. In short, the OCE cross efficiency method proposed in this paper improves the rationality of the cross efficiencies and the application value of each cross efficiency evaluated.

The remaining sections include a literature review and discussion of the limitations of previous studies in Section 2, basic methodologies for the efficiency evaluation of forest green economic management in Section 3, and the introduction of a new efficiency evaluation method in Section 4. Section 5 presents empirical studies into the forest green economic development efficiency in China. Finally, the conclusions and policy suggestions are mentioned in Section 6.

2. Literature Review

2.1. Efficiency Evaluation of Forestry Management

The methods that are used to calculate efficiency mainly include the stochastic frontier approach (SFA) and DEA. DEA has become the most important method for measuring efficiency because of its non-parametric and efficiency decomposability. Several studies have evaluated input–output forestry efficiency from a spatial perspective using the adjustment path. Others have analyzed the technological progress indicator of forestry production from a temporal perspective. Analysis of the forest productivity for timber in Japan using panel data indicated that government subsidies impede competition and that trade has a positive effect on productivity. In recent years, an increasing number of studies have focused on efficiency in terms of specific problems in forest development. Viitala and Hanninen [4] calculated the production efficiency of 19 public welfare forests in Finland using the DEA model and found that significant savings could be made in terms of the production input cost. Yin et al. [5] studied the dynamic changes and influence factors of forest carbon sequestration efficiency using the DEA Malmquist method at a province level in China. At present, low forestry investment, inadequate human resources, and low levels of economic development have rendered the forestry input–output efficiency low in China. The average comprehensive forestry input–output efficiency, which was 0.994 from 1993 to 2002, decreased to 0.932 during the period 2003 to 2010 [6], and the low efficiency has continued since. The three-stage DEA model was used to measure the total forestry productivity in terms of the included factors [7].

Indicators provide useful information for decision-makers (DMs) concerning developments and trends in commercial forests, supplying evidence about whether the economic, ecological, and social targets and goals for sustainable forestry have been achieved [8,9]. For example, an indicator of sustainable forestry can be constructed from the association between wildlife species, the forest structure, and land-use changes [4,10]. To explore the relationship between the total factor productivity and economic development in forests, an indicator system was established from the economic and ecological aspects [7,11]. To develop an assessment methodology paradigm, it is necessary to refer to the results of research on the socio-ecological and economic efficiency of forestry [12,13], and to solve issues such as sustainable forest management, reforestation, and international recognition of the ecological role of forests, the economic function of forests is generally not considered. The assessment of community forestry outcomes needs to include a wider range of factors such as the participatory governance, local economic benefits, and multiple forest uses [14,15]. Alongside the international recognition of the ecological role of forests, evaluating the

performance of forest-related benefits must consider the ecological role, economic function, and social values, if an accurate indicator system is to be constructed.

Limitation 1. *The benefits of forestry should be considered from the social, economic, and ecological aspects, among others. The existing literature ignores the multi-level representation of output indicators in evaluating forest efficiency. Moreover, forest efficiency evaluations are only from the perspective of self-evaluation, without considering the cross perspective between various decision-making units (DMUs); however, the competition and cooperation relationships of DMUs under different benefit output scenarios means that cross evaluation is not comprehensive when only the perspective of self-evaluation is considered.*

2.2. Cross Efficiency Models

Cross efficiency was proposed by Sexton [16], to solve the problem that multiple DMUs could not be distinguished in DEA. Both the self-evaluation for each DMU and the peer-evaluation of other DMUs needs to be considered under cross efficiency. This means that cross efficiency has a strong identification ability and can fully distinguish and rank each evaluated DMU; however, several problems in traditional cross efficiency methods may lead to inaccurate evaluation results and limit its effectiveness. Therefore, many scholars have proposed improved methods.

The first problem is that the multiple optimal weights included in the DMU input–output means that the cross efficiency is not unique. To solve this problem, secondary objectives were introduced into the cross efficiency model. Doyle et al. [17] proposed aggressive, benevolent strategies as a secondary goal to solve this problem. Wang et al. [18] believed that when a DMU is used to determine the weights of a set of inputs and outputs, the weights that are selected tend to prioritize the DMU itself. Other DMUs are not considered, allowing the construction of a neutral cross efficiency model. Many scholars have proposed secondary goals to solve this problem [19,20].

The second is the aggregation problem of the DEA cross efficiency matrix. The traditional method of DEA cross efficiency is to use the arithmetic mean, which cannot guarantee a Pareto optimization for the DEA cross efficiency. At the same time, the subjective preference of DMUs is not considered, and the relative importance of each efficiency value is ignored; therefore, Wu et al. [21] introduced cooperative game theory into cross efficiency and calculated the final cross efficiency value based on the Shapley value of each DMU. Wang et al. [22] emphasized the importance of subjective preference and introduced the preference of each decision unit into the decision-making process by using the ordered crossover operator (OWA) to achieve an aggregation of the crossover efficiency. Yang et al. [23] used the random multi-criteria acceptability analysis method to fully rank all DMUs in an interval crossover efficiency matrix. Yang et al. [24] converted the cross efficiency matrix into an evidence block via the ER method and aggregated the cross efficiency matrix by considering the preferences of each DMU. Ramón et al. [25] proposed using the weighted average instead of the arithmetic average to calculate the cross efficiency values. Wu et al. [26] transformed the cross efficiency matrix into an entropy matrix and obtained a set of weights to aggregate the cross efficiency matrix under the objective of obtaining the minimum entropy distance between a self-evaluation and the evaluation of other DMUs. Wang et al. [27] proposed three methods to determine the relative importance weights of cross efficiency from the perspective of the deviation degree and difference. Angiz et al. [28] first obtained the ranking of each DMU according to the cross efficiency matrix, and then proposed an order priority model that could calculate the weight of cross efficiency by prioritizing the self-evaluation efficiency of each DMU.

Limitation 2. *The existing cross efficiency aggregation methods have two limitations: (i) The existing literature considers only the similar relationship between self-evaluation and cross evaluation and ignores the optimal weight information of self-evaluation. (ii) Although the peer reviews*

between DMUs are the same, it is not reasonable to assign the same weights if their self-efficiencies differ greatly.

3. Method Introduction

3.1. Benevolent, Aggressive, and Neutral Cross Efficiency Models

Supposing that there are n DMUs and that each DMU has m inputs and s outputs, which are denoted as vectors $X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$ and $Y_j = (y_{1j}, y_{2j}, \cdots, y_{sj})^T$, a self-evaluating CCR model [29] can be established:

$$\begin{aligned} \text{Maximize } \theta_k = & \sum_{r=1}^{s} \mu_r y_{rk} \\ \text{Subject to} \quad & \sum_{i=1}^{m} v_i x_{ik} = 1, \\ & \sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ik} \le 0, \text{ j} = 1, \cdots, \text{n}, \\ & u_r \ge 0, v_i \ge 0, r = 1, \cdots, s, i = 1, \cdots, m \end{aligned} \tag{1}$$

where if $v_i (i = 1, \ldots, m)$ and $u_r (r = 1, \ldots, s)$ are input and output weights, respectively, and $\hat{v}_i (i = 1, \ldots, m)$ and $\hat{u}_r (r = 1, \ldots, s)$ are the optimal solutions to the above CCR model, then $\hat{\theta}_k = \sum_{r=1}^{s} \hat{u}_r y_{rk}$ is the self-efficiency of DMU_k, which is the best relative efficiency of DMU_k that can be obtained by self-evaluation.

The cross efficiency DEA method adopts the self-evaluation and peer-evaluation models based on secondary goals, using the following formula [16]:

$$\theta_{kj} = \sum_{r=1}^{s} \hat{u}_{rj} y_{rk} / \sum_{r=1}^{m} \hat{v}_{ij} x_{ij}, k, j = 1, 2, \cdots, n, \tag{2}$$

θ_{kj} is referred to as a cross efficiency value of DMU_j and reflects the peer evaluation of DMU_j to $DMU_k (j = 1, \cdots, n; j \ne k)$ and $\hat{u}_{rj}$ and $\hat{v}_{ij}$ are the optimal weight solutions of DMU_j based on model (1); when $j = k$, θ_{kk}=$\hat{\theta}_k$. The cross efficiency matrix is made up of all θ_{kj} values and is recorded as $E(\theta_{ij})$, and the cross efficiency vector by aggregation is $V = (\vartheta_1, \ldots, \vartheta_n)$, where $\vartheta_i = \sum_{j=1}^{n} w_j \theta_{ij}$.

To solve the problem that the optimal efficiency value in the traditional DEA is not unique, aggressive, benevolent [17], and neutral [18] cross efficiency models are proposed. As shown in models (3)–(5):

$$\begin{aligned} \text{Minimize} \quad & \sum_{r=1}^{s} u_{rk} \Big(\sum_{j=1, j \ne k}^{n} y_{rj} \Big) \\ \text{Subject to} \quad & \sum_{i=1}^{m} v_{ik} \Big(\sum_{j=1, j \ne k}^{n} X_{ij} \Big) = 1, \\ & \sum_{r=1}^{s} u_{rk} y_{rk} - \theta_{kk}^{*} \sum_{i=1}^{m} v_{ik} x_{ik} = 0, \\ & \sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \le 0, j = 1, \cdots, n; j \ne k, \\ & u_{rk} \ge 0, v_{ik} \ge 0, r = 1, \cdots, s, i = 1, \cdots, m \end{aligned} \tag{3}$$

and

$$\begin{aligned} \text{Maximize} \quad & \sum_{r=1}^{s} u_{rk}\Big(\sum_{j=1,j\neq k}^{n} y_{rj}\Big) \\ \text{Subject to} \quad & \sum_{i=1}^{m} v_{ik}\Big(\sum_{j=1,j\neq k}^{n} X_{ij}\Big) = 1, \\ & \sum_{r=1}^{s} u_{rk}y_{rk} - \theta^*_{kk}\sum_{i=1}^{m} v_{ik}x_{ik} = 0, \\ & \sum_{r=1}^{s} u_{rk}y_{rj} - \sum_{i=1}^{m} v_{ik}x_{ij} \leq 0, j = 1, \cdots, n; j \neq k, \\ & u_{rk} \geq 0, v_{ik} \geq 0, r = 1, \cdots, s, i = 1, \cdots, m \end{aligned} \tag{4}$$

and

$$\begin{aligned} \text{Maximize} \quad & \delta \\ \text{Subject to} \quad & \sum_{i=1}^{m} v_{ik}x_{ik} = 1, \\ & \sum_{r=1}^{s} u_{rk}y_{rk} = \theta^*_{kk}, \\ & \sum_{r=1}^{s} u_{rk}y_{rj} - \sum_{i=1}^{m} v_{ik}x_{ij} \leq 0, j = 1, \cdots, n; j \neq k, \\ & u_{rk}y_{rk} - \delta \geq 0, r = 1, \cdots s, \\ & u_{rk} \geq 0, v_{ik} \geq 0, r = 1, \cdots, s, i = 1, \cdots, m \end{aligned} \tag{5}$$

3.2. Evidence Reasoning

Evidence reasoning (ER) is a reasoning method in which utility theory is combined with a multi-attribute information fusion in uncertain environments. The method has good expansibility and can be applied to many fields with accurate, interval, or intuitionistic fuzzy values. The distributed confidence of the *r*-th indicator of the *l*-th evaluation subject is constructed through distributed modeling:

$$S(C_r(B_l)) = \{(H_z, \beta_{z,r}(B_l)), z = 1, \ldots, N\} \tag{6}$$

$\beta_{n,r}(B_l)$ represents the confidence level of indicator C_r for the evaluation subject B_l in the rating level H_n. Converting confidence into probability distribution:

$$m_{z,r} = m(H_z) = \omega^*_r \beta_{z,r}(B_l), z = 1, 2, \cdots, N; r = 1, 2, \cdots, s, \tag{7}$$

$$m_{H,r} = m_r(H) = 1 - \sum_{z=1}^{N} m_{z,r} = 1 - \omega^*_r \sum_{n=1}^{N} \beta_{z,r}(B_l), r = 1, \ldots, s, \tag{8}$$

$$\overline{m}_{H,r} = \overline{m}_r(H) = 1 - \omega^*_r, r = 1, 2, \cdots, s, \tag{9}$$

$$\widetilde{m}_{H,r} = \widetilde{m}_r(H) = \omega^*_r(1 - \sum_{n=1}^{N} \beta_{n,r}(B_l)), r = 1, 2, \cdots, s \tag{10}$$

$m_{n,r}$ represents the probability of the indicator on the evaluation level, $\overline{m}_{H,r}$ represents the uncertainty probability that is caused by the weight of the indicator, and $\widetilde{m}_{H,r}$ represents the uncertainty probability that results from the output indicator structure.

The indicator synthesis process is as follows:

$$m_n = k[\prod_{r=1}^{s}(m_{n,r} + \overline{m}_{H,r} + \widetilde{m}_{H,r}) - \prod_{r=1}^{s}(\overline{m}_{H,r} + \widetilde{m}_{H,r})], \tag{11}$$

$$\widetilde{m}_H = k[\prod_{r=1}^{s}(\overline{m}_{H,r} + \widetilde{m}_{H,r}) - \prod_{r=1}^{s}\overline{m}_{H,r}], \tag{12}$$

$$\overline{m}_H = k\prod_{r=1}^{s}\overline{m}_{H,r}, \tag{13}$$

$$k = [\sum_{n=1}^{N}\prod_{r=1}^{s}(m_{n,r} + \overline{m}_{H,r} + \widetilde{m}_{H,r}) - (N-1)\prod_{r=1}^{s}(\overline{m}_{H,r} + \widetilde{m}_{H,r})]^{-1} \tag{14}$$

Therefore, the overall distributed confidence can be synthesized from the basic distribution probability as:

$$\beta_z(B_l) = \frac{m_z}{1-\overline{m}_H}, z = 1, \ldots, N \tag{15}$$

The uncertain part after synthesis is:

$$\beta_H(B_l) = \frac{\widetilde{m}_z}{1-\overline{m}_H} \tag{16}$$

Assuming $u(H_z)$ is the utility value of the indicator on the evaluation level H_n, the maximum, minimum, and average values of the synthesized indicators are:

$$u_{\max}(B_l) = (\beta_N(B_l) + \beta_H(B_l))u(H_z) + \sum_{z=1}^{N-1}\beta_N(B_l)u(H_z), \tag{17}$$

$$u_{\min}(B_l) = \sum_{z=2}^{N}\beta_N(B_l)u(H_z) + (\beta_1(B_l) + \beta_H(B_l))u(H_1), \tag{18}$$

$$u_{avg}(B_l) = \frac{u_{\max}(B_l) + u_{\min}(B_l)}{2} \tag{19}$$

To better illustrate the ER method process, a flow chart illustrating the method is shown in Figure 1.

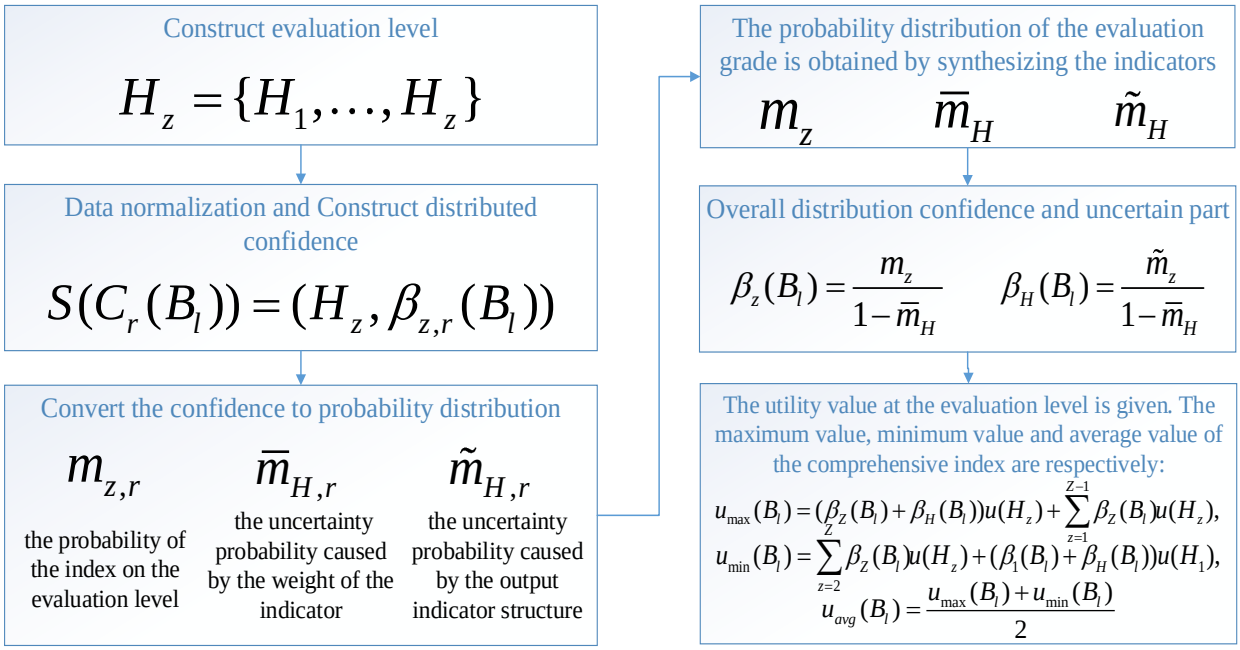


Figure 1. Flow chart showing the ER method.

4. Multi Cross Evaluation Model of Forestry Green Economy Based on Information Fusion

4.1. Self Efficiency Based on ER Fusion

ER is an uncertain reasoning method that can effectively deal with multi-attribute decision problems that have subjective uncertainty and the coexistence of qualitative and

quantitative indicators [30]. We begin by considering an indicator system with m input indicators $X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$ and multi-level output indicators.

First, the multi-level output indicators are fused to generate an output indicator for each DMU, $Y_j (j = 1, \ldots, n)$, which is based on the ER fusion method, before calculating the self-efficiency of DMUs [31].

As mentioned in Section 3.1, the evaluation level H_n is constructed as follows:

$$H_z = \{H_1, H_2, H_3, H_4, H_5, H_6\} = \{worst, bad, medium, good, well, excellent\}$$

The indicator information fusion of n DMUs $B_l (l = 1, \ldots, n)$ is first performed. The output indicator of each DMU is synthesized from c indicators $C_r (r = 1, 2, \cdots, c)$, with six evaluation levels for each indicator,$H_z (z = 1, \ldots, 6)$. The average weight of the rth forest resource indicator is assumed to be $\omega_r^* = \frac{1}{r}$. Meanwhile, the distributional confidence of the rth forest sustainability indicator for the lth province is expressed according to model (6).

The confidence is then converted to a probability distribution form according to models (7)–(10), and the indicator data is synthesized according to models (11)–(14). The distributed confidence of the overall forest sustainable development and the confidence in the uncertain part following synthesis can, thus, be derived from the basic distribution probability to produce models (15) and (16). For example, an output value of 0.45 obtained after normalization is considered to have an evaluation level of (0.6–0.45)/0.2, which is unacceptable, while $(0.45-0.4)/0.2$ results in a better evaluation level [32].

Finally, to more effectively use the subsequent calculations for output indicators, assuming that $v(H_n)$ is the utility value of the output indicator at evaluation level H_n, the combined value can be obtained using models (17) to (19) and the output indicators are merged into Y_0 through ER fusion.

For DMU_j, the above process is used to obtain a comprehensive output indicator Y_{0j}, which is then substituted along with the input indicator $X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$ into model (1) to obtain the self-evaluation efficiency θ_j. This means that one self-efficiency vector $\theta = (\theta_1, \theta_2, \cdots, \theta_n)$ can be obtained for all included DMUs.

4.2. Cross Efficiency Matrices from Aggressive, Benevolent, and Neutral Perspectives

A green economy is a sustainable development mode that differs significantly from a circular and low-carbon economy. The main purpose of low-carbon and circular economies is to solve the contradiction between environmental degradation and economic development. Humans are mainly concerned with improving the environment in which they live. The green economy refers to a collection of economic activities that rely on green technology and investment to achieve resource conservation and effective utilization while improving the economic level, achieving social equity, maintaining sustainable development, and improving the ecological environment. From the perspective of coordinated development, an efficiency evaluation of the forestry green economy should include four factors: economy, society, sustainability, and ecology. The cross efficiencies from these four different dimensions are defined as follows:

Definition 1. *The "Economic–Aggressive" cross efficiency determines the competition between the DMUs in terms of economic activity.*

Remark 1. *Capital, manpower, and other factors that influence production are limited, meaning that resource allocation is competitive. A competitive relationship between DMUs can promote economic development.*

Definition 2. *The "Ecology–Benevolent" cross efficiency addresses the problem of determining the cooperation between DMUs in terms of ecological activity.*

Remark 2. *As ecological development emphasizes coordination and requires regional balance, the DMUs exchange peer reviews as an incentive.*

Definition 3. *The "Sustainability–Neutral" cross efficiency is the problem of determining the neutral attitude between DMUs in sustainable activities.*

Remark 3. *In a broad sense, sustainability is the ability to maintain a certain process or state. In evaluating the efficiency of a forestry green economy, sustainability refers to the situation in which a forest maintains a certain vitality and develops in a healthy manner.*

Definition 4. *The "Social–Neutral" cross efficiency refers to the determination of a neutral attitude between the DMUs in terms of social activity.*

Remark 4. *The contribution of a forestry green economy to society usually refers to social benefits such as the employment opportunities within a region; therefore, DMs are generally neutral when evaluating social benefits.*

Considering that the development of a forestry green economy needs to be evaluated from four dimensions: economic, ecological, sustainability, and social benefits, DMUs hold different evaluation perspectives for different benefits within the evaluation. According to the models (3)–(5) in Section 2.1, peer evaluations are aggressive, benevolent, or neutral, and four cross efficiency matrices can be obtained: $E(\theta_{ij}^{En-A})$, $E(\theta_{ij}^{El-B})$, $E(\theta_{ij}^{Sc-N})$, and $E(\theta_{ij}^{St-N})$.

4.3. The OCE-Cross Efficiency Aggregation Method

In 1948, Shannon [33] introduced information entropy to describe the uncertainties in the decision information system (DIS). Based on entropy, Hu et al. [34] suggested the concept of OCE to explain the coordination of conditional and decision attributes. Since cross efficiency is evaluated on the basis of self-evaluation, cross efficiency evaluation aggregation can be considered a DIS that includes both conditional and decision attributes. Based on the theory of OCE, we propose a cross OCE aggregation method.

The description of this method includes the following definitions:

(i) By fully considering the mechanism of the cross evaluation model, a cross-decision information system is defined with self-evaluation as the conditional attribute set and cross evaluation as the decision attribute set (See Definition 5).
(ii) The different set operators under the orders are defined in accordance with the efficiency value (See Definition 6).
(iii) The consistency and coordination are described by defining the cross conditional entropy (See Definition 7).

Definition 5. $S = (U, C, D)$ is a DIS and $U = \{DMU_1, \cdots DMU_n\}$ is an ordinal classification sample set described by the efficiencies. C is the decision attribute set that includes the cross efficiencies vectors of all DMUs (C can thus be column vectors in the cross efficiency matrix) and $D = (\theta_1, \ldots \theta_n)$ *is the condition attribute set.*

Definition 6. *Given an ordinal classification sample set* $U = \{DMU_1, \ldots, DMU_n\}$ *described by* C, $\forall DMU \in U$,$E_i \subseteq C$, $E_i = \left\{ \theta_{ij} \middle| (j = 1, \ldots, n) \right\}$ *, the DMUcan be associated with the following sets:*

$$[DMU]_{\theta_{ii}}^{\geq} = \left\{ DMU_j \in U \middle| DMU_j \geq_{\theta_{ii}} DMU_i, j = 1, \ldots, n \right\} \tag{20}$$

$$[DMU]_{\theta_{ik}}^{\geq} = \left\{ DMU_j \in U \middle| DMU_j \geq_{\theta_{ik}} DMU_k, j = 1, \ldots, n \right\} \tag{21}$$

$$[DMU]_{\theta_i}^{\geq} = \left\{ DMU_j \in U \middle| DMU_j \geq_{\theta_i} DMU_i, j = 1, \ldots, n \right\} \tag{22}$$

where $DMU_j \geq_{\theta_{ii}} DMU_i \Rightarrow \theta_{ij} \geq \theta_{ii}$ (according to Formula (2), $\theta_{ii} = \theta_i$), $DMU_j \geq_{\theta_{ik}} DMU_k \Rightarrow \theta_{ij} \geq \theta_{ik}$, and $DMU_j \geq_{\theta_i} DMU_i \Rightarrow \theta_j \geq \theta_i$

In Definition 6, Formula (20) shows the upward order of the self-evaluation results of of DMU_i in the set $\{\theta_{i1}, \ldots, \theta_{in}\}$ (which results from peer evaluation by DMU_i), Formula (21) expresses the upward order of the peer evaluation from DMU_i to DMU_k in the set $\{\theta_{i1}, \ldots, \theta_{in}\}$, and Formula (22) expresses the upward order of the self-evaluation of DMU_i in the set $\{\theta_1, \ldots, \theta_n\}$ (which is the result of the self-evaluation of all DMUs).

To solve Limitation 2 that was mentioned in Section 2.2, we first consider the mechanism of the cross evaluation model. Cross evaluation includes two processes, a self-evaluation and peer evaluation. The first process is the premise on which the second is based, and its results (the optimal weight information of self-evaluation) directly affect the results of the second process (cross efficiency). Therefore, based on Definition 5, the conditional entropy of the decision attributes is calculated under the premise of the conditional attributes. The total order relation of a cross efficiency evaluation is an improvement as compared to self-evaluation by cross evaluation. In this study, uncertain information has been used to determine the entropy value, and the weight is allocated by the entropy value, overcoming the problems associated with direct weighting when obtained from the order relationship. According to the ordered conditional entropy theory proposed by Hu et al. [34], the cross efficiency OCE is defined by combining the upward order information with the evaluation results, as follows:

Definition 7. *$U = \{DMU_1, \ldots DMU_n\}$ is a set of samples that are described with cross-efficiencies or self-efficiencies, and the cross efficiency OCE of DMU_i ($i = 1, \ldots, n$) is defined as:*

$$RH^{\geq}_{E_i|\theta_i}(DMU_i) = -\frac{1}{|U|}\sum_{k=1}^{n} \log \frac{\left|[DMU]^{\geq}_{\theta_{ik}}] \cap [DMU]^{\geq}_{\theta_{ii}}]\right|}{[DMU]^{\geq}_{\theta_i}} \tag{23}$$

In Formula (23), the conditional attribute can provide entropy information concerning the self-evaluation weights for peer evaluation by considering the upward order of self-efficiency for the DMU_i (see the logarithm denominator). The decision attribute can provide entropy information concerning the effect that self-evaluation has on cross evaluation by considering the upward order entropy information of the DMU_i in all peer evaluations (see logarithm numerator). Small values that are calculated using Formula (23) indicate that the upward order of the self-evaluation value of DMU_i is close to that of the peer evaluation, indicating that the results of the self-evaluation and cross evaluation are highly consistent. In essence, cross OCE describes the degree of consistency between cross and self-evaluation. The smaller the value, the better the consistency. For DMUs with low cross efficiency ranking conditional entropy, more weights can be evaluated. The weight allocation formula is:

$$w_{DMU_i} = \frac{1 - RH^{\geq}_{E_i|\theta_i}(DMU_i)}{\sum_{j=1}^{n}\left(1 - RH^{\geq}_{E_i|\theta_i}(DMU_j)\right)} \tag{24}$$

According to the above series of definitions, the OCE cross efficiency aggregation method is conducted as follows:

Step 1: Let $E(\theta_{ij}) = \{E_1, \ldots, E_n\}$ and $E_i = \{\theta_{i1}, \ldots, \theta_{in}\}(i = 1, \ldots, n)$($E_i$ is the i th column vector in the cross efficiency matrix $E(\theta_{ij})$, and $RH^{\geq}_{E_i|\theta_i}(DMU_i)$ from Definition 7.

Step 2: The comprehensive cross efficiency vector $V = \{\vartheta_1, \ldots, \vartheta_n\}$ can be aggregated from the cross efficiency matrix using:

$$\vartheta_j = \sum_{i=1}^{n} \theta_{ij} w_{DMU_i} \tag{25}$$

Four cross efficiency matrices are aggregated to obtain four cross efficiency vectors based on the OCE-cross efficiency matrix aggregation.

Furthermore, based on the ER method, multi-dimensional output indicators can be combined to calculate the total neutral cross efficiency.

5. The Forestry Green Economy Development Efficiency Based on Information

5.1. Indicator Selection and Data Description

The efficiency of a forestry green economy is closely related to the indicators used; however, the existing calculations mainly use artificially selected indicators that are highly subjective and do not consider the comprehensiveness of the indicator data. The evaluation indicator system used in forestry green economic development should reflect all aspects involved in the development of a forest economy. The output indicators of a forestry green economy need to include the following aspects:

(1) The effects of forestry green economic growth. According to the connotations of the forest green economy and the opinions of experts, the output indicators for a green economy are constructed from four aspects [35]. Of these, the "gross output value of forestry products" refers to the total forestry products, expressed in currency. "Economic forest products" mainly refer to fruits and woody oil, beverages, seasonings, industrial raw materials, and medicinal materials.

(2) The social benefits of a forestry green economy. The social benefits of forestry green economic development include improvements to the human environment, for which indicators can be selected from the aspect of forest tourism. Of these, the "forest park area" refers to parks that comprise large areas of artificial or natural forests as a main body. The "forest carbon sink" is obtained using the forest biomass conversion factor method proposed by Xi et al. [36].

(3) The sustainable development of forest resources. Indicators of the sustainable development of forests should include both the current state and future development ability of a forest. "Forest coverage" refers to the percentage of forest to land in a particular administrative area. "Forest volume stock" refers to the total volume of tree trunks present within a forested area. "Standing timber volume per capita" refers to the per capita ownership of all tree stocks on an area of land within a certain range [37].

(4) The ecological benefits of forestry green economic development. The ecological benefit of forest resources is unique to forestry, and is a key factor determining the importance of forestry in the development of a national economy. The ecological functions of a forestry green economy include the ability of a forest to act as a carbon sink, air purification, the prevention of soil erosion, and the protection of biodiversity. The "afforested area" is the sum of the artificial forest area on barren hills and wasteland and the afforested area resulting from the air travel industry. The "forest tending area" describes the area in which tree husbandry occurs [38].

The input indicators are selected according to three aspects: human resources, capital, and land, meaning that the input indicators for the green development of a forest-based economy are: forestry investment, the land area covered by forest, and the number of forestry employees.

Details of the input–output indicators are given in Figure 2.

The data used in this study were obtained from the *China Statistical Yearbook* and the *Chinese Forestry and Grassland Statistical Yearbook*, and are the results of the ninth forest resources inventory that covers the period from 2014 to 2018. This study is, therefore, a comprehensive evaluation of the development level of the forestry green economy within 31 Chinese provinces in 2019.

First-level indicators	Second-level indicators	Third-level indicators
Input	X1.Completed amount of forestry investment X2.Wooded area X3.Forestry practitioners	
Output	Y1.Sustainability of Forest Resources	Y11.Forest coverage Y12.Arbor forest area Y13.Forest stock volume Y14.Standing timber volume per capita Y15.Forest pest control area
	Y2.Green Degree of Forestry Economic Growth	Y21.Gross output value of forestry industry Y22.Total economic forest products Y23.Proportion of forestry output value in GDP Y24.Urban green area
	Y3.Social Benefit of Forestry Economic Development	Y31.Number of forest parks Y32.Forest park area Y33.Annual tourist visits to Forest Park Y34.Forest carbon sink
	Y4.Ecological Benefit of Forestry Economic Development	Y41.Area of nature reserves Y42.Rainfall Y43.Afforestation area Y44.Forest tending area

Figure 2. Input–output indicators.

5.2. Model Construction

Based on the indicator system, the data in Section 5.1, and the method proposed in Section 4, the cross efficiency values of 31 provinces in China were calculated under different dimensions. The specific process is shown in Figure 3.

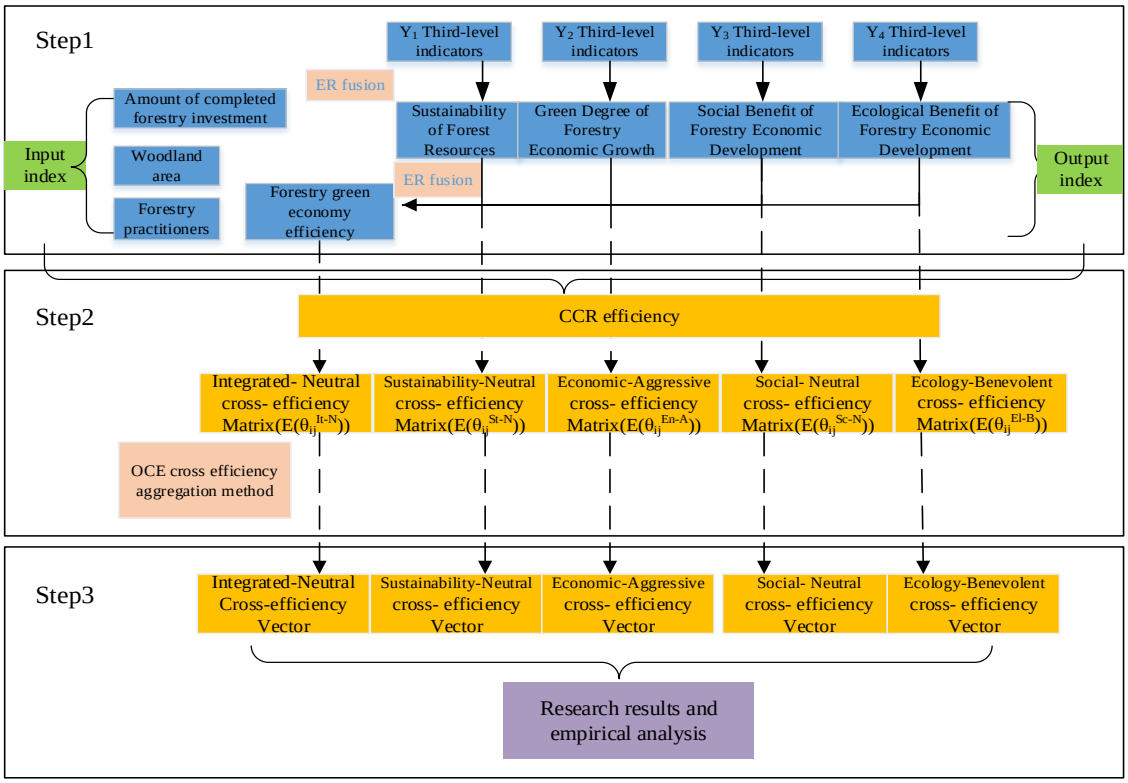


Figure 3. Step diagram showing the method used in this study.

Step 1: Construction of a forestry green economy development output indicator system. A total of 17 third-level indicators were grouped and ER fusion was used to combine these into four second-level indicators. This was followed by the ER fusion of the four second-level indicators into one first-level indicator.

Step 2: The CCR efficiency was calculated under different second-level output dimensions. Cross efficiency matrices describing the four second-level outputs were calculated according to the cross evaluation of sustainable neutrality, ecological neutrality, economic aggression, and social benevolence. The comprehensive neutral cross efficiency matrix was calculated for the first-level indicator that was obtained from fusion of the four second-level indicators.

Step 3: The OCE cross efficiency aggregation method was used to aggregate the cross efficiency matrix and obtain the cross efficiency vector. The forest green economic development efficiency of China was then analyzed using the models described in this paper.

5.3. Comparisons

5.3.1. Comparison between Self-Evaluation and Cross Efficiency Evaluation

Here, we compare the efficiencies based on the comprehensive output indicator, which is the first-level indicator obtained by ER fusion. Table 1 shows the results obtained in terms of self-efficiency and the comprehensive neutral cross efficiency, from which it is apparent that the coefficients of variation in self-efficiency and cross efficiency are 0.692186897 and 0.731540341, respectively. Cross evaluation, therefore, has the highest discrimination in terms of the DMUs. For example, DMUs with a self-efficiency value of 1 can be distinguished.

Table 1. Self-efficiencies, cross efficiencies, and ranks.

DMU	Number of DMU	Self-Efficiency	Integrated Cross Efficiency	DMU	Number of DMU	Self-Efficiency	Integrated Cross Efficiency
Beijing	1	0.219	0.0898	Hubei	17	0.1111	0.1046
Tianjing	2	1	1.0000	Hunan	18	0.3651	0.3002
Hebei	3	0.1482	0.1347	Guangdong	19	0.1205	0.0722
Shanxi	4	0.1693	0.1479	Guangxi	20	1	0.8453
Inner Mongolia IM	5	0.176	0.1439	Hainan	21	0.5589	0.5141
Liaoning	6	0.4844	0.3947	Chongqing	22	0.4471	0.2056
Jilin	7	0.272	0.1944	Sichuan	23	0.23	0.1977
Heilongjiang	8	0.2112	0.1441	Guizhou	24	0.3913	0.3443
Shanghai	9	1	0.2650	Yunnan	25	0.9038	0.6858
Jiangsu	10	0.3636	0.3063	Tibet	26	0.5201	0.2441
Zhejiang	11	0.3369	0.2966	Shanxi	27	0.2337	0.2040
Anhui	12	0.217	0.1971	Gansu	28	0.4574	0.3642
Fujian	13	0.324	0.2827	Qinghai	29	0.6374	0.5418
Jiangxi	14	0.1323	0.1184	Ningxia	30	0.1715	0.1594
Shandong	15	0.4519	0.3805	Xinjiang	31	0.9124	0.6586
Henan	16	0.1368	0.1226				

Cross evaluation can reduce the false high that is obtained by self-evaluation. The comprehensive neutral cross efficiencies in some provinces such as Shanghai, Yunnan, and Xinjiang have fallen sharply compared to the self-efficiencies in the same regions. Such a revision process is important for the classification of provinces. We thus divided the efficiency interval into three segments, which were low [0–0.3], medium [0.3–0.6], and high [0.6–1]; the 31 provinces were classified according to these segments and the classification results are shown in Table 2. As the cross efficiencies were smaller than the self-efficiencies, self-efficiency produced 14, 11, and 6 DMUs while cross efficiency produced 19, 8, and 4 DMUs, in the low, medium, and high segments, respectively. Thus, more provinces were in the middle and high segments under self-efficiency, while under cross efficiency, more were in the middle and low segments, with the classification of many provinces differing under each method. The biggest difference was observed in Shanghai, which

had a self-evaluation efficiency value of 1 and a cross evaluation efficiency of only 0.265, indicating a direct drop from high to low.

Table 2. The three segments of the efficiency.

Efficiency	Self-Efficiency	Cross Efficiency
0–0.3	Beijing, Hebei, Shanxi, Inner Mongolia IM, Jilin, Shanghai, Anhui, Jiangxi, Henan, Hubei, Guangdong, Sichuan, Shannxi, Ningxia. (A total of 14 provinces)	Beijing, Hebei, Shanxi, Inner Mongolia IM, Jilin, Shanghai, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Guangdong, Chongqing, Sichuan, Tibet, Shannxi, Ningxia. (A total of 19 provinces)
0.3–0.6	Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Hunan, Hainan, Chongqing, Guizhou, Tibet, Gansu. (A total of 11 provinces)	Liaoning, Jiangsu, Shandong, Hunan, Hainan, Guizhou, Gansu, Qinghai. (A total of 88 provinces)
0.6–1	Tianjin, Shanghai, Guangxi, Yunnan, Qinghai, Xinjiang. (A total of 6 provinces)	Tianjin, Guangxi, Yunnan, Xinjiang. (A total of 4 provinces)

In summary, the evaluation method of the comprehensive neutral crossover efficiency allows mutual peer evaluation to occur based on self-evaluation, rendering the evaluation results more objective and accurate.

5.3.2. Comparison between Different Cross Efficiency Aggregations

To assign weights to each DMU, a quantitative description of the effect of peer evaluation is required. The similarity theory defines the degree of correlation between cross evaluation and self-evaluation [27]. Entropy is utilized to show the uncertainty in the peer evaluation [39]. We used the order relation to define the correlation degree of peer evaluation and self-evaluation, and introduce the conditional entropy theory of a rough set to construct the OCE cross efficiency (see Formula (23)). The relationship between cross evaluation and self-evaluation is calculated through information entropy, similarity, and ordered conditional entropy. Next, we will compare and explain the differences between the results obtained.

Figure 4 shows the values obtained by aggregating the comprehensive neutral cross efficiency matrices with three different methods. The entropy value was reduced by a factor of ten for the sake of comparison. From the figure, the similarity value was the smallest and formed an approximate circle, indicating that the similarity difference among the DMUs was particularly small. The information entropy value was the largest, and presented as a circle. The shape obtained from the ordered condition entropy was uneven and fluctuated greatly, indicating that the DMUs obtained using this method differed significantly. This is likely because this method uses order as uncertain information in calculating the entropy, which overcomes the shortcoming of weighting that is associated with the order relation. Taking the group $DMU_{27–30}$ as an example, the cross efficiencies were close, and the small differences observed in the DMUs were only obtained by considering the uncertainties in the cross efficiencies. Similarly, the differences were not very large when the relationship between self-evaluation and cross evaluation was considered in terms of efficiency; however, although the cross efficiencies were very close, the self-efficiencies were very different. The self-efficiency of Shanxi was 0.2337 and that of Qinghai was 0.6347, indicating an obvious gap in their self-evaluation efficiency. Even if the cross evaluation of their peers were very close, it would not be reasonable to give both the same weight. The OCE method used in this study takes the self-evaluation results as the premise, thus, the aggregation results can reflect the influence that self-evaluation efficiency has on cross efficiency. The aggregation result for Shanxi (0.30104) was higher than that of Qinghai (0.0977), which indicates that a low self-evaluation efficiency has a greater impact on the evaluation results than a high self-evaluation efficiency when the results of cross evaluation are similar. This impact can be reflected by the ordinal information. The self-efficiency of Shanxi ranked relatively low in cross evaluation (from large to small), and its corresponding entropy was large; however, the opposite was observed for Qinghai.

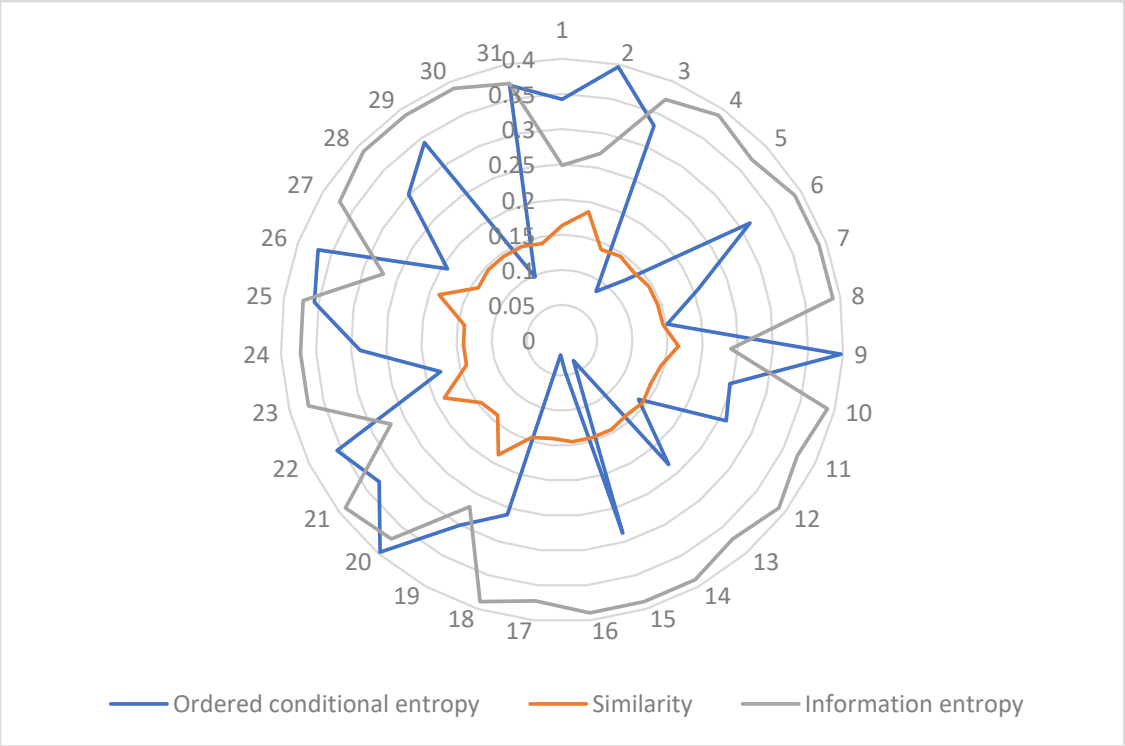


Figure 4. Aggregation results obtained using three different aggregation methods.

According to the above comparative analysis, it can be concluded that this method has the following two advantages:

(1) Self-efficiency can be taken as the premise, and the relationship between self-efficiency and cross efficiency can be explained through the conditional relationship. This method can reflect the mechanism of cross evaluation by including the impact of the self-evaluation efficiency on the cross efficiencies.

(2) Considering the order information of self-evaluation efficiency and the order information of cross efficiency together, the information entropy for the process of cross efficiency aggregation can be better determined. The information entropy aggregation that is based on the OCE method in this study is better differentiated, and the value is within a more reasonable range.

5.4. Empirical Analysis

In this section, the "Economic–Aggressive", "Ecology–Benevolent", "Sustainability–Neutral", "Social–Neutral", and comprehensive neutral cross efficiencies are calculated for the 31 provinces in China.

To analyze the relationships between output indicators and cross efficiencies, four quadrant diagrams were constructed. Compared with the average, the median considers the ordinal relationship, meaning that the planner can be divided into four quadrants based on the median output indicators (indicator system integration) and cross efficiency. A scatter plot was produced to obtain the classification and positioning of the output-efficiency for each province in the four quadrants.

In terms of the four quadrants, the first quadrant shows that the output indicator and cross efficiency was higher than the median level. The provinces in the first quadrant can be defined as "**Output Advantage—Efficient Type (A-E type)**". Provinces belonging to the A-E type can make full use of their advantages in terms of the forestry green economic output and have forestry green economic benefits. The cross efficiencies of the provinces were higher than the median level and the output indicators were lower than the median level in the second quadrant. We define these provinces as "**Output**

Disadvantage—Efficient Types (DA-E type)". Although the forestry green economy output was not high in these provinces, the efficiency was very high. Increasing the output level would allow the efficiency to be improved. Provinces in the third quadrant are defined as "**Output Disadvantage—Inefficiency Type (DA-IE type)**". Both output resources and the efficiencies were lower than the median level in these provinces, which were inefficient because of a limited output capacity; thus, the output requires improvement in future development. The output resources of provinces in the fourth quadrant were higher than the median level; thus, these provinces are defined as "**Output Advantage—Inefficiency Types (A-IE type)**". Although these provinces had good output indicators, the efficiency was not high, indicating redundancy in terms of the input. Efficiency could be improved by an appropriate adjustment of the input and output structure in these provinces.

Next, empirical analyses of the five different types of cross efficiencies were made.

5.4.1. Empirical Analysis Based on Secondary Indicators of Forestry Green Economy Development

(1) **Empirical analysis by Economic–Aggressive cross Efficiency**

Forest economic activity refers to the use of forest resources for profit-oriented production and operation. The forest green economy refers to the promotion of economic growth and development while ensuring that forest resources can continue to be maintained alongside environmental services for human well-being. Figure 5 illustrates the relationship between economic output indicators and economic–aggressive cross efficiencies.

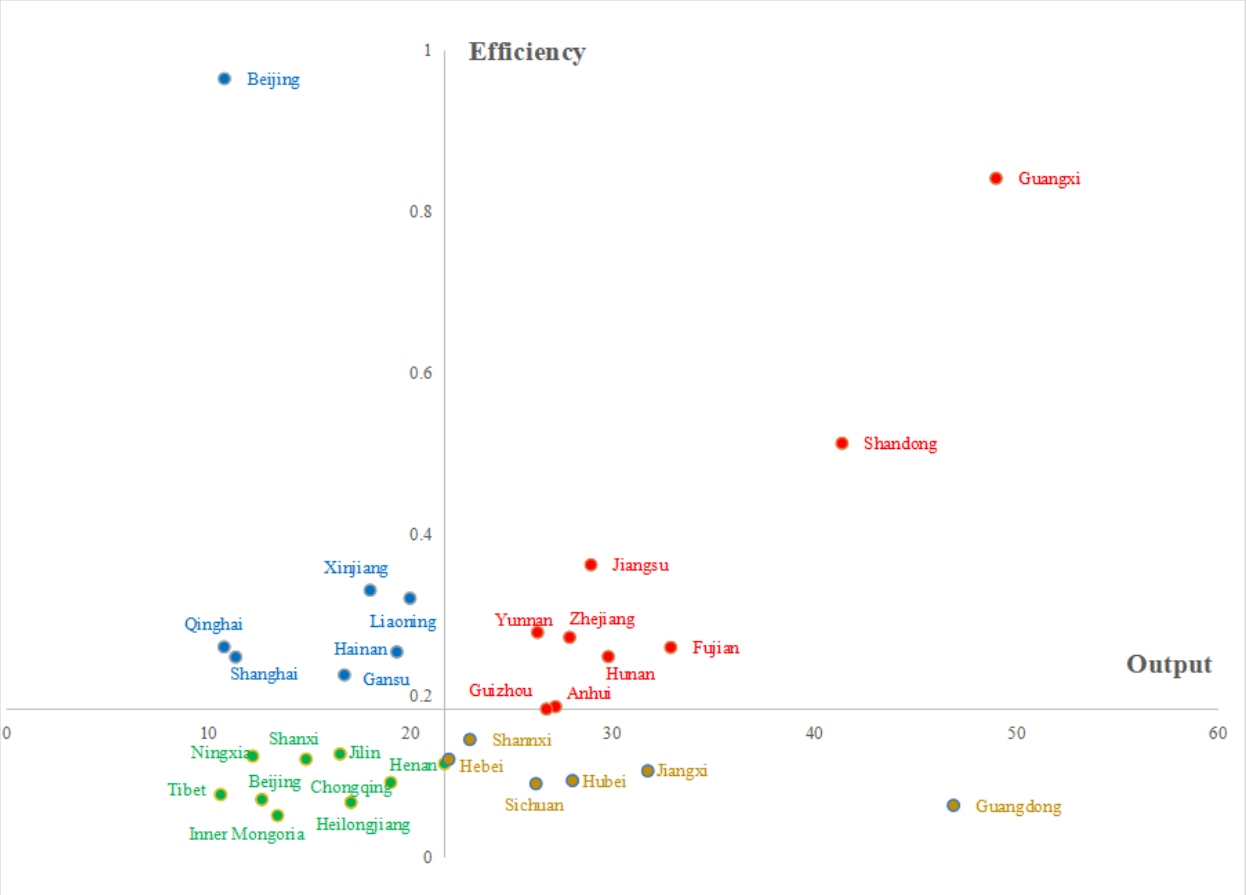


Figure 5. Degree of green forestry growth output from Economic–Aggressive efficiency.

As can be seen from Figure 5, Guangxi, Shandong, Jiangsu, and Fujian are typical "A-E type" provinces. The green output and green economic efficiency provided by the forest in these provinces are much higher than the median level. Guangxi is a major forest

province, and its income from the forestry industry accounts for a high proportion of its national income. In recent years, the development of forest science and technology and policy investment in Guangxi have been in the forefront, rendering the province a useful benchmark. Xinjiang, Qinghai, and Gansu are "DA-E type" provinces that are not rich in forest resources; however, the utilization rate of their forest resources is very high, the development of understory planting is good, and the forestry economic efficiency is very high. Although the "DA-E type" province Liaoning is rich in forest resources, the forest is mainly under ecological protection and the government does not pay enough attention to the development of secondary and tertiary forestry industries, and the forestry economic output is low; however, it is possible to improve the forest economic efficiency in this province by developing its forestry industry. Many provinces fall into the third "DA-IE type" quadrant in Figure 5. The forest ecological resources in these provinces are relatively scarce, and the development level of forestry industry, the economic output, and efficiency associated with forests are low. Heilongjiang differs slightly because, although it is rich in forest resources, the forests in this province are mainly under ecological protection and its forestry industry is insufficient. The low income from its forests is the main reason for the low economic efficiency of the forests in this province. Typical "A-IE type" provinces include Guangdong, Jiangxi, and Sichuan. These provinces do not allocate resources reasonably. Although the output level is high, the efficiency is particularly low, and the waste is serious. The economic development in Guangdong is mainly in electronics, manufacturing, and other tertiary industries; thus, the forestry output management is insufficient and the efficiency is low.

(2) **Empirical analysis by Social–Neutral Cross Efficiency**

The social benefit of the forest refers to the ability of a forest to develop and meet the needs of humans, which is mainly reflected in improvements to human well-being, reducing poverty, and achieving social equity. Figure 6 shows the relationship between output and efficiency in the provinces from the perspective of social development.

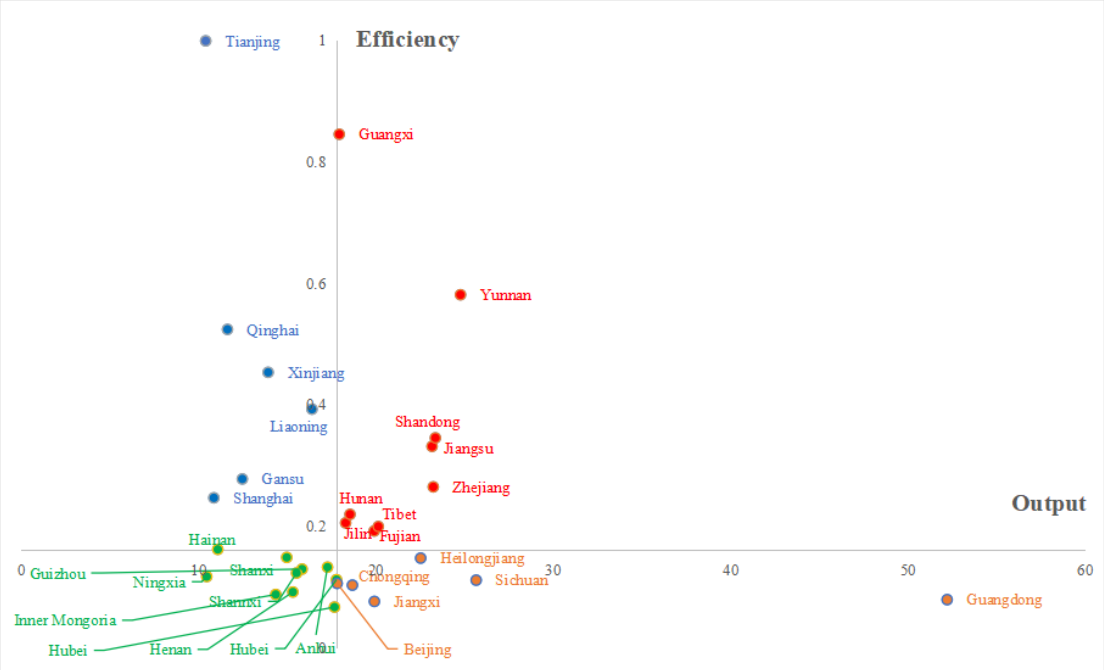


Figure 6. Social benefits of forestry economic development from Social–Neutral efficiency.

Figure 6 shows that the "A-E type" provinces such as Guangxi, Yunnan, and Tibei are rich in natural resources, with many people living around the mountains and rivers, and that the society in these provinces has high satisfaction in terms of forest development. The

Nyingchi area in Tibei has high forest coverage, and its rich forest resources have attracted widespread tourism. "DA-E type" provinces, such as Qinghai, Xinjiang, and Tianjng are vast and sparsely populated, with an amenable climate and high efficiency. The forest environmental conditions in these provinces should be optimized to increase the output and further improve the social benefits. Typical "DA-IE type" provinces such as Shanxi and Inner Mongolia suffer from large climatic differences that are accompanied by complex and diverse topography, which leads to a diversity of forest resources; however, the social and economic development and resource distribution are unbalanced, resulting in a low output and efficiency. Typical "A-IE type" provinces such as Guangdong and Sichuan have large areas of forest coverage, developed economies, and sufficient input factors in terms of production; however, their social efficiency is low and the structuring of their forest resources need to be adjusted.

(3) **Empirical analysis by Sustainability–Neutral cross Efficiency**

Resources are the foundation of all forestry development, and because forests improve the ecological environment, these features have become key to the coordinated and sustainable development of the environment and economy. Only with the sustainable development of forest resources can both forests and humans have a sustainable future; thus, we analyze the relationship between the sustainability output indicators and efficiency in the forestry green economy from the perspective of sustainable development. The distribution of the relationships between the output indicators and efficiencies in the 31 provinces are shown in Figure 7.

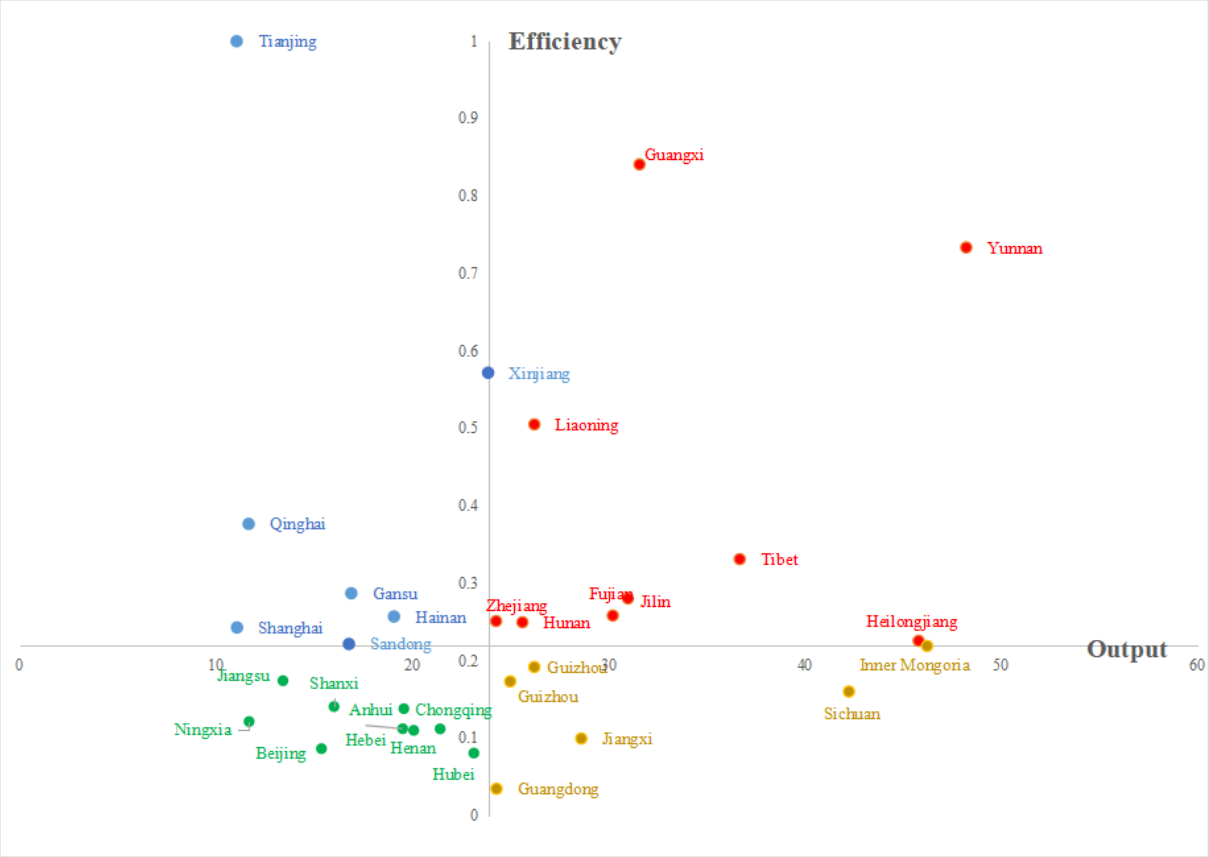


Figure 7. Forest resource Sustainability–Neutral efficiency.

From Figure 7 we see that the "A-E type" provinces, including Guangxi, Yunnan, and Liaoning have a good forest development status, good forest resource sustainability, a high forest development efficiency, and can rely on their own resource advantages to form a benign circulation situation. "DA-E type" provinces such as Qinghai, Gansu, Shanghai,

and Hainan have lower output indicators because of their resource constraints; however, the development trend has improved in these areas because of changes to the overall forest environmental protection and median sustainable efficiencies tend to reach the average level. More attention must be paid to sustainable governance if efficiency is to be improved in this type of province. From Figure 7, many provinces belong to the "DA-IE type", including Shanxi, Anhui, and Beijing. At present, the sustainable protection in these provinces is insufficient, and the forestry development efficiency is low. These provinces need to attach more importance to producing high-quality and sustainable construction, with a rational resource allocation and improved efficiency. "A-IE type" provinces such as Sichuan and Guizhou have high levels of output and low levels of efficiency. Emerging technological means should, thus, be used in these provinces to improve the protection and utilization of sustainable forest resources and to enhance efficiency.

(4) **Empirical analysis by Ecological–Benevolent Cross Efficiency**

Ecological benefits are mainly reflected in the improvements to the ecological environment, reduction in environmental risks, and decreasing ecological scarcity. The unique ecological benefit of the forest is the key factor that determines the importance of forest green economic development. In this study, the efficiency evaluation of the forestry ecology is mainly from the perspective of dynamic change; that is, evaluating the efficiency of ecological change so that the selected indicators refer to ecological change. Figure 8 is a four-quadrant diagram describing the ecological efficiency and output of the forest.

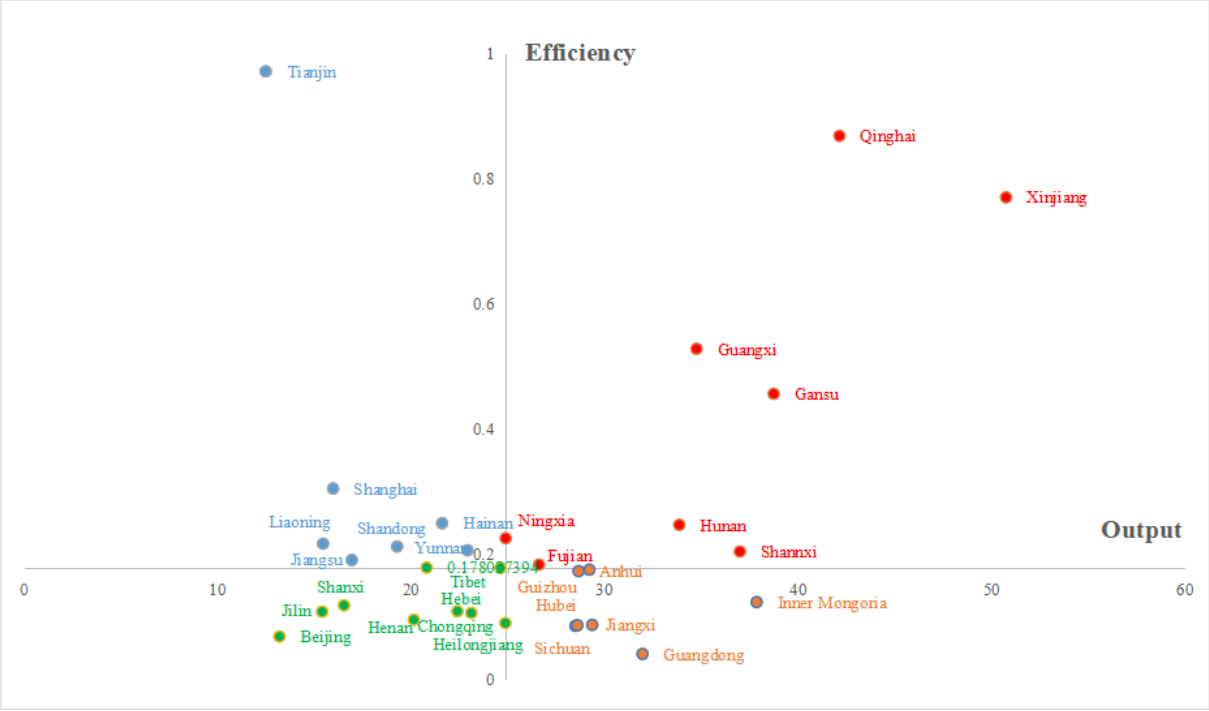


Figure 8. Ecological benefit of forestry-based economic development with Benevolent efficiency.

Figure 8 shows that the typical "A-E type" provinces, Xinjiang, Qinghai, Gansu, Shanxi, Fujian, Guangxi, and Hunan can be divided into two categories: provinces in northwest China and provinces with rich forest resources. In recent years, the Chinese government has significantly improved the water and soil conservation in the northwest of the country. In particular, the promotion of an "agroforestry ecosystem" has solved problems surrounding the lack of forest land in northwest China. The efficiency evaluation illustrates the necessity and effectiveness of policy support and technological upgrades, and indicates that provinces with rich forest resources make significant contributions to ecological protection and act as a benchmark for other provinces. "DA-E type" provinces

such as Tianjin and Shanghai have high economic development, and, although the efficiency of the forest-based ecological protection in these provinces is not low, the output scale of ecological protection requires improvement. Typical "DA-IE type" provinces such as Beijing and Jilin have not paid sufficient attention to the ecological construction of their forests in recent years, meaning that both their output and efficiency are low. It is, thus, necessary to strengthen the forest management in these areas. Typical "A-IE type" provinces such as Guangdong, Jiangxi, and Guizhou have achieved high results in terms of the ecological construction of their forests; however, the unreasonable utilization of forest resources has lowered the forestry ecological efficiency in these provinces.

5.4.2. Empirical Analysis Based on Comprehensive Output Indicators for the Green Development of a Forestry Economy

Comprehensive neutral cross efficiencies in the 31 provinces of China are calculated based on comprehensive indicators for the forestry green economy development output. An empirical analysis of China's overall forestry green economy development is made according to the calculation results. Figure 9 shows the relationship between the comprehensive forestry green economy output indicators and the efficiencies.

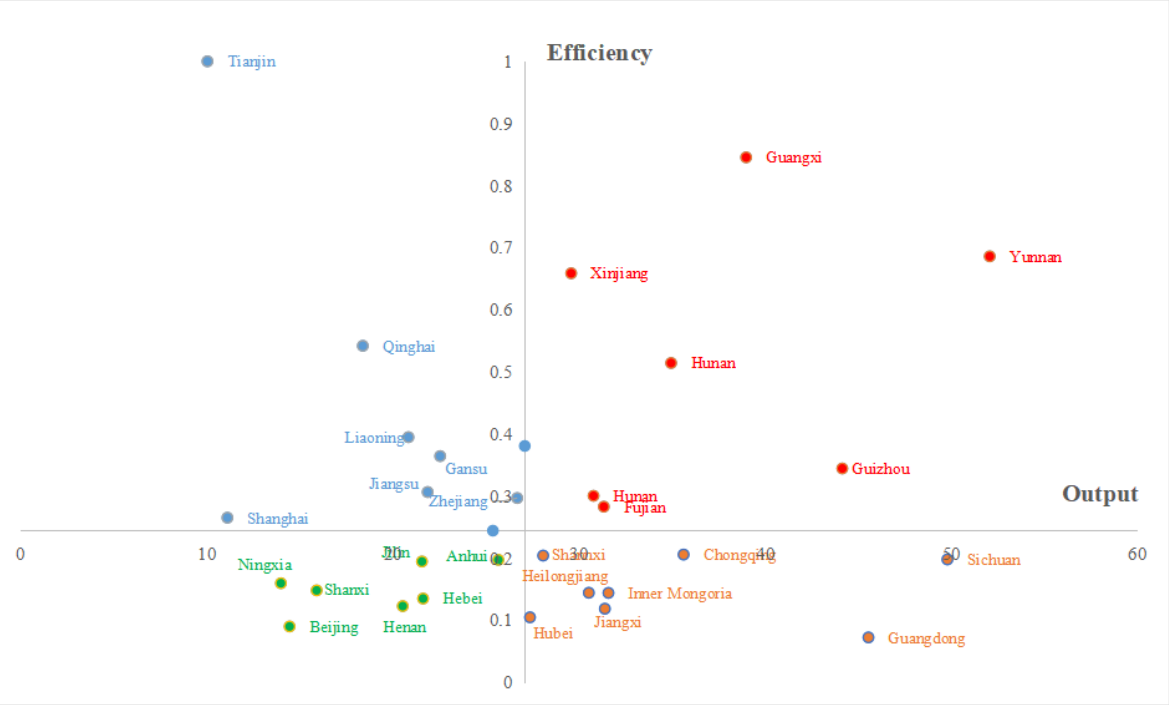


Figure 9. Comprehensive indicators of forestry-based green economy development from Neutral efficiency.

In Figure 9, the forest coverage in most "A-E type" regions was particularly high (for example, Fujian was first and Guangxi third in terms of forest coverage). Both provinces are in Southern China. Over the past two decades, the enthusiasm of southern forest farmers to invest in forestry and rationally distribute forestry income has improved because of governmental reforms in the collective forest ownership system. The results of the efficiency evaluation indicate that this reform has been particularly effective. Fujian, which has the highest forest coverage, was the first province in which the reform was enacted and the results are obvious. Fujian is an "A-E type" province, as indicated in Figures 5–9. Guangxi is the same type; however, forest industry accounts for a large proportion of the economy in this province, and Guangxi is more experienced in developing forestry green economy. Its efficiency value in all aspects has always been the highest in the country, and the province is considered a benchmark. Xinjiang is located in the northwest of China, but

its forestry green economic development potential cannot be ignored. Xinjiang's forest resources are mainly composed of natural forests in mountainous areas, oasis plantations, and desert river valleys. Forest accounts for 163 million mu in this region, the forest area covers more than 99 million mu, and the total volume of living trees is 339 million m^3. The forest area and forest volume rank 13th in the country. With abundant forest resources, the government in Xinjiang pays more attention to ecological protection and has introduced many scientific and technological means, allowing the forests to develop in a high-quality direction. The development level of the forestry green economy in Xinjiang ranks in the forefront of the country.

In "DA-E type" areas, the comprehensive forestry output is still ahead of the national median; however, the comprehensive neutral cross efficiencies in these provinces are not high. Comparing the results in Figures 5–8, the main reason for the low comprehensive cross efficiency in these provinces is the low ecological efficiency of forestry. For example, Shanxi is an important coal production area, Hubei and Heilongjiang are industrial cities, and Guangdong is the most economically developed province in China. These provinces have not yet been able to coordinate the contradiction between economic development and environmental protection.

From the perspective of a comprehensive evaluation, only seven provinces are in the "DA-IE type" quadrant: Ningxia, Jilin, Anhui, Beijing, Shanxi, Hebei, and Henan. Except for Ningxia and Anhui, these provinces are not rich in forest resources, which directly limits the development efficiency of a forestry green economy in these regions. Ningxia and Anhui are more prominent in terms of ecological protection (see Figure 8). The ratio of forestry output in Ningxia is low, and the forestry green economy is poor. This is because the forests in Ningxia are mainly protected with an ecological function, and cannot be harvested or traded. Crops are generally planted beneath the forests; thus, the output and efficiency obtained from the analysis of the output data were low. The comprehensive evaluation of Anhui was not high because of its small social contribution. As can be seen from Figure 6, the cross efficiency of its forestry society was basically the lowest in the country.

Provinces in the "DA-E type" quadrant are all resource-saving forestry development models. For example, little natural vegetation is present in Shanghai, but it attaches great importance to the development of a forestry green economy, with close focus on carbon neutrality, the application of high and new technology in forestry development, and the scientific realization of an organic unity between an economic benefit and ecological efficiency.

Based on the above analysis, the provinces with abundant forest resources had relatively high benefits or efficiency in the development of forestry green economy, with Fujian and Guangxi being the most prominent. Figures 5–9 indicate that such provinces are always located in the "A-E type" quadrants. "DA-E type" provinces are resource-saving. In these provinces, increasing the investment in forestry will improve the development efficiency of the forestry green economy to a greater extent. Of these provinces, Shanghai performed best. From Figures 5–9, Shanghai is always located in the "DA-E type" quadrant. Shanghai's forest coverage is not high, but the reason for its higher efficiency is that it applies high-tech approaches to forestry development to scientifically realize the organic unity between economic and ecological benefits. There are two situations in which the production efficiency of a forestry green economy development was low: one was the waste of resources, such as that seen in the "A-IE type" provinces such as Guangdong and Sichuan. From Figures 5–9, these two provinces have always belonged to the "A-IE type" quadrant, and were not only rich in forest resources, but also had a high level of economic development; however, the forestry green economy development efficiency in these provinces was not high. These areas need to optimize the structure of their forestry resource allocation and pay more attention to development. Resource deficiency can also lead to inefficiency, as observed in provinces such as Shanxi and Henan.

Remark 5. *Most of the existing articles only consider the study of forestry efficiency under a single indicator and a single perspective* [35,37,40]. *This study constructs a multi-indicator system, and then comprehensively explores the development status of a forestry green economy from different dimensions through cross efficiency models under different perspectives.*

6. Conclusions and Suggestions

This study proposes a multi-dimensional cross efficiency evaluation method of forest green development that is based on an information fusion by reviewing the literature, describing the existing forest efficiency evaluation (e.g., efficiency, indicators, and methods), and constructing an output indicator system for a forestry green economy from four dimensions: ecology, economy, society, and sustainability. The forestry green economy efficiency was evaluated based on the cross evaluation method, the output indicators of the four dimensions were integrated, and the comprehensive cross efficiency value was calculated.

Based on this method, the development status of a forestry green economy in the 31 provinces of China were analyzed. The research conclusions are as follows:

1. In terms of methods, there are two conclusions. Compared with self-evaluation methods, the efficiency of cross evaluation is more objective from the perspective of peers. From the evaluation results of 31 provinces in China, the cross evaluation model overcomes the problems associated with overestimation that is observed in the results obtained by self-evaluation. The efficiency grouping of the 31 provinces is more realistic. In contrast, using the conditional entropy of the rough set to construct the cross efficiency aggregation model can effectively reflect the sequence of self-evaluation and cross evaluation and the important role of order in cross evaluation. The empirical results show that, compared with the simple use of entropy information or the similar relationship between self-evaluation and peer evaluation, the aggregation method more reasonably considers the order relationship between self-evaluation and peer evaluation, and the aggregation information obtained has a greater degree of differentiation. Therefore, the aggregation method used in this study makes better use of the objectivity and accuracy of efficiency grouping.
2. In terms of application, the proposed multidimensional cross efficiency evaluation method can better analyze the output-efficiency relationship in forestry green economic development. The empirical conclusion illustrates two problems:

First, on the whole, the efficiency evaluation results show that the regional development of China's forestry green economy is unbalanced. From the perspective of a single dimension analysis: (i) The evaluation results of the economic cross efficiency show that only areas with rich resources and a high proportion of forestry industry in their economic development have balanced and good relationships between the different output efficiencies. Other regions need to further improve their efficiency by increasing the forestry economic outputs or inputs. (ii) In terms of sustainable development, resource advantages are particularly important, and areas with insufficient resource advantages must improve resource utilization. (iii) From the analysis results of the ecological dimension, the ecological efficiency of provinces with good forest resources is good; however, regions that pay too much attention to economic development suffer in terms of their ecological output efficiency. (iv) From the perspective of social benefit, the high ecological efficiency of provinces that are rich in forest resources and pay attention to the development of forest tourism could act as a benchmark for provinces that are not rich in forest resources and have little forest tourism or significant urban construction.

Second, the output benefits of each dimension are integrated to calculate the comprehensive cross efficiency value. Through a comparison of the comprehensive efficiency value and the efficiency evaluation results of various dimensions, the development of many provinces in different dimensions was found to be particularly uneven. Some provinces that are rich in forest resources rely heavily on the forestry industry in their economic development, leading to high economic efficiency; however, the efficiency of the other three

aspects is low. Therefore, the analysis results of this paper could be used by the provinces to ascertain the path by which a forestry green economy efficiency can be improved in terms of the four dimensions.

We put forward some suggestions for improving the efficiency of forestry green economy development in terms of the four dimensions:

1. Ecology: the significant requirements for strengthening ecological protection suggest that implementation of a management and control system, which includes ecological protection and strengthens the monitoring, management, and scientific utilization of forest, wetland, and grassland resources is required. We further suggest the implementation of biodiversity conservation projects, protecting wild animals and plants in their important habitats, and rescuing the precious and endangered species.
2. Economy: adherence to the promotion of an integrated development of primary, secondary, and tertiary industries should be accompanied by the creation of green development demonstration areas: (i) It is necessary to extend and strengthen the existing industrial structure, while building a complete industrial chain for processing wood and bamboo. The building of national forestry industry demonstration parks and provincial forestry key parks should be considered. (ii) The commercial timber forest project, the bamboo flowers and flowers project, and the well-known economic forest project should be continued, while encouraging the development of short-term industrial raw material forests and the vigorous cultivation of fast-growing and high-yield forests, with large-diameter timber forests to improve the self-sufficiency rate of timber. (iii) The government should further implement forest tourism and aid those that live in the forest, with forest health care projects and the integration of medicine, health care, sports, culture, and other industries to form new, forest-based, business models.
3. Sustainability: To achieve sustainable forestry development, it is necessary to plan, adjust, and optimize the economic structure according to local characteristics and conditions, develop forestry products, and develop construction projects that combine employment with the economy. At the same time, the development of science and technology is a fundamental strategy by which sustainable forestry development can be achieved, changing the traditional extensive economic development model at the expense of the environment and natural resources, implementing science and technology to revitalize forests, and continuously improving the scientific and technological forms of forestry construction.
4. Social: The social benefits are manifested in the greening of cities, visual improvements to the human living environment, and enhancing happiness. It is necessary to develop the construction of urban parks that can improve urban functions and meet the needs of citizens, enhancing the value and livability of cities. If proper landscape gardening was integrated into urban planning and design, urban constructions could have the characteristics and charm of gardens. At the same time, vegetation covering projects need to be vigorously promoted in both road and residential areas to meet the need for green forests and improve green satisfaction.

Author Contributions: Y.H. conducted the conceptualization, methodology, formal analysis research, drafted the manuscript, and provided management oversight of the project. X.H. performed the investigation, validation, formal analysis, and data management. S.H. performed data collection and helped draft the manuscript. Y.D. was responsible for resources, writing reviews and editing, supervision, project management, and funding. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (No. 72001042, 72001043), the China Postdoctoral Science Foundation (2021M700781) and "Research on Benchmarking and Optimization of Forest Carbon Sink Efficiency under Uncertain Environment", Science and Technology Innovation Special Fund of Fujian Agriculture and Forestry University (Social Sciences) (CXZX2021029).

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.

References

1. Sadowska, B.; Grzegorz, Z.; Stępnicka, N. Forest fires and losses caused by fires—An economic approach. *WSEAS Trans. Environ. Dev.* **2021**, *17*, 181–191. [CrossRef]
2. Mason, L.R.; Melton, C.C.; Gray, D.; Swallow, A.L. Climate Change, Social Work, and the Transition Away from Fossil Fuels: A Scoping Review. *Sustainability* **2022**, *14*, 7086. [CrossRef]
3. Lee, C.C.; Wang, C.W.; Ho, S.J. The dimension of green economy: Culture viewpoint. *Econ. Anal. Policy* **2022**, *74*, 122–138. [CrossRef]
4. Vierikko, K.; Pellikka, J.; Hanski, L.K.; Myllyviita, T.; Niemelä, J.; Vehkamäki, S.; Lindén, H. Indicators of sustainable forestry: The association between wildlife species and forest structure in Finland. *Ecol. Indic.* **2009**, *10*, 361–369. [CrossRef]
5. Yin, S.W.; Gong, Z.W.; Gu, L.; Deng, Y.J.; Niu, Y.J. Driving forces of the efficiency of forest carbon sequestration production: Spatial panel data from the national forest inventory in China. *J. Clean. Prod.* **2022**, *330*, 129776. [CrossRef]
6. Tian, S.; Xu, W. Evaluation of China's forestry input-output efficiency based on DEA modeling. *Resour. Sci.* **2012**, *10*, 1944–1950.
7. Gao, D.; Zhang, B.; Li, S. Spatial Effect Analysis of Total Factor Productivity and Forestry Economic Growth. *Forests* **2021**, *12*, 702. [CrossRef]
8. Larsson, T.-B. Biodiversity evaluation tools for European forests. *Ecol. Bull.* **2001**, *75*, 50.
9. Gough, A.D.; Innes, J.L.; Allen, D.S. Development of common indicators of sustainable forest management. *Ecol. Indic.* **2008**, *8*, 425–430. [CrossRef]
10. Kallio, M.; Hänninen, R.; Vainikainen, N.; Luque, S. Biodiversity value and the optimal location of forest conservation sites in Southern Finland. *Ecol. Econ.* **2008**, *67*, 232–243. [CrossRef]
11. Zang, L.Z.; Zhang, C.H.C. Spatial-temporal evolution of total factor productivity in China's forestry industry. *Stat. Decis.* **2016**, *5*, 118–122.
12. Marla, M.L.; Mark, E.B.; Brett, J.B.; Matthew, J.D.; Jonathan, H.; David, B.K.; Danelle, L.; Meghan, G.M.; David, O.; Jonathan, R. Thompson. Compounding the Disturbance: Family Forest Owner Reactions to Invasive Forest Insects. *Ecol. Econ.* **2020**, *167*, 106461.
13. Bezrukova, T.L.; Gyiazov, A.T.; Kuksova, I.V. Socio-ecological and economic efficiency of the territories of forestry. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *595*, 012050. [CrossRef]
14. Karanina, E.; Alekseev, S.; Loginov, D. Sustainable development and economic security of the region. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *403*, 012152. [CrossRef]
15. Abanina, E.N.; Ustinova, A.N.; Urkaev, O.O. Factors and conditions for effective forestry in the context of the transition to sustainable development. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *723*, 022092. [CrossRef]
16. Sexton, T.R.; Silkman, R.H. Andrew J. Hogan. Data envelopment analysis: Critique and extensions. *Evol. Anthropol. Issues News Rev.* **1986**, *1986*, 77–105.
17. Doyle, J.; Green, R. Efficiency and Cross-Efficiency in DEA: Derivations, Meanings and Uses. *J. Oper. Res. Soc.* **1994**, *45*, 567–578. [CrossRef]
18. Wang, Y.M.; Chin, K.S. A neutral DEA model for cross-efficiency evaluation and its extension. *Expert Syst. Appl.* **2009**, *37*, 3666–3675. [CrossRef]
19. Chen, L.; Wang, Y.M. DEA target setting approach within the cross efficiency framework. *Omega* **2020**, *96*, 102072. [CrossRef]
20. Toloo, M.; Hančlová, J. Multi-valued measures in DEA in the presence of undesirable outputs. *Omega* **2020**, *94*, 102041. [CrossRef]
21. Wu, J.; Liang, L.; Yang, F. Determination of weights for the ultimate cross efficiency using Shapley Value In cooperative game. *Expert Syst. Appl.* **2007**, *36*, 872–876. [CrossRef]
22. Wang, Y.M.; Chin, K.S. The use of OWA operator weights for cross-efficiency aggregation. *Omega* **2010**, *39*, 493–503. [CrossRef]
23. Yang, F.; Ang, S.; Xia, Q.; Yang, C.C. Ranking DMUs by using interval DEA cross efficiency matrix with acceptability analysis. *Eur. J. Oper. Res.* **2012**, *223*, 483–488. [CrossRef]
24. Yang, G.L.; Yang, J.B.; Liu, W.B.; Li, X.X. Cross-efficiency aggregation in DEA models using the evidential-reasoning approach. *Eur. J. Oper. Res.* **2013**, *231*, 393–404. [CrossRef]
25. Ramón, N.; Ruiz, J.L.; Sirvent, I. Common sets of weights as summaries of DEA profiles of weights: With an application to the ranking of professional tennis players. *Expert Syst. Appl.* **2011**, *39*, 4882–4889. [CrossRef]
26. Wu, J.; Sun, J.S.; Liang, L.; Zha, Y.C. Determination of weights for ultimate cross efficiency using Shannon entropy. *Expert Syst. Appl.* **2011**, *38*, 5162–5165. [CrossRef]
27. Wang, Y.M.; Wang, S. Approaches to determining the relative importance weights for cross-efficiency aggregation in data envelopment analysis. *J. Oper. Res. Soc.* **2013**, *64*, 60–69. [CrossRef]
28. Angiz, M.Z.; Mustafa, A.; Kamali, M.J. Cross-ranking of Decision Making Units in Data Envelopment Analysis. *Appl. Math. Model.* **2013**, *37*, 398–405. [CrossRef]

29. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
30. Zhang, X.X.; Wang, Y.M. A hybrid multi-attribute group decision making method considering evidence weight and reliability. *Syst. Sci. Math.* **2021**, *41*, 1305–1327.
31. Ye, F.F.; Yang, L.H.; Wang, Y.M. Area environment pollution measurement and classification study of efficiency. *Syst. Sci. Math.* **2020**, *40*, 984–1003.
32. Yang, J.B. Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *Eur. J. Oper. Res.* **2001**, *131*, 31–61. [CrossRef]
33. Shannon, C.E. A Mathematical Theory of Communication. *Bell Syst. Tech. J.* **1948**, *27*, 623–656. [CrossRef]
34. Hu, Q.H.; Guo, M.Z.; Yu, D.R.; Liu, J.F. Information entropy for ordinal classification. *Sci. China Inf. Sci.* **2010**, *53*, 1188–1200. [CrossRef]
35. Liu, M.; Chen, W.H.; Liu, Z.H. Green forestry economic evaluation framework for research and trial. *J. For. Econ.* **2016**, *38*, 3–10.
36. Xi, T.T.; Li, S.L. Analysis of forest carbon sink potential in Heilongjiang Province. *For. Econ. Issues* **2006**, *6*, 519–522+526.
37. Xu, M.; Chen, W.H.; Liu, J.C. Research of the forestry evaluation index system of green economy development. *J. For. Econ.* **2015**, *37*, 24–28+67.
38. Xu, Q.H. Research on modern forestry evaluation index system. *Hubei For. Sci. Technol.* **2009**, *2*, 43–47.
39. Ahlswede, R.; Ahlswede, A.; Althöfer, I.; Deppe, C.; Tamm, U. The Entropy as a Measure of Uncertainty. In *Storing and Transmitting Data*; Springer: Berlin/Heidelberg, Germany, 2014; Volume 10, pp. 39–78.
40. Lv, J.H.; Sun, J.Y.; Cai, X.T. Analysis of spatial and temporal evolution of green total factor productivity in Chinese forestry. *J. Agric. For. Econ. Manag.* **2022**, *21*, 320–330.