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Exploring the Measurement of Regional Forestry Eco-Efficiency and Influencing Factors in China Based on the Super-Efficient DEA-Tobit Two Stage Model

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Abstract: This paper adopts the super-efficient DEA (data envelopment analysis) model to measure the forestry eco-efficiency (FECO) of 30 Chinese provinces and cities from 2008 to 2021, and then introduces the Tobit model to explore the influencing factors of FECO to better understand the sustainable development level of forestry. It draws the following conclusions: (1) The average value of FECO in China is 0.504, which is still at a low level, and the FECO of each region has significant regional heterogeneity; the provinces with higher FECO are mainly concentrated in the eastern region, while the FECO of the central and western regions is lower; (2) In terms of the main factors affecting FECO in China, the regression coefficients of market-based environmental regulations are significantly positive in the national, eastern and central regions, while they are significantly negative in the western region. The coefficient of impact of scientific research funding investment on forestry industry eco-efficiency is negative and shows a significant promotion effect in the eastern region, but the elasticity coefficient in the central and western regions is negative but not significant. Economic development has a positive but insignificant effect on FECO, with the eastern region showing a positive correlation, while the central and western regions are insignificant. Industrial structure has a significant negative effect on FECO in the national, eastern and central regions, but the effect of industrial structure on FECO in the western region is not significant. The effect of foreign direct investment on FECO was negative for the national, central and western regions, but the central region did not pass the significance test, while the eastern region reflected a significant promotion effect.

Keywords: forestry; eco-efficiency; sustainable development; forestry resources

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1. Introduction

From a worldwide perspective, energy, resource and ecological emergencies have become serious challenges. Economist Daly [1] pointed out that man-made capital has become relatively abundant and the constraints to human development have been transformed into scarce natural capital. Zeb et al. [2] argued that the depletion of natural resources and the adverse effects of environmental degradation, including desertification, drought, land degradation, lack of freshwater resources and loss of biodiversity are increasing and worsening the various challenges facing humanity. Forestry has multiple benefits and can provide practical solutions to address these issues. The green development of forestry and the improvement of forestry eco-efficiency have become the focus of attention of the international community [3,4].

As an important basic industry of the national economy, forestry plays a pivotal role in human societal development. For a long time, China's forestry economic growth mode has been characterized by a large number of factor inputs; this is a crude economic growth mode relying on the massive consumption of resources to promote [5] it. Under the current conditions of resource scarcity in China, this type of crude forestry economic growth will encounter a "limit"; when growth approaches its "limit" or people are aware of this "limit", economic growth needs to improve the use efficiency of input factors of production to break through this "limit", that is, to increase the share of the total factor productivity contribution to forestry economic growth. According to relevant economic theories, the growth of output can depend on factor inputs as well as technological progress [6,7]. The development of China's forestry industry is so rapid that it is obvious to measure it numerically, but the question remains: what is the real quality of this forestry development? In today's increasingly prominent resource and environmental problems, ensuring rapid economic development while reducing environmental pollution and resource waste is not only a sizable challenge for social development, but also one of the urgent tasks facing the future development of forestry. Therefore, a scientific and objective discussion of the quality of forestry development is conducive to a better understanding of what will be the sustainable development level of forestry in the future [8–10]. Schaltegger and Sturm [11] proposed an eco-efficiency concept, which has been widely recognized by scholars in various fields. Specifically in the field of forestry, eco-efficiency is a measure of the level of sustainable development of forestry, and its objective is to measure whether forestry can minimize environmental pollution and resource consumption while achieving multifaceted value in a comprehensive manner, with the premise of ensuring the quality of forest products [12]. Focusing on FECO improvement is conducive to advocating for modern forestry development through the concept of coordinated and sustainable development of society, economy and ecology [13,14].

The following are this paper's main contributions: (1) Existing studies mainly study productivity and explore its efficiency from the perspective of production, while the issue of forest efficiency from an ecological perspective has rarely been addressed; this paper considers the inputs and undesired outputs and measures regional forest eco-efficiency in China, which is a useful supplement to the existing studies; (2) Existing studies mainly focus on specific regions and lack comparative studies between regions; this paper provides theoretical support by comparing the east, central and west regions; (3) Exploring forest eco-efficiency in the context of sustainable development and proposing corresponding policies can provide a reference for regional green development. Therefore, this paper adopts the super-efficient DEA model to measure the forestry eco-efficiency of 30 Chinese provinces and cities (except Hong Kong, Macao, Taiwan and Tibet) for 14 years from 2008 to 2021, and then introduces the Tobit model to analyze the influencing factors for forestry eco-efficiency in order to better understand the sustainable development level of forestry and provide some theoretical support for the sustainable development of modern forestry in the future.

2. Literature Review

2.1. Connotation of Eco-Efficiency in Forestry

Eco-efficiency is the ratio of the value of economic and social development (GDP) to the physical amount of resource and environmental consumption, which creatively connects three indicators: resources, economy and environment. It emphasizes the unity of environmental and economic benefits, establishes a connection between the best economic and environmental goals and provides a link between regions; it provides an important evaluation tool for the sustainable development of regions and industries, and becomes an important reference for policy makers [15,16]. This concept is generally accepted and widely used in the evaluation and research of the forest industry by domestic and foreign scholars, such as Wu and Zhang [17]. They considered that the eco-efficiency of the forest industry refers to the direct impact on the forest's ecological environment caused by the inputs of technological improvement and environmental management, such as air quality improvement and wastewater treatment, in order to ameliorate the ecological impact brought by the forestry industry, i.e., industrial efficiency in the forestry industry. According to Chen et al. [18], FECO is a measure of the sustainable development of forestry, and its objective is to measure whether forestry can minimize environmental pollution and resource consumption while ensuring the quantity and quality of forest products and achieving its multifaceted value in a comprehensive manner. Hong et al. [19] pointed out that for forestry to be sustainable, coordination between input and output factors should be ensured. Zheng and Yin [20] argued that FECO facilitates a win-win input and output relationship between economic and social benefits.

2.2. Measurement of FECO

Academics have analyzed FECO from different perspectives, and the differences are mainly reflected in the research methods and regional selection. In the process of measuring FECO, the stochastic frontier approach (SFA), the ratio method and the DEA evaluation model are mainly used in China. For example, Can et al. [21] used the SFA method to measure the ecological efficiency of plain forestry and analyzed the degree of ecological contribution of farmland forest networks and small forests to total agricultural output value, plantation output value and livestock output value. Weerawat et al. [22] used the ratio method to analyze several rubber plantation areas in Thailand and made recommendations. Most studies using the DEA evaluation, such as Li et al. [23], measured the forestry input-output efficiency using the DEA model, but the output indicators they selected did not reflect the social benefits of forestry; in addition, the only reflected the situation in 2006. Tian and Xu [24] measured the forestry input-output efficiency from 1993 to 2010 in China. At the local level, Lai and Zhang [25] used the super-efficient DEA model to measure the forestry input-output efficiency of 21 cities in Guangdong province and ranked and classified them; Zang et al. [26] measured the technical efficiency of forestry production and its influencing factors from the perspective of forestry production in Chongqing. Zhang and Kang [27] selected the super-efficient DEA-Tobit model to measure forestry production efficiency in 30 Chinese provinces from 2000 to 2014, and pointed out that its efficiency is lower, with significant spatial divergence. Luo et al. [28] also used the DEA model to measure the forestry efficiency of each province and further analyzed the spatial differences using the Gini coefficient and Moran index and concluded that forestry efficiency increased year by year but was still low in general. Tian et al. [29] used the C2R-DEA model (DEA model without considering returns to scale) and the SE-DEA model to measure forestry production efficiency in China. In 2012, Tian et al. [29] analyzed and measured the input-output efficiency of forestry using the super-efficient DEA model.

2.3. Influencing Factors of FECO

In recent years, many scholars have used DEA measurements to evaluate regional FECO and constructed an index system to study the key factors affecting FECO in the region. For example, Zheng et al. [30] examined the impact of industrial agglomeration on FECO through an econometric model and found that the level of industrial agglomeration and eco-efficiency in provinces with high levels of forestry industry development in China showed different degrees of increase during the study period. Chen and Geng [31] pointed out that the economy of scale efficiency of the forestry industry would be affected by property rights factors, local government intervention behavior, market concentration, market entry barriers and externalities. Jiang et al. [32] argued that the industrialization of forestry is an objective requirement, an inevitable result of the market economy and an effective way to improve efficiency in modern forestry. Hou [33] believed that the economic productivity or environmental productivity of forestry can be improved through the division of labor and specialization. Li and Tang [34] considered that the rationalization of the industrial structure is an effective means to improve the efficiency of forestry. Tian and Xu [24] measured the input-output efficiency of forestry in China from 1993 to 2010 and analyzed its influencing factors in depth. Zang et al. [26] measured the technical efficiency of forestry production and its influencing factors from the perspective of forestry production of Chongqing foresters. Zhang and Xiong [35] concluded that forestry ecological construction and protection, forest ecological compensation and forestry prevention and control inputs have negative and significant effects on the comprehensive FECO.

The studies that have been conducted lack an analysis of forestry eco-efficiency, and in the field of forestry in China, a unified definition of forestry eco-efficiency has not been clearly established. This is mainly because, although the development of forestry has the dual attributes of economic value and ecological value, there are problems such as long investment recovery cycles and economic externalities, which, together with the emergence of natural and man-made disasters, do not guarantee that forestry development can meet people's expectations. In the process of pursuing the economic value of forestry, people gradually ignore the ecological benefits. Therefore, this paper measures the forestry eco-efficiency of 30 provinces in China from the provincial panel data of 30 provinces from 2008–2021 (due to limited data sources, Hong Kong, Macao, Taiwan and Tibetan areas are not considered for the time being), and further explores the regional differences and spatial and temporal characteristics of forestry eco-efficiency. On this basis, the factors affecting forestry eco-efficiency are explored to better protect the diversity of forestry ecosystems. While the forestry ecological economy is developing continuously, we should also pay attention to the protection of forestry ecology, so as to realize people's expectations for a better ecological environment in the near future.

3. Methods

The main methods currently used for eco-efficiency evaluation are the single ratio method, the indicator system method and the model analysis (DEA) method. Although the single ratio method is relatively simple, it cannot distinguish the impact of different environments, give the optimal set of ratios or give decision makers flexibility in their choices. The indicator system method can reflect the level of development and coordination of social, economic and natural subsystems, but it requires artificial weighting, so there is often subjective interference. The use of the model analysis method can better compensate for the above shortcomings, so the data envelopment analysis method is widely used in the empirical study of eco-efficiency.

3.1. FECO Measurement Method

3.1.1. Super-Efficient DEA

Data envelopment analysis is a typical class of nonparametric analysis, referred to as DEA analysis, which was proposed by Charnes et al. [36]. They studied the optimization of resource allocation in the production process by evaluating the relative efficiency ratio of inputs and outputs within each decision unit. In the production process, the ratio between the input quantity of resource consumption and the output quantity of the product determines the production efficiency value within the decision unit, and the weighting of the input and output values can be used to analyze multiple input and output problems. For the study of green issues, in the process of constructing the DEA model, pollution factor indicators and negative ecological indicators can be classified as non-desired outputs, and the DEA model will be based on the "asymmetric" curve measurement of each type of output to accurately estimate the eco-economic efficiency value. The DEA model will accurately estimate the eco-economic efficiency values based on "asymmetric" curve measures for each type of output, and through projection analysis, ensure sufficient output and appropriate inputs while strictly controlling the amount of undesired output [37]. The estimation of desired and undesired outputs in the production process is achieved by means of the radial measure of the curve and the inverse of the curve measure, respectively. The DEA is the curve radial measure, without function expressions and without hypothesis testing [38].

1. Introduction of CCR-DEA model

The CCR-DEA model was proposed by Charnes et al. [39]; it is an input-oriented DEA model. The CCR model is the most basic DEA model with n DMU (i = 1, 2, . . . , n), which satisfies the assumption of homogeneity and are all comparable. Each DMU has the same t inputs, and the input vector is:

$$x_i = (x_{1i}, x_{2i}, \ldots, x_{ti})^T, i = 1, 2, \ldots, n \,. \tag{1}$$

Each DMU has the same s outputs, then there is an output vector of

$$y_i = (y_{1i}, y_{2i}, \ldots, y_{si})^T, i = 1, 2, \ldots, n, \tag{2}$$

i.e., each DMU has the same t inputs and s output types. Where x_{ji} denotes the input quantity of the i-th DMU to the j-th DMU, and y_{ji} denotes the output quantity of the i-th DMU to the j-th DMU. In order to integrate all the DMUs in a uniform way, each input and output needs to be assigned a value, so that the weight vectors of the input and output are

$$v = \left(v_1, v_2, \ldots, v_j\right)^T, \tag{3}$$

$$u = (u_1, u_2, \ldots, u_r)^T, \tag{4}$$

where v_j denotes the j-th type of input weight and u_r denotes the rth type of output weight. At this point, the combined value of the i-th decision unit input is $\sum_{j=1}^{t} v_j x_{ji}$, and the combined value of the output is $\sum_{r=1}^{s} u_r y_{ri}$, so the efficiency evaluation index of each DMUi is defined as

$$h_i = \frac{\sum_{r=1}^{s} u_r y_{ri}}{\sum_{j=1}^{t} v_j x_{ji}}, \tag{5}$$

$$\begin{cases} max h_{i0} = \frac{\sum_{r=1}^{s} u_r y_{ri0}}{\sum_{j=1}^{t} v_j x_{ji0}} \\ \frac{\sum_{r=1}^{s} u_r y_{ri}}{\sum_{j=1}^{t} v_j x_{ji}} \leq 1, i = 1, 2, \ldots, n \\ v = \left(v_1, v_2, \ldots, v_j\right)^T \geq 0 \\ u = (u_1, u_2, \ldots, u_r)^T \geq 0 \end{cases}. \tag{6}$$

2. Introduction to the BCC-DEA model

The CCR-DEA model based on the premise of constant returns to scale is slightly different from reality; the returns to scale are not constant in actual economic production activities, so Banker et al. [39] proposed an extension of the DEA analysis with the variable returns to scale model, namely the BBC-DEA model analysis method.

The assumptions in the BBC-DEA model are variable payoffs of scale, and also a decomposition of technical efficiency into two components. The BBC-DEA model incorporates convexity constraints, and its input-oriented model is:

$$\begin{cases} max\left(u^T y_0 + \mu_0\right) \\ s.t. \omega^T x_i - \mu^T y_i \geq 0 \\ \omega^T x_0 = 0 \\ \omega \geq 0, \mu \geq 0, i = 1, 2, \ldots n \end{cases}, \tag{7}$$

where μ_0 denotes the payoff of scale; ω is the portfolio ratio of effective decision units

3. Introduction of the super-efficient DEA analysis method

In the analysis results of the traditional DEA model, there will be multiple effective decision units at the same time, i.e., there are multiple efficiency values of 1, and thus the individual decision units cannot be ranked according to their high efficiency values. For this situation, then some scholars proposed Super-efficient DEA [40,41]. The Super-Efficiency DEA analysis method allows the simultaneous efficient decision units to be further analyzed and all DMUs reordered. With variable payoffs to scale, the super-efficient DEA is as follows:

$$\begin{cases} min\left[\theta - \varepsilon\left(\hat{e}^T S^- + e^T S^+\right)\right] \\ s.t. \sum_{i=1}^{n} \lambda_i x_i + S^- = \theta x_0 \\ \sum_{i=1}^{n} \lambda_i y_i + S^+ = y_0 \\ S^- \geq 0, S^+ \geq 0, \lambda_i \geq 0, i = 1, 2, \ldots n \end{cases}, \tag{8}$$

where λ represents the slack variable, and the next step introduces the slack variable S^+ and the residual variable S^-; θ is the efficiency value required in the paper.

3.1.2. Variable Selection and Data Sources

1. Input variables

One of the most critical aspects of the super-efficient DEA evaluation model is the selection of input-output indicators and samples because they have a great impact on the final evaluation results. According to Pedraja—Chaparro and Salinas-Jimenez [42], for ensuring the credibility of the model's results, the inputs and outputs must be highly correlated. Forestry inputs should be the various factors of production that are invested to promote forestry development. In this paper, we study the ecological efficiency of forestry, therefore, the eco-forestry input and output index system should not only include the resource consumption factor component, but also the environmental pollution factor.

Forestry labor input: Labor input is the first influencing factor. As in other means of production, human capital is also a of means of production and plays an important role in production activities. In his study of economics, Quaker pointed out that people are the primary factor in the process of wealth creation. Labor input affects technical efficiency through both quantity and quality. In this paper, labor input refers only to the quantity of labor input, using the year-end number of forestry system employees to measure forestry labor input.

Forestry capital input: This paper uses the amount of forestry fixed asset investment in the current year as the capital input variable. Investment in forestry fixed assets refers to the monetary sum of man-hours or costs required for the construction and acquisition of forestry fixed assets in forestry production. Technical efficiency improvement of forestry production by forestry fixed assets is continuous and long-term and has an important role in forestry production. The impact of forestry fixed investment on eco-efficiency is not only expressed in the scale of investment, but also in the stability and continuity of the sources of forestry investment which will also improve FECO. For this reason, forestry fixed asset investment can well reflect funds and the smoothness of funding channels impact on FECO.

Forestry ecological input: It is expressed by the forestry ecological construction input.

Forestry livelihood inputs: It is expressed by the forestry infrastructure inputs.

2. Output variables

Desired output: This is the total output value of the forestry industry in each province, converted to constant prices in 2008 according to the CPI index, in order to exclude the influence of price changes

Non-desired output: Considering that it is difficult to characterize the environmental pressure by a single indicator, this paper uses "three waste" emissions from each region to represent pollution emissions: wastewater emissions from the secondary forestry industry in each province for wastewater, gas emissions from the secondary forestry industry in each province for gas emissions, and solid waste emissions from the secondary forestry industry in each province for solid waste. Specific variables and descriptive statistics are shown as follows in Table 1.

3.2. FECO Impact Factor Analysis Method

3.2.1. DEA Two-Stage Method and Tobit Model

The DEA two-stage method is an advanced model derived to further explore the influencing factors and their degree of influence on efficiency values. In the first stage, the efficiency value of each DMU is calculated using the DEA method; in the second stage, the efficiency value calculated in the first stage is used as the dependent variable, and the factors influencing efficiency are used as the independent variables for regression analysis. The efficiency values measured by the DEA model are between 0 and 1, and the direct use of ordinary least squares (OLS) would cause bias and inconsistency problems. Therefore, the Tobit model is used in this paper and the maximum likelihood estimation method is applied for regression analysis [43].

Table 1. Results of input-output indicator selection and descriptive statistics.

Indicators	Category	Indicator Measure	Unit	Mean	Standard Deviation
Input Indicators	Forestry Labor Input	Number of employees in forestry system at the end of the year	people	125,626.98	143,349.54
	Forestry Capital Inputs	Forestry fixed asset investment	million yuan	67,432.332	74,093.23
	Forestry Livelihood Inputs	Forestry infrastructure investment	million yuan	19,225.982	21,923.442
	Forestry Ecological Inputs	Forestry ecological construction investment	million yuan	11,228.453	12,664.021
Output Indicators	Desired Output	Total output value of forestry industry by province	million yuan	48,958.332	51,027.816
	Non-desired Output	Forestry secondary industry wastewater emissions	million tons	44.985	29.384
		Forestry secondary industry solid waste emissions	million tons	499,683.331	987,350.119
		Forestry secondary industry waste gas emissions	million tons	998.672	884.013

The sample data used for the analysis are obtained from the China Forestry Statistical Yearbook and the provincial Statistical Yearbooks from 2008–2021.

The Tobit model is suitable for regressions where the dependent variable is restricted. The standard form of Tobit model is:

$$Y_i = \begin{cases} \beta_0 + \sum_{t=1}^{n} \beta_t x_t + \mu_t,\ if\ \beta_0 + \sum_{t=1}^{n} \beta_t x_t + \mu_t > 0 \\ 0,\ if\ \beta_0 + \sum_{t=1}^{n} \beta_t x_t + \mu_t \leq 0 \end{cases}, \tag{9}$$

where Y_i denotes the actual dependent variable, i.e., the efficiency value of the ith DMU; x_t denotes the independent variable; β_0 denotes the constant term; β_t denotes the regression coefficient of the independent variable; μ_t denotes the independent error disturbance term and obeys a normal distribution of $\mathrm{N}(0, \sigma^2)$.

3.2.2. Variable Selection and Data Sources

1. Explained variables

FECO. In this paper, the forestry eco-efficiency values of different regions in China will be selected as the explanatory variables, the statistical data of 30 provincial administrative regions in China will be selected as the support, and the values measured using super-efficiency DEA will be analyzed from the national sample and different regions, respectively.

2. Explanatory variables

Industrial structure (IS). With the total ban on commercial logging in state-owned forest areas, forest areas that once had tree harvesting and wood product processing as their main economic development model must adjust their industrial structure in order to steadily develop their economy while ensuring sustainable forest development. At present, different forestry bureaus in forest areas have different dominant industries, and therefore their main mode of operation is not the same. The primary forestry industry's main mode of operation is the above-mentioned planting and breeding of forest products; the secondary forestry industry's main mode of operation is the processing of wood products; and the tertiary forestry industry's main mode of operation is the vigorous development of forest tourism and the service industry in the process. In the process of development and operation of these industries, there is bound to be spatial spillover and spatial benefit of forestry economic development, therefore the industrial structure is also one of the influencing factors of FECO. To make this study dynamic, this paper uses the proportion of forest industry output value to total forestry output value to express [44].

Economic development (PGDP). This paper uses GDP per capita to reflect the sum of the value of products in a country or region in that year, which to a certain extent shows the degree of economic development of a region. Economic growth can promote scientific and technological progress, and a high level of economic development will lead to a higher demand for technology by the inhabitants of that place, which will lead to a higher eco-efficiency of local production through a demand-induced effect [45]. In economically developed areas, urbanization is bound to develop rapidly, which leads to the rapid development of the real estate and decoration markets, which provide good opportunities for the development of the forest products market. Meanwhile, people's demand for a good ecological environment is increasing. Urban gardening, greening, forest tourism, tourism forestry and other industries will develop rapidly. In summary, a good economic environment can promote forestry industry development as well as the optimization and upgrading of the forestry structure.

Foreign direct investment (FDI). Based on the analysis of FDI technology spillover channels, from the perspective of the competition effect, foreign enterprises usually enter China's forestry field by virtue of their capital, technology, scale and other advantages. On the one hand, they will introduce advanced technology, which is conducive to improving forest enterprises' ability to introduce, absorb and apply new technologies and promote technological progress; these can be understood as improvements brought by competition, which are positive spillover effects. On the other hand, forestry FDI generally does not choose to invest in greenfield sites, but is more involved in competition for existing forestry resources and markets, leading to a reduction in the market share of local enterprises, and coupled with China's preferential policies for foreign investors, it is easy to squeeze out domestic capital, thus inhibiting the improvement of TFP, which is a negative spillover effect. Whether the positive or negative effect is larger or smaller has not been determined, but to some extent, it can explain the negative effect of FDI on total factor productivity in Chinese forestry [46]. In this paper, the ratio of forestry FDI to total forestry output is used to measure FDI intensity.

Investment in scientific research (TI). Forestry is one of the most special industries in the national economic system, with very strong benefit spillovers. In addition to providing a large number of products and services for people's lives and social production, there are also generally sizable ecological benefits. In addition, forestry has an important role in ensuring the basic livelihood of forest farmers in forest areas and in rural revitalization. The most prominent feature of forestry is the long cycle, which determines a longer scientific research cycle, so the adequacy and stability of scientific research funding is particularly important [47]. In the paper, the ratio of research funding to GDP is chosen to represent the intensity of research funding.

Market-based environmental regulation (ER). Environmental regulation includes command-and-control and market-based. The former mainly includes setting environmental standards, pollutant emission standards and technical standards; the latter mainly includes establishing an emission charging or taxation system and an emission rights trading system [48]. In this paper, we use the proportion of the total emission fee levied by the forestry industry to the total regional forestry output value.

Due to the constraints of the eco-efficiency index calculation formula, the eco-efficiency values measured by the DEA method range between 0 and 2. In this case, if the traditional ordinary least squares (OLS) method is used to analyze the actual effect of each influencing factor on eco-efficiency, the results will be biased and inconsistent. In order to avoid the bias, the Tobit model was selected to analyze the factors influencing forestry eco-efficiency. Based on the above variable selection, the Tobit model was constructed as follows:

$$\mathrm{FECO}_{it} = c + \beta_1 IS_{it} + \beta_2 PGDP_{it} + \beta_3 FDI_{it} + \beta_4 TI_{it} + \beta_5 ER_{it} + \varepsilon_{it}, \quad (10)$$

where β is the elasticity coefficient of variables; FECO_{it} is the explanatory variable of FECO; IS_{it}, $PGDP_{it}$, FDI_{it}, TI_{it} and ER_{it} are the industrial structure, economic development, foreign direct investment, investment in scientific research and environmental regulation, respectively. The data are mainly obtained from the statistical yearbooks of each province.

4. Results

4.1. Results of Regional FECO Measurement in China

This paper is based on the input-output panel data from 2008 to 2021 (Tibet is not included in the analysis because of incomplete data), and the FECO of each province is measured based on EMS software. Considering the existence of regional heterogeneity, this paper divides the 30 provinces (regions and municipalities) into three major regions: east, central and west, with 11 provinces (municipalities) in the east, 8 provinces in the central and 11 provinces in the west. The measurement results are shown in Table 2.

Table 2. Results of forestry eco-efficiency by province in China from 2008 to 2021.

	Region	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**Mean**
Eastern	Beijing	0.546	0.557	0.588	0.589	0.593	0.603	0.611	0.614	0.628	0.637	0.655	0.672	0.679	0.699	0.619
	Tianjin	0.446	0.458	0.468	0.473	0.487	0.499	0.513	0.522	0.546	0.578	0.611	0.624	0.633	0.664	0.537
	Hebei	0.412	0.435	0.458	0.478	0.495	0.513	0.543	0.577	0.593	0.623	0.658	0.711	0.733	0.766	0.571
	Liaoning	0.233	0.245	0.257	0.267	0.278	0.288	0.291	0.294	0.301	0.311	0.323	0.326	0.335	0.345	0.292
	Shanghai	0.712	0.733	0.756	0.788	0.804	0.825	0.866	0.889	0.934	1.114	1.246	1.289	1.355	1.467	0.984
	Jiangsu	0.678	0.698	0.716	0.775	0.812	0.866	0.894	0.911	0.928	0.945	0.968	0.977	1.112	1.213	0.892
	Zhejiang	0.544	0.576	0.593	0.627	0.655	0.689	0.705	0.727	0.756	0.789	0.822	0.856	0.894	0.912	0.725
	Fujian	0.711	0.722	0.746	0.768	0.789	0.844	0.868	0.898	0.843	0.889	0.945	0.978	1.117	1.232	0.882
	Shandong	0.678	0.698	0.735	0.787	0.856	0.893	0.944	0.969	1.014	1.115	1.213	1.236	1.278	1.301	0.980
	Guangdong	0.588	0.598	0.611	0.624	0.645	0.698	0.723	0.759	0.798	0.834	0.876	0.912	0.944	0.976	0.756
	Hainan	0.445	0.457	0.466	0.483	0.496	0.523	0.546	0.569	0.597	0.611	0.635	0.657	0.689	0.788	0.569
Central	Shanxi	0.344	0.367	0.379	0.389	0.428	0.458	0.481	0.544	0.566	0.589	0.595	0.604	0.621	0.677	0.503
	Jilin	0.214	0.223	0.236	0.247	0.255	0.267	0.273	0.288	0.301	0.311	0.314	0.318	0.334	0.358	0.281
	Heilongjiang	0.211	0.215	0.226	0.236	0.245	0.266	0.274	0.279	0.286	0.293	0.301	0.311	0.315	0.325	0.270
	Anhui	0.364	0.375	0.398	0.423	0.447	0.459	0.476	0.498	0.533	0.576	0.589	0.627	0.655	0.725	0.510
	Jiangxi	0.675	0.688	0.698	0.734	0.779	0.823	0.839	0.856	0.873	0.895	0.988	1.118	1.128	1.216	0.879
	Henan	0.445	0.457	0.476	0.489	0.511	0.537	0.566	0.599	0.613	0.633	0.644	0.658	0.687	0.712	0.573
	Hubei	0.388	0.398	0.421	0.433	0.445	0.476	0.498	0.511	0.533	0.556	0.588	0.615	0.633	0.697	0.514
	Hunan	0.387	0.391	0.398	0.412	0.425	0.452	0.487	0.513	0.539	0.546	0.568	0.59	0.644	0.662	0.501
Western	Neimenggu	0.113	0.116	0.145	0.152	0.167	0.183	0.196	0.207	0.218	0.234	0.258	0.276	0.283	0.311	0.204
	Guangxi	0.168	0.178	0.199	0.216	0.236	0.256	0.289	0.318	0.334	0.357	0.387	0.399	0.416	0.498	0.304
	Chongqing	0.435	0.447	0.457	0.487	0.498	0.512	0.523	0.535	0.546	0.567	0.572	0.583	0.591	0.657	0.529
	Sichuan	0.301	0.311	0.319	0.326	0.334	0.347	0.358	0.366	0.378	0.399	0.411	0.417	0.424	0.446	0.367
	Guizhou	0.244	0.259	0.266	0.279	0.299	0.311	0.326	0.338	0.348	0.362	0.379	0.398	0.411	0.423	0.332
	Yunnan	0.211	0.223	0.236	0.247	0.268	0.287	0.295	0.311	0.325	0.346	0.357	0.377	0.398	0.443	0.309
	Shanxi	0.339	0.347	0.354	0.367	0.377	0.379	0.382	0.393	0.402	0.411	0.422	0.431	0.438	0.447	0.392
	Gansu	0.099	0.102	0.116	0.136	0.142	0.148	0.152	0.166	0.173	0.179	0.188	0.193	0.225	0.258	0.163
	Qinghai	0.111	0.114	0.121	0.125	0.132	0.137	0.144	0.165	0.179	0.189	0.193	0.216	0.226	0.268	0.166
	Ningxia	0.278	0.299	0.311	0.314	0.325	0.329	0.334	0.356	0.366	0.371	0.374	0.388	0.389	0.394	0.345
	Xinjiang	0.087	0.094	0.104	0.113	0.124	0.135	0.147	0.159	0.172	0.188	0.197	0.214	0.223	0.257	0.158
National mean		0.380	0.393	0.408	0.426	0.445	0.467	0.485	0.504	0.521	0.548	0.576	0.599	0.627	0.671	0.504

From the above table, it can be seen that from 2008–2021, the integrated efficiency of Shandong and Shanghai exceeds or approaches 1.0, and the integrated efficiency of Jiangsu, Jiangxi and Fujian approaches 0.9. Shandong, Shanghai and Jiangsu show an upward trend, indicating that the above regions have been effective in adjusting the balance between forestry production output and environmental pollution. The comprehensive efficiency of provinces such as Inner Mongolia, Heilongjiang, Jilin and Liaoning is below 0.3. Although the forestry resource stock and forestry output values of these provinces are high, the input consumption in forestry production is too large, which makes their comprehensive efficiency hover at a low level. The low ecological overall efficiency of forestry in Beijing and Tianjin is due to the innate condition of their limited forestry resource stocks. The comprehensive ecological efficiency of forestry in western provinces such as Xinjiang, Gansu and Qinghai is less than 0.2. These regions are constrained by topography, resources and other factors that do not release the scale benefit; the desertification of land is serious, which affects forestry production and leads to low comprehensive efficiency.

The average FECO values of the three major economic regions in the country in the 14-year period are, in descending order, the eastern, central and western regions. The mean value FECO in the eastern region is significantly higher than the national average and the rest of the provinces and cities, except Hebei, have relatively high efficiency. Hebei province is a special case and in the preferred position to undertake the transfer of high pollution industries from Beijing and Tianjin, resulting in its low FECO. Beijing, because of its special location and position as a political and economic center, has a low level of FECO due to its inherent condition of limited forestry resource stock; generally speaking, the forestry input and output of the eastern provinces and cities are more reasonable. The FECO in the central region is basically above 0.5, except for Jilin and Heilongjiang. Shanxi Province, with a forest cover of 20.5% in 2016, has relatively few forestry resources and mainly focuses on coal energy production, and pays less attention to the development and utilization of forestry resources, resulting in a backward production technology level; this leads to a low FECO. Hunan Province, with abundant forestry resources, has a low FECO level in the early stage due to the model of exchanging resources for economic development, and then in the process of undertaking industrial transformation, actively adjusts the strategic structure for industry. In the process of undertaking industrial transformation, Hunan Province actively adjusted its strategic structure for industrial upgrading and transformation, and FECO reached above 0.5 after 2015. The overall FECO value in the western region is low, but Chongqing's FECO is much higher than other western regions due to its special geographical location and economic level in the west.

4.2. Analysis of Factors Influencing FECO

4.2.1. Multicollinearity Test

Before establishing the model, it is necessary to judge whether there is multicollinearity among variables. If there is multicollinearity, the partial least squares model is the best choice, hence it is necessary to conduct the diagnosis of covariance. The higher the variance inflation factor is, the more serious the multicollinearity is, and there is a positive correlation between them. Usually, the largest variance inflation factor among all independent variables is used as an indicator of multicollinearity. If the value is greater than 10, it means that the corresponding independent variables are approximately linearly combined with other variables in the linear regression analysis. This will affect the least squares estimation and the accuracy and reliability of the linear regression analysis cannot be guaranteed, i.e., the multicollinearity is serious and not suitable for linear regression analysis. Based on this, SPSS was used to verify the results, and the results can be seen in Table 3.

Table 3. Results of multicollinearity test.

Method	IS	PGDP	ER	TI	FDI
VIF	3.44	4.56	1.47	3.55	2.47
1/VIF	0.291	0.219	0.680	0.282	0.405

Analyzing the multicollinearity among the influencing factors of FECO, the variance inflation factor among the independent variables has a maximum of 4.56, thus it can be determined that there is no significant correlation among the respective variables; hence, there is no multicollinearity problem. If the problem is serious, the least squares model cannot be chosen, and the construction of the Tobit model is a better choice.

4.2.2. Unit Root Test

Panel data may have variable data that are not smooth, thus affecting the authenticity and credibility of the final estimation results and creating the problem of pseudo-regression. In order to obtain more robust regression results, the unit root test is conducted on the panel data before parameter estimation. The more commonly used testing methods are the Im-Pesaran-Shin (IPS) test, the Augmented Dickey-Fuller (ADF) test and the Levin-Lin-Chu (LLC) test, whose original hypothesis is the existence of a unit root. To avoid the problem of inaccurate test results brought by a single test method, this paper integrates the above three test methods to verify whether there is a unit root in the panel data. If the above three methods are passed, this indicates that there is no unit root in the sample data. The results are shown in Table 4.

Table 4. Unit root test results.

Variables	LLC Test	IPS Test	ADF Test	Unit Root
IS	−94.1390 ***	0.9986	11.4808 ***	exist
PGDP	−4.2216 ***	3.1436	2.7853 ***	exist
ER	−5.4437 ***	−1.2346	5.7784 ***	exist
TI	18.2231	8.5521	−0.7622	exist
FDI	6.3242	9.0053	0.9843	exist
D.IS	−66.1453 ***	−2.3348 ***	9.0622 ***	not exist
D.PGDP	−33.4571 ***	−4.6782 ***	7.7768 ***	not exist
D.ER	−39.8953 ***	−5.12398 ***	7.0954 ***	not exist
D.TI	−9.6473 ***	−4.3346 ***	3.5562 ****	not exist
D.FDI	3.3456 ***	3.4516 ***	1.5674 ***	not exist

Note: ***, **** means $p < 0.05$ and $p < 0.01$, respectively.

As can be seen from Table 4, all variables fail to reject the original hypothesis, indicating the existence of a unit root for each variable, while the first-order difference terms of each variable can reject the original hypothesis at the 1% significance level. This indicates that there is no unit root in the first-order difference series of each variable, which in turn indicates that the panel data are first-order single integer and can be subjected to the next step of regression analysis.

4.2.3. Model Selection Test

There are two methods for model regression, i.e., the fixed-effects model and the random-effects model; Hausman's test is required to determine the choice of model. The original hypothesis model was selected as the random effects model, and the Hausman test results (in Table 5) were obtained through Eview 6.0.

Table 5. Hausman test results.

Test Summary	Chi-Sq.Statistic	Chi-Sq.d.f	Prob.
Cross-section random	77.1389	6	0.0000

From the analysis results, the p value is 0, so the original hypothesis is rejected, i.e., the original random effects model hypothesis is rejected, and the fixed effects model is adopted

4.2.4. Model Regression Results

According to the regression model and test method, the regressions were conducted in China as a whole, and the east, central and west to explore the effects of the same influencing factors on different regions; this is because regions face various differences in their development environment, their geography and their development level which are heterogeneous. The results can be seen in Table 6.

Table 6. Regression results.

Explanatory Variables	National	East	Centra	West
IS	−0.1499 **	−0.1543 ***	−0.0998 ***	−0.1987
PGDP	0.2102	0.1125 ***	0.0761	0.1024
ER	0.0495 **	0.1203 ***	0.0833 *	−0.0293 ***
TI	−0.0428 ***	0.0908 ***	−0.0765	−0.1239
FDI	−0.0765 ***	0.0345 ***	−0.1235 ***	−0.1897 ***

Note: *, **, *** means $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

The regression coefficients of market-based environmental regulation are significantly positive in the country, in the eastern and central regions and significantly negative in the west. Due to the significant differences in the marketization process between regions, some developed provinces in the east and central regions, most of which have entered the post-industrialization period, have more sound market mechanisms and a higher degree of marketization; they rely mainly on market incentives to solve environmental problems. The western region has relatively low environmental costs, and in order to promote regional economic development, it takes over some of the low-end forestry industries transferred from home and abroad. Some forestry enterprises take the payment of sewage charges as an excuse to continue polluting, and the expenditure on pollution control follows the marginal decreasing cost: the sewage charges paid are far from enough to cover the costs of environmental treatment and ecological restoration.

As a whole, investment in scientific research will promote FECO, but from the empirical perspective, the current impact coefficient of research funding input intensity on the eco-efficiency of the forestry industry in China is negative and the correlation is significant. This indicates that current investment in scientific research in China fails to meet the needs of the forestry industry to improve eco-efficiency. To a certain extent this hinders the development of forestry eco-safety, as well as the subsequent need to further improve the technological content and technological level of the forestry industry to make the development of modern forestry go in the direction of the circular economy and eco-efficiency improvement. The intensity of scientific research investment in the eastern region shows a significant promotion effect, which indicates that forestry industry development in the eastern region tends to be intensive; the eastern economy is developed, and sufficient investment in scientific research can meet the needs of regional forestry development, thus showing a promotion effect. Forestry industry development in the central and western regions is still based on the scale of rough growth, rather than high-tech orientation, which in the long run is important for forestry industry development and the improvement of FECO. However, the elasticity coefficient of central and western China is negative but not significant, indicating that the negative impact is not significant.

Economic development has a positive but insignificant effect on FECO. Forestry plantations and the forest industry itself are a more complete industrial chain. The higher the level of economic development, the more likely it is to make use of industrial policies, extend the industrial chain, acquire advanced resources such as technology and increase productivity. Forestry cannot be separated from forests, which have long regeneration cycles and extremely uneven distribution, and are also constrained by specific factors such as land. The higher the level of economic development, the stronger the demand for the multifunctional use of forests, i.e., the more wood, carbon sink and tourism use. The more prominent the multifunctional problems are, the more obvious the problem of wood resource supply constraints faced by forestry development. Therefore, even though the degree of economic development is high, it is difficult to obtain an effective allocation of capital and technology in the case of shortage of timber resources, which in turn restricts the improvement of total factor productivity. However, there are large differences among regions: the eastern region shows a positive correlation, indicating that the eastern region is more mature in the allocation of resources and technology and is qualitatively better than the central and western regions; hence, in the east it is significant to enhance eco-efficiency, while it is not significant in the central and western regions.

The industrial structure inhibits FECO. This means that the FECO of the regions with a high proportion of secondary forestry industry in China is relatively low at present, i.e., the ecological and environmental costs of increased output value in the forestry industry are large. Specifically, the negative effect of the eastern region is more significant, which may be due to the fact that the paper industry, as the main component of the forest industry, is mostly concentrated in the eastern region. The central region is the main concentration of China's wood processing industry, probably because it is a lightly polluting industry, so the impact of the industrial structure is less than in the east; the impact of industrial structure on FECO in the western region is not significant. However, with further optimization of the three industrial structures, it is expected that FECO will be gradually improved in the future as the proportion of tertiary industries in forestry increases.

The impact of external openness on regional FECOs varies greatly among regions. The elasticity coefficients of foreign direct investment in the eastern, central and western regions were 0.0345, -0.1235 and -0.1897, respectively, and all regions passed the significance level test except for the central region, which did not pass the significance test. It can be seen that the environmental access threshold of the forestry industry in the eastern region is higher than other regions, and the quality requirements of foreign businessmen are higher, thus reflecting a positive effect. Foreign enterprises have a "pollution transfer effect" on the forestry industry in the central and western regions, i.e., the pollution-intensive forestry industry undertaken by these regions aggravates the regional environmental pollution problem. However, the negative correlation at the national level indicates that foreign direct investment is still dominated by the pollution transfer effect, but it does not pass the significance test, indicating that this negative effect is tending to be insignificant, and that FECO can be improved by improving the quality of foreign investment introduced.

4.3. Discussion

This paper adopts the super-efficient DEA model to measure the forestry eco-efficiency of 30 Chinese provinces and cities (except Hong Kong, Macao, Taiwan and Tibet) for 14 years from 2008 to 2021, and then introduces the Tobit model to analyze the influencing factors of forestry eco-efficiency in order to better understand the sustainable development level of forestry. Existing studies mainly focus on studying forestry production efficiency. For example, Xu et al. [49], Wei [50] and Tan et al. [51] all measured the regional forestry production efficiency in China based on the Malmquist-DEA model without considering the impact of forestry industry development on the environment, thus this paper incorporates environmental factors to study forestry eco-efficiency; this is complementary to existing studies. Different regions showed significant heterogeneity with large regional differences in this study, which is consistent with the conclusions reached by most scholars. For example, Zheng and Yin [20] concluded that the eastern region has significantly higher eco-efficiency values than other regions and has been at a high efficiency level of about 0.9, while the western and central regions have slowly increased eco-efficiency values to approximately the 0.6 level. Wu and Zhang [52] also found the same trend for forestry eco-efficiency.

However, there are some scholars who came to different conclusions. Chen et al. [18] and Hong et al. [19] concluded that the western region is higher than the central region, and the opposite conclusion exists with this paper. This is probably because the above scholars used the traditional DEA model in evaluating eco-efficiency and came to the result that the maximum is one, and the ones greater than the data are all one. This paper uses the super-efficient DEA model to break through the efficiency boundary of one and can be greater than one, which more accurately reflects the actual value of the results and provides a more accurate depiction of the problem. Meanwhile, this paper uses the Tobit model to verify the influence of some economic variables on forestry eco-efficiency; it analyzes the influence on forestry eco-efficiency from environmental regulation, marketization, research funding, industrial structure and openness to the outside world, respectively, which are more variables than previous scholars had considered. The data used are also up-to-date, which can more accurately illustrate the influence relationship between variables. However, compared with other scholars, the research in this paper is dominated by linear relationship research, and does not explore the nonlinear relationship between variables; for example, Jiang et al. [53] verified the study of the threshold effect of environmental regulation on forestry eco-efficiency, which is the direction of future research for this paper, i.e., exploring nonlinear relationships between variables.

5. Conclusions and Implications

5.1. Conclusions

In this study, the super-efficient DEA model is used to measure the FECO of 30 provinces from 2008 to 2021, and then the Tobit model is introduced to explore the influencing factors of FECO. The conclusions are as follows.

1. The average value of FECO in the three major economic regions of the country over 14 years is 0.5586, which is still at a low level; this may be related to the rough development model of Chinese forestry. There is still more room for improvement when compared with developed countries. The FECO of each region has significant regional heterogeneity, and the provinces with higher FECO are mainly concentrated in the eastern region, while the FECO in the central and western regions is lower. However, FECO in the central region is higher than that in the western region.
2. From the viewpoint of the main factors affecting FECO in China, the regression coefficients of market-based environmental regulations are significantly positive in the national, eastern and central regions, while they are significantly negative in the western region mainly because the environmental costs in the western region are relatively low. There is no environmental regulation system in place in order to promote regional economic development and undertake the transfer of some low-end forestry industries at home and abroad; the intensity of environmental regulations is low, which means that the ecological efficiency of forestry in this type of regions has a negative impact. The impact coefficient of scientific research funding investment on forestry industry eco-efficiency is negative and shows a significant promotion effect in the eastern region; the elasticity coefficient in the central and western regions is negative but not significant, indicating that the negative impact is not significant. The level of economic development has a positive but insignificant effect on the eco-efficiency of China's forestry industry. However, it varies significantly across regions, with the eastern region showing a positive correlation, while the central and western regions are not significant. Industrial structure has a significant negative effect on forestry industry eco-efficiency in the national, eastern and central regions, but the effect of industrial structure on FECO in the western region is not significant. Foreign direct investment has a negative effect on FECO in the national, central and western regions, but the central region does not pass the significance test because the environmental access threshold of the forestry industry in the eastern region is higher than other regions, and the quality requirements of foreign investors are higher, thus reflecting a positive effect.

5.2. Recommendations

Rational utilization of foreign investment means taking advantage of forest areas. The use of foreign capital in forestry significantly affects regional ecological efficiency, and foreign capital is a major thrust for forestry industry development in terms of capital. The reasonable and effective use of foreign capital is conducive to improving regional forestry ecological efficiency. To this end, we should continue to develop the advantages of regional and forest resources and make reasonable use of foreign capital. Specific suggestions are as follows: (1) Broaden the channels of attracting foreign capital and diversify the sources of foreign capital; (2) Rationalize the use and distribution of foreign capital and optimize the utilization structure of foreign capital; (3) Create and establish local forestry characteristic brands, study and learn from foreign advanced forestry experience, and strengthen international exchange and cooperation in forestry; (4) Develop and implement realistic industrial environmental protection standards and guide enterprises in technological innovation; (5) Increase the research, development and application of industrial environmental protection technologies; (6) Promote advanced and mature production technologies to improve resource utilization efficiency.

Local governments should focus on the construction and improvement of environmental protection infrastructure and increase investment in the development of environmental protection technologies; in addition, they should strengthen environmental supervision and regulate the awareness and behavior of forestry enterprises in environmental protection with legal systems to promote FECO. At the same time, the ecological audit system should be implemented in the internal management process of forestry enterprises to incorporate ecological and environmental management into the daily production process of enterprises and to realize the supervision and evaluation of forestry production processes. A reduction in production costs and environmental pollution, and ultimately the enhancement of the comprehensive competitiveness of forest products in domestic and international markets, can be achieved through continuous technological innovation and management innovation of enterprises to improve the quality and grade of forest products.

There must be rational use of forestry resources and a change of forestry production methods. Whether between regions or provinces, the quantity of forestry resources invested, and the level of eco-efficiency are not absolutely the same. The average value of FECO is east > central > west. The rational use of resources and appropriate transformation of forestry production methods to enhance FECO are beneficial. Sending also fully illustrates the importance of rational use of resources and development of forestry according to local conditions. The economically-developed eastern major forestry provinces such as the provinces of Laoning and Fujian can vigorously develop the local forestry economy. The central provinces such as Jiangxi and Anhui, which are rich in forestry resources and have a low level of economic development, can make full use of their abundant forestry resources to vigorously develop low-carbon industries such as ecological forestry. The provinces and cities with scattered and low-scale forestry production methods in each region should change their active forestry development methods. Only in this way can the FECO be improved and forestry be placed on the road of sustainable development.

Each region should design differentiated environmental regulation tools for the forestry industry according to its ecological carrying capacity and the current situation of the FECO. With the aim of improving the FECO, targeted regulatory objectives and policy measures should be formulated according to the actual situation of the region. For most of the central and western regions with low FECO and backward development levels, more attention should be paid to the strength and manner of environmental regulation in future development, especially to prevent the ecological destruction and environmental damage caused by the westward migration of polluting industries from the developed eastern regions. The developed eastern regions with strong economic, financial and technological strength can consider further increasing the intensity of environmental regulations to stimulate enterprises to strengthen the research, development and application of new technologies in the field of ecology and environment. When formulating environmental regulation policies and measures, all regions should consider including the requirement to improve the eco-efficiency of forestry in their environmental policies.

There are several guidelines for reducing the "pollution paradise" effect. The "pollution paradise" effect has caused affected forestry enterprises in provinces and municipalities that have reformed their sewage charges to move their production lines to provinces and municipalities that have not reformed their sewage charges and to "export" their pollution to other provinces. This makes the effectiveness of the policy implementation greatly reduced and further places the pollution pressure on the forestry industry in the provinces that have not been reformed. Therefore, in order to reduce the "pollution paradise" effect, the relevant departments should introduce relevant policies to guide the expectations of local governments, so that the provinces that have not reformed the sewage levy standards will not give unconditional acceptance to high-pollution high-emission industries in economic development considerations. This will also enable the levy standard to be improved comprehensively, and the decline of eco-efficiency will be mitigated to a certain extent as the transfer of high-pollution and high-emission industries receives restrictions. On the other hand, the relevant departments should also guide the expectations of enterprises in the provinces where the reform is carried out so that they will not take any chances and transfer high-pollution and high-emission enterprises out of the country recklessly; this would make the implementation of the reform of the emission levy standard achieve the reduction in relevant pollutant emissions in the provinces where it is carried out.

5.3. Limitations and Prospects

1. There is no uniform definition in existing research for forestry eco-efficiency; hence, this paper provides a definition based on previous scholarly research and the actual situation of China's forestry development. This may be subjective and needs to be improved in the future;
2. The study of forestry eco-efficiency is relatively new and the literature of related studies is relatively small; thus, in terms of the selection of influencing variables, they can only be selected exploratively in combination with previous scholars' studies. Verifying the influence of more variables on forestry eco-efficiency in future studies is worthwhile;
3. Economic variables have spatial correlation, for example, forestry eco-efficiency improvement in this region may have an impact on forestry eco-efficiency in neighboring regions, but this paper does not consider spatial effects which may lead to bias in the research results; thus; the spatial effects of variables can be further explored in future studies.

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