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Efficiency Calculation and Evaluation of Environmental Governance Using the Theory of Production, Life, and Ecology Based on Panel Data from 27 Provinces in China from 2003 to 2020

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Abstract: Promoting green development and promoting harmonious coexistence between humans and nature are strategic tasks for the construction of ecological civilization in China in the new era. Currently, the growing environmental governance investment in China has not performed well, and the low efficiency of environmental governance has become the main problem facing the development of ecological civilization in China. Therefore, it is of great practical significance to scientifically measure the efficiency of environmental governance and improve the efficiency of environmental governance input factors to achieve green development and overcome the difficulties in the construction of ecological civilization. In this study, an improved three-stage SBM model and cloud model combined with the Theory of production, life, and ecology were used to measure the environmental governance efficiency of 27 provinces in China from 2003 to 2020 and conduct in-depth analysis and evaluation. The results show that: First, the influence of random error factors and external environmental conditions on the efficiency of rural domestic sewage treatment in China is significant. Their existence will underestimate the environmental governance efficiency in the central and western regions of China and overestimate the environmental governance efficiency in the eastern regions of China, except for Hainan Province. Second, after excluding the influence of random errors and external environment conditions, the adjusted efficiency mean value of the central and western regions significantly increases, while the environmental governance efficiency of most provinces in the eastern region, except for Hainan Province, decreases significantly. Third, the overall environmental governance efficiency of the 27 provinces in China still presents a situation wherein the western region is ranked first in efficiency, the eastern region ranks second, and the central region ranks third. The environmental governance efficiency of the 27 provinces shows a “large at both ends, small in the middle” and “low efficiency in the eastern and central regions, and instability in the western region” state, and there is a large difference in the degree of environmental governance efficiency among the various provinces. In this regard, for the eastern and central regions, special attention should be paid to their government’s transformation of development thinking, placing greater emphasis on balanced and coordinated development between urbanization, industrialization, and the environment. As for the western region, due to its harsh environmental conditions, it attaches more importance to environmental governance. However, efforts should be made to strengthen its economic development to ensure sufficient provision of material conditions such as infrastructure and equipment required for environmental governance in order to achieve stable environmental governance efficiency in the western region. For the central region, both the economy and the environment need to be further strengthened.

Keywords: theory of production; life and ecology; environmental management efficiency; three-stage SBM model; cloud model

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1. Introduction

The report of the 20th National Congress of the Communist Party of China has elevated "modernization featuring harmonious coexistence between humans and nature" to one of the connotations of "Chinese-style modernization", reaffirming the strategic task of ecological civilization construction in the new era, with the overall objective of promoting green development and facilitating harmonious coexistence between humans and nature. In promoting "green development and facilitating harmonious coexistence between humans and nature", it is also necessary to focus on the improvement of urban and rural living environments. According to official data, the total investment in environmental pollution control in China in 2020 was RMB 1.06389 trillion, accounting for 1.0% of the country's Gross Domestic Product (GDP), an increase of RMB 148.7 billion compared to 2019. However, the annually increasing investment in environmental governance has not achieved satisfactory results [1]. For example, in Fujian Province, large amounts of human, material, and financial resources have been invested in pig farming, but the results have been unsatisfactory, leading to conflicts and contradictions between economic development and environmental governance [2]. Similar cases are not uncommon in China [3,4]. In recent years, although governments at all levels have attached great importance to environmental pollution control and the improvement of the ecological environment and have successively issued numerous environmental protection policies, and although great achievements have been made in ecological environment construction, the trend of ecological environment deterioration has not fundamentally improved and the environmental situation remains unsatisfactory [5–9]. Therefore, how to improve the efficiency of environmental governance has become the main problem facing China's ecological civilization construction. It is urgent to improve the efficiency of the use of investment elements in environmental governance. Therefore, it is necessary to conduct effective environmental efficiency measurements of various provinces to analyze the overall situation, trends, and differences of environmental governance efficiency in various provinces and regions, and to scientifically and effectively evaluate the efficiency of environmental governance. This is a prerequisite for improving environmental governance policies and conducting in-depth research on the prospects of environmental governance in various provinces. Therefore, it is necessary to re-calculate the efficiency of environmental governance scientifically, to analyze in-depth the reasons for "high input and low output" in environmental governance in China, and to develop significant practical measures that can be taken to improve the efficiency of environmental governance and improve environmental governance policies, under the constraints of energy conservation and emission reduction, by more accurately measuring the real level, trend, and differences of inter-provincial environmental efficiency in China and finding the space that can contribute to improving environmental governance policies. This research uses 27 provinces in China as research objects, using panel data from 2003 to 2020. The study aims to re-evaluate and assess the environmental governance efficiency of each province in China, given that the environment is still deteriorating or improving very slowly despite the trend of increasing overall environmental investment. This is to ensure that provincial governments pay more attention to improving environmental governance efficiency, so that increasing environmental investment can yield higher returns each year.

According to existing research, the current research categories for environmental governance efficiency mainly include comprehensive environmental pollution control efficiency, water pollution control efficiency, industrial pollution control efficiency, and atmospheric pollution control efficiency [10–16]. In order to analyze the reasons for the low environmental governance efficiency, scholars at home and abroad have conducted analysis and research, mainly focusing on the measurement of environmental governance efficiency and the analysis of influencing factors.

In terms of research on the measurement of environmental governance efficiency, it can be divided into three aspects of literature reviews and introductions. The first aspect is the measurement methods used for measuring environmental governance efficiency. A large amount of research commonly uses efficiency measurement models such as DEA, three-stage DEA, improved three-stage DEA, and SBM for measurement. For studies using the DEA model, they only explore the input and output variables of environmental governance efficiency, and the efficiency evaluation idea is that inputs should be reduced as much as possible, while outputs should be expanded as much as possible [17]. However, this is not always the case in practical applications, and there may often be some negative output effects, also known as "undesirable outputs". Undesirable outputs must be as small as possible to achieve maximum efficiency [18]. Compared to the DEA model, the SBM model takes into account the existence of "undesirable outputs", which can be more objective and accurate in measuring environmental governance efficiency. The three-stage DEA model is a further development of the DEA model, which further considers the influence of environmental variables. It uses the redundancy of input variables calculated in the first stage as the dependent variable and the environmental variables for stochastic frontier regression analysis (SFA) and adjusts the random errors obtained from the regression analysis for input variables before conducting the third-stage DEA analysis. The improved three-stage DEA model replaces the first- and third-stage DEA models with the SBM model. The second aspect is the selection of measurement indicators used for measuring environmental governance efficiency. In terms of the selection of input variables, previous studies mainly select from the levels of human resources, financial resources, material resources, and technological resources. Common input variables include government environmental protection investment, environmental management practitioners, the number of waste gas treatment facilities, and the technological level of environmental governance. In terms of the selection of output variables, previous studies mainly include expected outputs and undesirable outputs. Common expected output variables include comprehensive utilization rate of solid waste, green coverage rate, air quality, and the popularity rate of sanitary toilets. Common undesirable output variables include emissions of sulfur dioxide, wastewater discharge, and smoke (dust) emissions. In terms of the selection of external environmental variables, common external environmental variables include GDP, fiscal pressure, population density, the urbanization rate, and the marketization rate [3,5,19–27]. The third aspect is the interpretation of the efficiency results of environmental governance measurements. Currently, the results obtained from different indicators and methods often vary greatly in research. There are inherent differences in the environment among different provinces in China, and it is inaccurate to measure all provinces using the same standard. Secondly, existing research shows that environmental governance efficiency in various provinces of China is generally not optimistic [27]. Therefore, it is necessary to use theories and indicators scientifically and objectively to measure the environmental governance efficiency of each province in China.

Existing studies on environmental governance efficiency provide a basis for the selection of models and indicators for this research. However, the review of existing literature shows that, first, the selection of indicators in previous studies has common and individual characteristics and the number of indicators used for measuring efficiency is too small, typically consisting of only 3–4 input-output variables and external environmental variables, which cannot provide an objective and accurate measurement of environmental governance efficiency in different regions. Second, the selection of methods mainly relies on traditional DEA and SBM models, with very few studies using the three-stage DEA model or improved three-stage DEA model. Traditional DEA and SBM models are strongly affected by random errors and environmental factors and their adjustments to input and output variables can only be done proportionally, which cannot ensure the objectivity of the efficiency evaluation results. Third, using the same set of indicators to evaluate the environmental governance efficiency of different regions raises questions about its validity. Studies have shown that the construction of different models and indicator systems leads to significant differences in the measured environmental governance efficiency. Therefore, it is important to identify natural resource conditions and environmental pollution problems in different provinces and regions and to classify them for the measurement of environmental governance efficiency [28]. Finally, the current studies on environmental governance efficiency lack theoretical support and the construction of indicator systems is often based on reference to existing studies or on local environmental governance practice experience and governance characteristics. The lack of theoretical models may result in incomplete construction of the indicator system, and the measured environmental governance efficiency may not accurately and objectively reflect the actual environmental governance efficiency issues. The 20th report of China states that "humanity and nature are a community of life, and endless demands or even destruction of nature will inevitably result in retaliation from nature. We adhere to the policy of sustainable development, prioritize conservation, protection, and natural restoration. We must protect nature and the ecological environment like we protect our own eyes, and steadfastly follow the path of civilized development that integrates production, affluent life, and a sound ecology, in order to achieve the sustainable development of the Chinese nation". Harmony and coexistence between humanity and nature means that we should pursue coordinated development in production, life, and ecology. This is both an internal requirement of ecological civilization construction and an inevitable choice for high-quality development. Therefore, adopting the "production, life, ecology" concept to construct an efficiency index system for environmental governance is in line with the current development theme of China, and such a concept can help objectively and accurately measure the environmental governance efficiency of each province.

In summary, based on the literature review and problem analysis in the previous sections, the main marginal contributions of this study are as follows: (1) Currently, the major sources of environmental pollution in China are domestic waste pollution, industrial production pollution, and ecological environment destruction. To address this issue, this study constructs input-output indicators in three dimensions of production, life, and ecology using the Theory of production, life, and ecology [28]. Compared with existing input-output indicators, this approach supplements and improves the theory and richness of the indicators, with certain theoretical significance. (2) Considering that environmental problems vary across different regions, this study uses an improved three-stage SBM model. The first stage estimates the environmental governance efficiency of each province and city. The second stage uses the SFA model to exclude the influence of external environmental factors, eliminate interference from environmental factors and random errors, re-estimate the input variable values, and analyze the impact of external environmental factors and random errors on the input variables. The third stage re-estimates the environmental governance efficiency of each province and city using the SBM model and compares it with the first-stage SBM model to more accurately measure the environmental governance efficiency of each province and city. Finally, using cloud model analysis, this study conducts an in-depth analysis of the environmental governance efficiency of each province and city. The combination of the three-stage SBM model and the cloud model is a bold attempt, which breaks the traditional approach of using simple linear graphs to analyze the trend of environmental governance efficiency and replaces it with the cloud model for analysis. This provides a better evaluation of the overall environmental governance efficiency and a more in-depth analysis of the development prospects of environmental governance efficiency in each province and city. Thus, the results of this analysis are more comprehensive. (3) This study uses panel data from 27 provinces obtained between 2003 and 2020, making the research results more reliable and practical. The findings can better provide suggestions and strategies for improving China's environmental governance efficiency.

2. Environmental Management Efficiency Measurement

2.1. Research Methodology

2.1.1. First Stage Super-Efficient SBM Model

In the first stage, an input-oriented super-efficient SBM model with constant payoffs of scale is used to avoid the neglect of slack variables in traditional DEA models and the bias and influence brought by radial direction [29] (Tone, 2001), and the efficiency of rural domestic wastewater treatment is calculated for each decision unit, as shown in Equation (1):

$$\begin{gathered}\min\rho=\frac{1-\frac{1}{m}\sum_{i=1}^{m}s_i^-/x_{i0}}{1+\frac{1}{s}\sum_{j=1}^{s}s_j^+/y_{j0}}\\ s.t.\quad x_0=X\lambda+s^-\\ y_0=Y\lambda-s^+\\ \lambda\geq 0,\quad s^-\geq 0,\ s^+\geq 0,\end{gathered}\tag{1}$$

where ρ is the efficiency value; m and s denote the number of categories of input and output indicators, respectively; s^- and s^+ are slack variables, representing input and output redundancy, respectively; x_0 and y_0 are the input and output vectors of the decision unit, respectively; x_{i0} and y_{j0} are the vectors x_0 and y_0 in the i and j elements; X and Y are the input and output matrices composed of all decision units, respectively; and λ is the weight vector.

When the relaxation variables $s^-=0$ and $s^+=0$, i.e., when there is no input and output redundancy, the $DMU(x_{0,}\ y_0)$ is valid, i.e., $\rho^*=1$. To differentiate between efficient decision units, Tone [30] proposed an input-oriented super-efficient SBM model based on the input-oriented SBM model, as shown in Equation (2):

$$\begin{gathered}\delta_I^*=\min\delta=\frac{1}{m}\sum_{i=1}^{m}\overline{x_i}/x_{i0}\\ s.t.\quad \overline{x}\geq\sum_{j=1,\neq 0}^{n}\lambda_j x_j\\ \overline{y}\leq\sum_{j=1,\neq 0}^{n}\lambda_j y_j\\ \overline{x}\geq x_0,\ \overline{y}=y_0,\ \lambda\geq 0\end{gathered}\tag{2}$$

Among them, $\overline{x}$ and $\overline{y}$ are new production possibilities that do not contain $(x_0,\ y_0)$, a new subset of production possibilities for

$$P\backslash(x_0,\ y_0)=\left\{(\overline{x},\overline{y})\middle|\overline{x}\geq\sum_{j=1,\neq 0}^{n}\lambda_j x_j, 0\leq\overline{y}\leq\sum_{j=1,\neq 0}^{n}\lambda_j x_j,\ \lambda\leq 0\right\}$$

The input vector and output vector in δ^* are the efficiency values of the super-efficient SBM model, and the remaining parameters have the same meaning as in Equation (1).

2.1.2. Second-Stage Stochastic Frontier Regression Analysis Model

Since the decision unit is affected by environmental factors, management factors, and random errors, Fried et al. [31] proposed a three-stage DEA model that uses the SFA model to remove the interference caused by environmental factors and random errors. The SFA regression function is as follows:

$$S_{ni}=f(Z_i;\beta_n)+v_{ni}+\mu_{ni}(i=1,\ 2,\ \ldots,\ I;\ n=1,\ 2,\ \ldots,\ N),\tag{3}$$

where S_{ni} denotes the first i decision unit of the first n redundancy of an input; Zi denotes the environmental variable; βn denotes the coefficient to be estimated; $\varepsilon_{ni}=v_{ni}+\mu_{ni}$ denotes the mixed error term; and v_{ni} denotes the random error term while μ_{ni} denotes the management inefficiency term, and both of which are independent and are usually assumed to obey the normal distribution, i.e., $v\sim N\left(0,\sigma_v^2\right)$ assumes μ obeys the truncated normal distribution, i.e., $\mu\sim N^+\left(0,\sigma_\mu^2\right)$. In order to adjust all decision units to the same external environment, the management inefficiency term is separated according to the regression results μ_{ni}, then the random error $v_{ni} = \varepsilon_{ni} - \mu_{ni}$, thus adjusting the data for the input variables with the following equation:

$$X_{ni}^{*} = X_{ni} + \left\{max\left[f\left(Z_i;\ \hat{\beta}_n\right) - f\left(Z_i;\ \hat{\beta}_n\right)\right]\right\} + [\max(v_{ni}) - v_{ni}] \\ (i = 1,\ 2,\ \ldots,\ I;\ n = 1,\ 2,\ \ldots,\ N), \tag{4}$$

where X_{ni} is the original input data before adjustment and X_{ni}^{*} is the input data after adjustment, enotes adjusting all decision units to the same effect of environmental factors, and $[max(v_{ni}) - v_{ni}]$ denotes adjusting all decision units to the same effect of random error.

2.1.3. Third-Stage Super-Efficient SBM Model

The value of the second stage after excluding the influence of the external environment and random factors X_{ni}^{*} lies in the fact that the efficiency evaluation results obtained are more objective and accurate since they are brought into the super-efficient SBM model again for efficiency measurement. By using the three-stage super-efficient SBM–DEA model, we can eliminate the influence of external environmental factors such as economic, demographic, and policy factors and random factors on governance efficiency, and its measurement results can more objectively reflect the internal management level of decision-making units compared to the traditional DEA model.

2.1.4. Cloud Model

The cloud model is a common fuzzy mathematical algorithm analysis method, mostly used in the comprehensive evaluation of things. Its main role is to achieve qualitative and quantitative mutual transformation through the quantitative calculation of the results of the evaluation in terms of the mean value (E_x), consistency (E_n), and the concentration of distribution (H_e). These three aspects of the evaluation results are visualized in terms of mean (E_x), consistency (E_n) and concentration of distribution (H_e), which facilitate analysis and discussion [32,33].

Two main methods exist for cloud modeling, the forward cloud generator method and the inverse cloud generator method. The inverse cloud generator uses quantitative-to-qualitative diffraction, and the forward cloud generator uses qualitative-to-quantitative diffraction. The inverse cloud generator uses the process of reducing the three numerical features of C (E_x, E_n, and H_e) by inputting a certain number of cloud droplets, and the specific calculation operation process of the inverse cloud generator is as follows:

First, calculate the cloud drop sample mean (E_x) with the sample variance (S_n).

Second, calculate the entropy of the cloud droplet sample (E_n).

$$E_n = \sqrt{\pi/2} \times \frac{1}{N} \sum\nolimits_{i=1}^{N} \backslash x_i - E_x \backslash \tag{5}$$

In Equation (6), N is the total number of samples, and x_i is the observed value of the ith sample.

Third, calculate the cloud droplet sample hyperentropy (H_e).

$$H_e = \sqrt{S_n^2 - E_n^2} \tag{6}$$

Fourth, the output cloud droplet numerical features (E_x, E_n , H_e).

2.2. Application Ideas and Theoretical Framework

This study uses a super-efficiency SBM model to measure the environmental governance efficiency of 27 provinces in China from 2003 to 2020. Secondly, the redundant input variables calculated in the first stage are used as dependent variables in an SFA model to eliminate the influence of environmental variables and random errors on the input variables and to form input variables that eliminate the impact of environmental variables and random errors. Then, the super-efficiency SBM model is used again to recalculate the environmental governance efficiency of the 27 provinces from 2003 to 2020 and to compare and analyze the results with those obtained in the first stage to obtain a preliminary understanding of the environmental governance efficiency of the 27 provinces and three major regions in China. Finally, using cloud models, evaluation interval cloud parameters are formed for the eastern, central, and western regions, as well as the national scope. The cloud parameter values belonging to each province are compared with the corresponding regional evaluation cloud parameters to determine the environmental governance efficiency of each province and conduct in-depth analysis. The cloud parameters for the environmental governance efficiency of the 27 provinces are analyzed and compared on a national scale to obtain the overall characteristics of China's environmental governance efficiency and conduct further analysis. See Figure 1 for a detailed analysis framework.

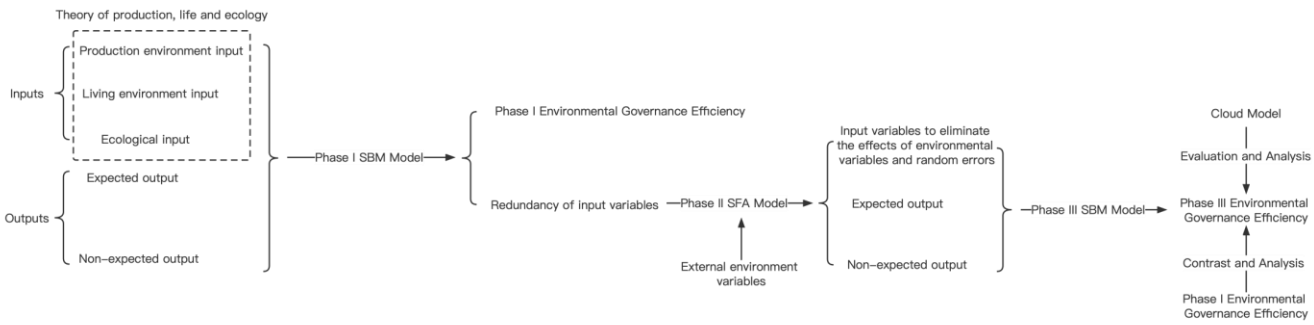

Figure 1. Theoretical framework diagram.

2.3. Indicator Construction

With reference to the indicators selected from related literature and combined with the Theory of production, life and ecology, the following evaluation index system of environmental governance efficiency is proposed, including input variables at the level of the production environment, input variables at the level of the living environment, input variables at the level of the ecological environment, the expected output, the non-expected output, and the environmental variables, as detailed in Table 1.

2.4. Data Description

According to the constructed index system, this article uses panel data from 27 provinces in China from 2003 to 2020 (excluding Tibet, Liaoning, Heilongjiang, Jilin, Hong Kong, Macao, and Taiwan) in empirical analysis and establishes a three-stage SBM model to quantitatively evaluate China's environmental governance efficiency with dynamic and regional comparisons made horizontally and vertically.

Table 1. Environmental governance efficiency evaluation index system.

Target Layer	Guideline Layer	Indicator Name	Calculation Method	Indicator Unit
Input Indicators	Production environment level	Investment in the treatment of three wastes	Total investment in waste gas treatment, solid waste treatment, and wastewater treatment	million yuan
		Total power of agricultural machinery	–	million kilowatts
	Living environment Level	Water, environment, and public facilities management industry employees	–	10,000 people
		Living Environment Investment	Total investment in environmental pollution control and urban environmental infrastructure construction	million yuan
	Ecological environment Level	Ecosystem Investment	Forestry investment; local government environmental protection expenditure; and agriculture, forestry, and water affairs expenditure are added together	million yuan

Table 1. *Cont.*

Target Layer	Guideline Layer	Indicator Name	Calculation Method	Indicator Unit
Output Indicators	Expected output	Soil erosion control area	–	Thousands of hectares
		Household waste disposal rate	–	%
	Non-desired outputs	Total industrial emissions of three wastes	Industrial wastewater emissions, industrial sulfur dioxide emissions, and industrial smoke (dust) emissions are added together	million tons
		Total agricultural pollution	The sum of the comprehensive amount of agricultural non-point source pollution and the total amount of agricultural carbon emissions is calculated, among which the comprehensive amount of agricultural non-point source pollution is characterized by the amount of nitrogen fertilizer and phosphorus fertilizer loss, ineffective pesticide use and residual film covering as indicators of the level of agricultural non-point source pollution. The total amount of agricultural carbon emissions is calculated by multiplying the carbon emission coefficients of fertilizer, pesticide, residual film, agricultural machinery, plowing, and irrigation by the total amount (area) of each part used.	million tons
Environment Variables	–	Level of Urbanization	Ratio of urban population to total resident population	%
		Degree of industrialization	Share of secondary sector in GDP	%
		Level of regional GDP per capita	Natural logarithm of GDP per capita level	Yuan
		Population density	Resident population per square kilometer	People per square kilometer
		Fiscal revenue size	(Public revenue/GDP) × 100%	%
		Degree of openness to the outside world	(Total exports and imports/GDP) × 100%	%
		Economic growth rate	Gross regional product index (previous year = 100)	%
		Government Size	Scale of public finance expenditure/regional GDP	%
		Number of industrial enterprises above the scale	The number of industrial enterprises above the scale (main business income of 20 million yuan or more)	individual

The data required for empirical analysis in this article mainly come from the "China Statistical Yearbook", "China Environmental Statistical Yearbook", "China Rural Statistical Yearbook", and ESP database from 2003 to 2020. To facilitate regional comparisons, the 27 provinces are divided into four major regions: east, central, west, and northeast (referring to the division of regions in the China Environmental Yearbook), as shown in Table 2.

Table 2. Breakdown of each region.

Large Area	Eastern Region	Northeast Region	Central Region	Western Region
Provincial administrative areas	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang Fujian, Shandong, Guangdong, and Hainan	Liaoning, Jilin, and Heilongjiang	Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan	Inner Mongolia, Shaanxi, Gansu, Ningxia, Xinjiang, Qinghai, Tibet, Guangxi, Chongqing, Sichuan, Guizhou, and Yunnan

3. Analysis of Results

3.1. Analysis of the Results of the First-Stage Super-Efficient SBM Model

According to the efficiency evaluation index system shown in Table 1, the input and output variables are selected and the super-efficient SBM model is used to measure the initial efficiency of environmental governance in 27 provinces in China for the period 2003–2020. The results are detailed in Table 3.

As shown in Table 3, there were significant regional differences in China's environmental governance efficiency from 2003 to 2020. In terms of average efficiency, the western region had the highest pollution control efficiency with an average efficiency of 0.718, followed by the eastern region with an average efficiency of 0.499. The central region had the lowest environmental governance efficiency, with an average efficiency of 0.310. In terms of inter-provincial comparison, Qinghai had the highest environmental governance efficiency with an average efficiency value of 1.317, while Jiangsu had the lowest environmental governance efficiency, with an average efficiency of only 0.070. Furthermore, only 7 out of

27 provinces achieved effective environmental governance efficiency, accounting for only 26%, while the remaining provinces had ineffective environmental governance efficiency. Among them, only Beijing, Shanghai, and Hainan in the eastern region achieved effective environmental governance efficiency, accounting for 30%, while no province in the central region achieved effective environmental governance efficiency, accounting for 0%. In the western region, Inner Mongolia, Gansu, Ningxia, and Qinghai had effective environmental governance efficiency, accounting for 36.4%. In terms of the trend, all provinces showed a fluctuating trend of ups and downs and the national efficiency mean value showed a wave-like changing trend. Overall, China's environmental governance is still in a "high input, low efficiency" governance situation, without excluding the influence of environmental and random factors.

Table 3. Table of environmental governance efficiency of 27 provinces in the first phase.

Region	Province	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average Value	Ranking
East	Beijing	0.186	0.196	0.192	0.215	1.029	1.105	1.140	1.146	1.225	1.145	1.220	1.241	1.212	1.283	1.326	1.400	1.449	1.430	1.008	7
	Tianjin	0.102	0.113	1.032	1.044	1.060	1.117	1.124	1.098	1.027	1.020	0.317	0.248	0.208	0.493	1.004	1.075	1.055	1.100	0.791	8
	Hebei	0.199	0.180	0.186	0.194	0.226	0.244	0.286	0.284	0.227	0.212	0.216	0.192	0.200	0.231	0.166	0.158	0.174	0.171	0.208	18
	Shanghai	0.002	0.003	1.042	1.150	1.179	1.153	1.158	1.161	1.098	1.158	1.160	1.176	1.174	1.181	1.181	1.166	1.168	1.165	1.026	5
	Jiang Su	0.066	0.060	0.054	0.057	0.059	0.069	0.091	0.085	0.076	0.065	0.075	0.082	0.076	0.084	0.068	0.070	0.069	0.061	0.070	27
	Zhejiang	0.163	0.155	0.152	0.149	0.160	0.178	0.223	0.202	0.188	0.254	0.268	0.245	0.229	0.226	0.200	0.208	0.187	0.185	0.199	20
	Fukushima	0.238	0.199	0.194	0.184	0.236	0.285	0.326	0.277	0.222	0.368	0.380	0.385	0.358	0.407	0.319	0.335	0.326	0.295	0.296	16
	Shandong	0.130	0.121	0.111	0.118	0.125	0.134	0.155	0.151	0.130	0.112	0.122	0.111	0.112	0.115	0.097	0.100	0.091	0.094	0.118	25
	Guangdong	0.070	0.072	0.073	0.076	0.088	0.108	0.121	0.088	0.109	0.107	0.129	0.136	0.130	0.152	0.107	0.105	0.100	0.092	0.103	26
	Hainan	1.087	1.046	1.039	1.034	1.095	1.173	1.262	1.170	1.060	1.076	1.132	1.129	1.220	1.308	1.299	1.295	1.301	1.294	1.168	2
	Average value	0.224	0.214	0.407	0.422	0.526	0.557	0.588	0.566	0.536	0.552	0.502	0.495	0.492	0.548	0.577	0.591	0.592	0.589	0.499	–
Central	Shanxi	0.285	0.148	0.158	0.222	0.274	0.288	0.314	0.373	0.357	0.409	0.419	0.444	0.452	0.482	1.022	1.019	1.010	1.007	0.482	14
	An Hui	0.132	0.110	0.084	0.142	0.147	0.155	0.204	0.226	0.220	0.150	0.169	0.195	0.178	0.169	0.126	0.144	0.118	0.107	0.154	23
	Jiangxi	1.043	0.310	0.339	0.346	0.403	0.571	1.138	0.481	1.066	1.139	0.561	0.629	0.474	0.496	0.345	0.375	0.375	0.328	0.579	12
	Henan	0.164	0.145	0.142	0.130	0.153	0.181	0.227	0.248	0.188	0.197	0.185	0.172	0.168	0.163	0.119	0.125	0.112	0.117	0.163	22
	Hubei	0.288	0.250	0.238	0.178	0.215	0.264	0.237	0.262	0.306	0.366	0.391	0.356	0.330	0.279	0.240	0.254	0.247	0.223	0.274	17
	Huanan	0.135	0.142	0.152	0.160	0.184	0.184	0.200	0.216	0.230	0.227	0.247	0.271	0.214	0.284	0.205	0.219	0.245	0.220	0.207	19
	Average value	0.341	0.184	0.186	0.196	0.229	0.274	0.387	0.301	0.395	0.415	0.329	0.344	0.303	0.312	0.343	0.356	0.351	0.334	0.310	–
West	Inner Mongolia	1.067	1.087	1.177	1.042	1.045	1.052	1.042	1.086	1.029	1.062	1.059	1.051	1.043	1.044	1.042	1.045	1.162	1.107	1.069	4
	Guang Xi	0.165	0.171	0.148	0.166	0.161	0.176	0.190	0.171	0.183	0.176	0.177	0.198	0.160	0.222	0.176	0.206	0.252	0.195	0.183	21
	Chong Qing	0.181	0.273	0.279	0.294	0.311	0.371	0.460	0.405	0.427	1.034	0.538	1.241	0.531	1.008	0.388	0.483	0.527	0.374	0.507	13
	Shikawa	0.183	0.160	0.175	0.208	0.231	0.314	0.489	1.039	0.349	1.007	0.547	0.463	0.441	0.498	0.331	0.326	0.358	0.315	0.413	15
	Guizhou	0.365	0.360	0.438	0.459	0.547	1.022	1.070	1.118	0.454	1.086	1.054	0.717	0.713	1.109	0.570	0.549	0.565	0.473	0.704	10
	Yunnan	0.395	0.405	0.432	0.310	1.018	0.542	0.575	0.540	0.456	0.716	1.006	1.015	1.012	0.664	0.629	0.631	0.612	0.555	0.640	11
	Shaanxi	1.045	1.039	1.039	1.167	1.114	1.083	1.041	1.042	1.040	0.574	0.596	0.555	0.530	0.546	0.420	0.441	0.415	0.395	0.782	9
	Gan Su	1.141	1.155	1.141	1.138	1.132	1.148	1.143	1.148	1.165	1.077	1.092	1.131	1.228	1.097	1.155	1.135	1.163	1.159	1.142	3
	Ningxia	0.506	0.410	1.026	1.043	1.047	1.022	1.004	1.077	1.007	1.019	1.114	1.120	1.144	1.147	1.097	1.118	1.164	1.098	1.009	6
	Qinghai	1.296	1.392	1.312	1.444	1.439	1.374	1.288	1.252	1.320	1.307	1.298	1.283	1.193	1.235	1.329	1.267	1.266	1.407	1.317	1
	Xinjiang	0.051	0.052	0.054	0.061	0.061	0.112	0.135	0.153	0.137	0.166	0.172	0.149	0.171	0.216	0.153	0.168	0.163	0.156	0.129	24
	Average value	0.581	0.591	0.656	0.667	0.737	0.747	0.767	0.821	0.688	0.839	0.787	0.811	0.742	0.799	0.663	0.670	0.695	0.658	0.718	–
National average		0.396	0.361	0.460	0.472	0.546	0.571	0.616	0.611	0.567	0.638	0.579	0.590	0.552	0.598	0.560	0.571	0.581	0.560	0.546	–

3.2. Analysis of the Second-Stage Stochastic Frontier Regression Results

To eliminate the influence of the external environment and random noise on agricultural land productivity, the slack values of input factors in the first stage are taken as the dependent variables, and the environmental factors in Table 1 are taken as the independent variables. The Frontier4.1 software is used for data analysis. A positive regression coefficient indicates that there is input redundancy that is not conducive to improving environmental governance efficiency. Conversely, a negative coefficient value is beneficial for improving environmental governance efficiency. The specific regression results are shown in Table 4.

According to Table 4, most of the environmental variables are significantly related to the input slack variables at a significance level of 1%, indicating a close correlation between external environmental factors and the efficiency of environmental governance in China.

Table 4. Results of the second-stage stochastic frontier regression.

	Redundant Investment in the Treatment of Three Wastes		Total Power Redundancy of Agricultural Machinery		Water, Environment, and Public Facilities Management Industry Employee Redundancy		Living Environment Investment Redundancy		Eco-Investment Redundancy	
	Coefficient	Standard Deviation	Coefficient	Standard Deviation	Coefficient	Standard Deviation	Coefficient	Standard Deviation	Coefficient	Standard Deviation
Constant term	−704,213.230 ***	1.000	−12,252.142 ***	1342.521	−12.023 ***	4.041	−17,357,229.000 ***	10.385	−30,769,481.000 ***	1.049
Level of Urbanization	1781.106 ***	1.000	−13.119	9.420	−0.106 ***	0.022	−33,773.123 ***	1667.121	10,655.853 ***	27.875
Degree of industrialization	−1916.066 ***	1.000	−49.182 ***	8.477	−0.046 **	0.019	−11,720.361 ***	441.885	48,032.305 ***	13.963
GDP per capita level	−7931.819 ***	1.000	−8.224	34.702	0.047	0.077	−88,976.849 ***	164.031	−202,657.470 ***	2.623
Population density	−3.024 ***	1.000	−1.068 ***	0.378	0.002 **	0.001	601.032 ***	209.419	461.033 **	195.090
Fiscal revenue size	1823.217 ***	1.000	50.092 ***	18.997	−0.074	0.058	60,354.138 ***	258.696	233,293.500 ***	5.041
Degree of openness to the outside world	334.258 ***	1.000	4.907	3.075	0.020 ***	0.007	23,334.433 ***	2106.621	11,858.782 ***	5.198
Economic Growth Rate	5121.147 ***	1.000	78.807 ***	11.705	0.059 *	0.034	148,256.870 ***	1209.039	223,633.410 ***	34.911
Government Size	101,363.170 ***	1.000	−167.963 *	101.879	9.266 ***	2.327	161,294.410 ***	5.525	−3,803,834.600 ***	1.014
Number of industrial enterprises	−4.757 ***	0.459	−0.068 ***	0.006	0.000 ***	0.000	−177.872 ***	11.439	−148.689 ***	15.986
Sigma2	23,543,092,000.000 ***	1.000	10,543,359.000 ***	1.557	64.414 ***	22.336	6,924,207,300,000.000 ***	1.000	8,745,754,400,000.000 ***	1.000
γ	0.630 ***	0.025	0.971 ***	0.002	0.973 ***	0.010	0.500 ***	0.025	0.522 ***	0.031
log likelihood function	−6313.117 ***		−3885.532 ***		−894.743 ***		−7732.103 ***		−7778.878 ***	

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

For redundant investment in the treatment of industrial waste, the level of industrialization, per capita GDP, and population density negatively and significantly affect the redundant investment in the treatment of industrial waste, which is conducive to improving environmental governance efficiency. However, the level of urbanization, fiscal revenue scale, degree of openness, economic growth rate, and government size have a positive and significant impact on redundant investment in the treatment of industrial waste, which is not conducive to improving environmental governance efficiency.

For redundant total power in agricultural machinery, the level of industrialization, population density, government size, and the number of industrial enterprises negatively and significantly affect the redundant total power in agricultural machinery, which is conducive to improving environmental governance efficiency. However, the scale of fiscal revenue and economic growth rate have a positive and significant impact on the redundant total power in agricultural machinery, which is not conducive to improving environmental governance efficiency.

For redundant employees in water, environmental, and public facility management, the level of urbanization and industrialization negatively and significantly affect the redundant employees in water, environmental, and public facility management, which is conducive to improving environmental governance efficiency. However, population density, degree of openness, economic growth rate, government size, and the number of industrial enterprises have a positive and significant impact on redundant employees in water, environmental, and public facility management, which is not conducive to improving environmental governance efficiency.

For redundant investment in the living environment, the level of urbanization, industrialization, per capita GDP, and the number of industrial enterprises negatively and significantly affect the redundant investment in the living environment, which is conducive to improving environmental governance efficiency. However, population density, fiscal revenue scale, degree of openness, economic growth rate, and government size have a positive and significant impact on redundant investment in living environment, which is not conducive to improving environmental governance efficiency.

For redundant investment in the ecological environment, per capita GDP, government size, and the number of industrial enterprises negatively and significantly affect redundant investment in the ecological environment, which is conducive to improving environmental governance efficiency. However, the level of urbanization, industrialization, population density, fiscal revenue scale, degree of openness, and economic growth rate have a positive and significant impact on redundant investment in the ecological environment, which is not conducive to improving environmental governance efficiency.

It can be seen that for the two input variable redundancies in the production environment, the factors that have a positive impact are mostly economic factors, indicating that the more economically developed the region is, the more likely it is to have input variable redundancy, and it also indicates that the more economically developed the region is, the larger the scope and difficulty of environmental governance will be, and it will be more likely to have a "high input, low output" characterization. At the same time, economic development and environmental governance usually have an inverted "U" relationship, indicating that China is still in the upward phase of the EKC curve, that is, the stage of sacrificing the environment for economic development, and has not yet reached the turning point of the EKC curve. For the input variable redundancy in the living environment and ecological environment, in addition to economic factors, population factors will also have a positive impact, indicating that the efficiency of governance in the living environment and ecological environment will be affected by both economic factors and population factors. Overall, external environmental factors have different impacts on various input redundancies. Based on this comprehensive analysis, due to the different external environments in different regions, the factors affecting the efficiency of environmental governance and their directions and magnitudes of influence are inevitably different. These differences will lead to deviations in environmental governance efficiency. Therefore, it is necessary to eliminate the influence of environmental variables and recalculate efficiency.

3.3. Analysis of the Results of the Adjusted Super-Efficient SBM Model in the Third Stage

The original input values are adjusted, and the input data and the original output data, after excluding random errors and environmental variables, are again substituted into the SBM model, and the calculated results are presented in Tables 5 and 6.

Table 5. Table of environmental governance efficiency in 27 provinces in the third phase.

Region	Province	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average Value	Ranking
East	Beijing	0.304	0.323	0.257	0.354	1.006	1.047	1.073	1.059	1.093	1.051	1.019	1.017	0.262	0.252	0.311	0.372	0.353	0.341	0.638	9
	Tianjin	0.030	0.027	0.069	1.018	1.040	1.063	1.066	1.044	1.045	1.027	1.004	0.129	0.090	0.194	0.080	0.094	0.083	1.008	0.562	10
	Hebei	0.329	0.298	0.270	0.290	0.312	0.311	0.314	0.326	0.274	0.194	0.197	0.208	0.231	0.245	0.214	0.185	0.204	0.233	0.258	19
	Shanghai	0.000	0.000	0.000	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.003	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.001	27
	Jiang Su	0.172	0.139	0.119	0.133	0.132	0.116	0.130	0.124	0.118	0.076	0.080	0.099	0.091	0.088	0.090	0.089	0.083	0.078	0.109	26
	Zhejiang	0.283	0.226	0.201	0.212	0.209	0.218	0.237	0.197	0.227	0.216	0.214	0.219	0.202	0.195	0.205	0.207	0.186	0.185	0.213	21
	Fukushima	0.330	0.274	0.258	0.232	0.309	0.424	0.480	0.301	0.261	0.292	0.298	0.344	0.308	0.336	0.318	0.314	0.300	0.290	0.315	16
	Shandong	0.278	0.233	0.161	0.183	0.189	0.191	0.200	0.191	0.168	0.116	0.123	0.125	0.127	0.128	0.120	0.123	0.112	0.124	0.161	24
	Guangdong	0.137	0.128	0.116	0.136	0.146	0.165	0.153	0.102	0.140	0.130	0.132	0.146	0.139	0.150	0.146	0.139	0.123	0.132	0.137	25
	Hainan	1.332	1.343	1.400	1.425	1.399	1.679	1.558	1.424	1.549	1.610	1.582	1.591	1.611	1.627	1.925	1.295	1.372	1.293	1.501	2
	Average value	0.319	0.299	0.285	0.398	0.474	0.522	0.521	0.477	0.488	0.471	0.465	0.388	0.306	0.322	0.341	0.282	0.282	0.368	0.389	–
Central	Shanxi	0.404	0.279	0.249	0.347	0.370	0.354	0.374	0.447	0.428	0.358	0.383	0.488	0.513	0.475	0.494	0.523	0.497	0.487	0.415	14
	An Hui	0.213	0.173	0.139	0.198	0.219	0.243	0.251	0.243	0.272	0.197	0.204	0.237	0.220	0.194	0.176	0.193	0.161	0.164	0.205	22
	Jiangxi	0.485	0.391	0.371	0.423	0.469	0.629	1.042	0.502	1.043	1.013	0.516	0.621	0.508	0.475	0.400	0.404	0.387	0.367	0.558	11
	Henan	0.322	0.268	0.247	0.225	0.239	0.267	0.288	0.289	0.259	0.207	0.189	0.204	0.206	0.188	0.163	0.167	0.147	0.172	0.225	20
	Hubei	0.401	0.351	0.321	0.280	0.298	0.334	0.286	0.295	0.335	0.322	0.347	0.382	0.366	0.290	0.294	0.299	0.283	0.259	0.319	15
	Huanan	0.200	0.213	0.210	0.229	0.256	0.279	0.270	0.284	0.307	0.258	0.265	0.321	0.266	0.298	0.281	0.283	0.280	0.270	0.265	18
	Average value	0.338	0.279	0.256	0.284	0.309	0.351	0.418	0.343	0.441	0.393	0.317	0.376	0.346	0.320	0.301	0.311	0.292	0.286	0.331	–
West	Inner Mongolia	1.105	1.110	1.186	1.084	1.083	1.084	1.127	1.127	1.059	1.090	1.085	1.059	1.059	1.052	1.054	1.060	1.116	1.094	1.091	4
	Guang Xi	0.318	0.298	0.260	0.287	0.283	0.357	0.331	0.273	0.279	0.252	0.223	0.256	0.220	0.253	0.280	0.293	0.303	0.294	0.281	17
	Chong Qing	0.209	0.324	0.314	0.380	0.452	0.592	1.009	0.471	0.684	1.013	0.551	1.124	0.525	0.572	0.459	0.477	0.434	0.405	0.555	12
	Shikawa	0.360	0.328	0.324	0.398	0.415	0.454	0.531	1.000	0.447	0.517	1.005	0.508	0.509	0.512	0.409	0.387	0.408	0.403	0.495	13
	Guizhou	1.156	1.097	1.091	1.036	1.063	1.099	1.175	1.097	1.001	1.132	1.110	1.050	1.050	1.124	1.005	0.774	0.669	0.582	1.017	5
	Yunnan	0.656	1.001	1.001	0.532	1.032	1.015	1.009	0.762	0.631	1.008	1.029	1.070	1.041	1.031	1.062	1.037	0.768	0.694	0.910	6
	Shaanxi	1.030	1.004	1.006	1.113	1.051	1.112	1.036	1.034	1.089	0.529	0.554	0.582	0.595	0.538	0.453	0.460	0.425	0.423	0.780	8
	Gan Su	1.022	1.031	1.053	1.076	1.062	1.068	1.060	1.135	1.101	1.058	1.072	1.113	1.145	1.082	1.148	1.140	1.159	1.153	1.093	3
	Ningxia	0.390	0.312	0.452	0.552	0.517	0.606	0.619	1.080	0.626	0.589	1.046	1.063	1.088	1.047	1.057	1.072	1.084	1.059	0.792	7
	Qinghai	1.278	1.425	1.457	1.533	1.491	1.369	2.400	1.710	1.866	1.784	2.192	2.400	1.916	2.400	1.789	1.682	2.223	1.863	1.821	1
	Xinjiang	0.066	0.084	0.092	0.118	0.122	0.185	0.177	0.205	0.194	0.246	0.216	0.204	0.232	0.251	0.242	0.252	0.228	0.275	0.188	23
	Average value	0.690	0.729	0.749	0.737	0.779	0.813	0.952	0.899	0.816	0.838	0.917	0.948	0.853	0.897	0.814	0.785	0.801	0.749	0.820	–
National average		0.474	0.470	0.468	0.511	0.562	0.602	0.674	0.619	0.611	0.603	0.616	0.614	0.538	0.556	0.525	0.493	0.496	0.505	0.552	–

Overall, as shown in Tables 5 and 6, there are significant changes in the efficiency values after the third-stage adjustment compared to the first stage. On average, the adjusted efficiency means of the central and western regions have significantly improved, increasing from 0.31 to 0.331 and from 0.718 to 0.82, respectively. Moreover, after eliminating the influence of environmental factors, the efficiency rankings of most provinces in the central and western regions have improved, indicating that the presence of external environmental factors and random factors has significantly underestimated the environmental governance efficiency in these regions. For the eastern region, after eliminating the effects of external environmental and random factors, the adjusted efficiency mean has significantly decreased from 0.499 to 0.389. Except for Hainan, where the overall environmental governance efficiency and ranking have remained stable, the environmental governance efficiency of most provinces in the eastern region has significantly decreased, with Shanghai experiencing the most severe decline. This indicates that the presence of external environmental and random factors has significantly overestimated the environmental governance efficiency in the eastern region of China. Overall, there have been varying degrees of improvement or decline in the environmental governance efficiency of different provinces. However, after eliminating the influence of external environmental variables, the overall environmental governance efficiency still ranks first in the western region, second in the eastern region, and third in the central region. Moreover, the number of effective provinces has decreased from seven to five, indicating that the overall environmental governance efficiency in China is still ineffective. Therefore, it is imperative to improve environmental governance efficiency.

Table 6. Comparison of the efficiency of environmental management governance in 27 provinces in the first and third stages.

Region	Province	Phase I		Phase II	
		Average Value	**Sort by**	**Average Value**	**Sort by**
East	Beijing	1.008	7	0.638	9
	Tianjin	0.791	8	0.562	10
	Hebei	0.208	18	0.258	19
	Shanghai	1.026	5	0.001	27
	Jiang Su	0.07	27	0.109	26
	Zhejiang	0.199	20	0.213	21
	Fukushima	0.296	16	0.315	16
	Shandong	0.118	25	0.161	24
	Guangdong	0.103	26	0.137	25
	Hainan	1.168	2	1.501	2
	Average value	0.499	–	0.389	–
Central	Shanxi	0.482	14	0.415	14
	An Hui	0.154	23	0.205	22
	Jiangxi	0.579	12	0.558	11
	Henan	0.163	22	0.225	20
	Hubei	0.274	17	0.319	15
	Huanan	0.207	19	0.265	18
	Average value	0.31	–	0.331	–
West	Inner Mongolia	1.069	4	1.091	4
	Guang Xi	0.183	21	0.281	17
	Chong Qing	0.507	13	0.555	12
	Shikawa	0.413	15	0.495	13
	Guizhou	0.704	10	1.017	5
	Yunnan	0.64	11	0.910	6
	Shaanxi	0.782	9	0.780	8
	Gan Su	1.142	3	1.093	3
	Ningxia	1.009	6	0.792	7
	Qinghai	1.317	1	1.821	1
	Xinjiang	0.129	24	0.188	23
	Average value	0.718	–	0.820	–
National average		0.546	–	0.552	–

In conclusion, there are significant differences in the measurement results of China's environmental governance efficiency before and after adjustment, which confirms the significant impact of external environmental factors and random factors on governance efficiency and the differences in the magnitude of their effects on different provinces due to their different external environments. Therefore, it is necessary to eliminate the influence of external environmental factors and random factors to obtain an objective evaluation result of environmental governance efficiency.

3.4. Evaluation of Environmental Governance Efficiency Based on the Cloud Model

To explore the spatial differentiation trend of China's environmental governance efficiency, this paper combines the mean deviation method with the cloud model, and uses the adjusted environmental governance efficiency as the basis to divide 27 provinces into five levels, from low to high: low environmental governance efficiency, relatively low environmental governance efficiency, general environmental governance efficiency, relatively high environmental governance efficiency, and high environmental governance efficiency. In order to more accurately measure the environmental governance efficiency of each province, considering that each province and region faces different environmental problems and economic conditions, it is obviously unreliable to simply apply an evaluation system to evaluate all provinces. Setting up an evaluation system for each region to evaluate environmental governance efficiency is more scientific and objective. Therefore, evaluation systems are generated for the eastern, central, western, and national regions to evaluate the provinces in different regions, and the national evaluation system evaluates the overall environmental governance efficiency of the three regions.

According to the cloud model principle, the environmental governance efficiency evaluation index system is taken as the theoretical domain, each research object is taken as a cloud drop, and the overall characteristics of the cloud formed according to the integrated results of all research objects' evaluation of all indicators reflect the environmental governance efficiency, according to which the process of the environmental governance efficiency evaluation method is designed as follows:

- Step 1: Determine the set of factors

Due to the difference in the measurement scale of the research index system, it is not necessary to normalize the environmental governance efficiency data.

- Step 2: Determine the evaluation cloud and evaluation set

First, according to the mean deviation method, the five evaluation level ranges are confirmed, and then according to the bilateral constraint criterion, the value of each rubric is taken within the limited family domain, and the minimum value of the rubric is set T_{min} and the maximum value is T_{max}. The three numerical characteristics of the evaluation criteria cloud are calculated as follows.

$$\begin{cases} E_x = (T_{min} + T_{max})/2 \\ E_n = (T_{max} - T_{min})/6 \\ H_e = k \end{cases} \quad (7)$$

In Equation (7), k denotes randomness, and in this paper, k is taken as 0.01.

- Step 3: Determine the numerical characteristics of each cloud parameter

Calculations are performed according to the equations of the inverse cloud model above, as detailed in Equations (5) and (6), to derive the cloud parameters for each province.

The numerical characteristics of the cloud models corresponding to the evaluation levels are specified in Table 7. The parameters of the cloud model scores for each province and region are detailed in Table 8.

Based on the above data, we organize our main observations into four categories:

(1) Evaluation of the environmental governance efficiencies of provinces in the eastern region. Based on the comparison of cloud parameters of provinces in the eastern region with the evaluation of the cloud parameters of the eastern region, it can be observed that Beijing, Tianjin, and Hainan belong to provinces with high environmental governance efficiencies; Fujian belongs to a province and city with general environmental governance efficiencies; and Hainan has achieved effective environmental governance. Hebei belongs to a province with relatively low environmental governance efficiency and Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong belong to provinces with low environmental governance efficiencies. Therefore, the environmental governance efficiencies of the vast majority of provinces in the eastern region are not high. Moreover, through entropy analysis, it can be observed that although Beijing, Tianjin, and Hainan have high environmental governance efficiencies, their entropy values are also ranked in the top three, indicating that there is a large span of environmental governance efficiencies in these three provinces from 2003 to 2020, and although their governance efficiencies are high, their overall states are unstable. The entropy values of the other provinces are generally low, indicating that the environmental governance efficiencies of the other provinces are generally stable. Among them, the super-entropy values of Zhejiang, Fujian, and Guangdong are greater than 0, indicating that the cloud model curves of Zhejiang, Fujian, and Guangdong have a certain degree of fuzziness, which means that the development of environmental governance efficiencies in these three provinces from 2003 to 2020 are not balanced, and there may be uneven development among factors that affect environmental governance efficiency or they may be affected by government public value preferences or policies. The super-entropy

values of the other provinces are all 0, indicating that the development of environmental governance efficiencies in the other provinces is generally stable. Overall, taking into account the allocation of expected values, entropy, and super-entropy, it can be concluded that the environmental governance efficiency of Fujian best represents the overall situation in the eastern region.

(2) Evaluation of the environmental governance efficiencies of provinces in the central region. After comparing the cloud parameters of provinces in the central region with the evaluation of the cloud parameters of the central region, it was found that Jiangxi belongs to the province with high environmental governance efficiency, Shanxi belongs to the province with relatively high environmental governance efficiency, Hubei belongs to the province with average environmental governance efficiency, Hunan belongs to the province with relatively low environmental governance efficiency, and Anhui and Henan belong to the provinces with low environmental governance efficiencies. It can be seen that the environmental governance efficiencies in the central region show a normal distribution overall, and the overall distribution is relatively balanced. Through the entropy value, it can be observed that although Jiangxi has the highest environmental governance efficiency in the central region, the span of its environmental governance efficiency is also the largest, indicating that its environmental governance efficiency is in a certain state of instability. The entropy values of the other provinces are basically consistent, indicating that the changes in the environmental governance efficiencies of the other provinces are more stable. From the super-entropy value, it can be observed that the super entropies of Anhui, Jiangxi, and Hunan are all greater than 0, indicating that there are differences between the factors that affect their environmental governance efficiencies, or that there are other factors that may have an impact, resulting in more unstable and hazy states of their environmental governance efficiencies. Overall, considering the values of expectation, entropy, and super entropy, it can be concluded that the environmental governance efficiency of Hubei best represents the overall situation in the central region.

(3) Evaluation of the environmental governance efficiencies of provinces in western China. After comparing the cloud parameters of each province and city in western China with the evaluation of the cloud parameters of western China, it was found that Inner Mongolia, Guizhou, Gansu, and Qinghai belong to provinces with high environmental governance efficiencies, and all four provinces have achieved effective environmental governance. Yunnan belongs to provinces with relatively high environmental governance efficiencies, Shaanxi and Ningxia belong to provinces with average environmental governance efficiencies, and Guangxi, Chongqing, Sichuan, and Xinjiang belong to provinces with low environmental governance efficiencies. Therefore, the environmental governance efficiency in western China generally exhibits a distribution characteristic of a normal distribution, and the overall distribution is relatively balanced. Through entropy analysis, we can see that the entropy values of Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Ningxia, and Qinghai are all high, indicating that the environmental governance efficiencies of these seven provinces exhibit a certain degree of instability and fluctuate greatly from 2003 to 2020. On the other hand, the environmental governance efficiency fluctuations of Inner Mongolia, Guangxi, Gansu, and Xinjiang are smaller and tend to be stable. From the perspective of super entropy, the super-entropy values of Inner Mongolia, Guangxi, Chongqing, Sichuan, and Guizhou are all greater than 0, indicating that there are differences between the factors affecting their environmental governance efficiencies, or that there are other factors affecting these efficiencies, leading to more unstable and fuzzy states. Overall, considering the values of expectation, entropy, and super entropy, it can be concluded that the environmental governance efficiency of Yunnan best represents the overall situation in western China.

Table 7. Cloud model evaluation set.

Evaluation Levels	Eastern Assignment Score Interval	Numerical Characteristics of the Eastern Region Evaluation Gathering Cloud Model	Central Assignment Score Interval	Numerical Characteristics of the Central Region Evaluation Gathering Cloud Model	Western Assignment Score Interval	Numerical Characteristics of the Western Region Evaluation Gathering Cloud Model	National Assignment Score Interval	National Evaluation Set Cloud Model Digital Features
Highest efficiency of environmental governance efficiency	(0.56, 1]	(0.78, 0.073, 0.01)	(0.43, 1]	(0.715, 0.095, 0.01)	(0.97, 1]	(0.985, 0.005, 0.01)	(0.67, 1]	(0.835, 0.055, 0.01)
Higher efficiency of environmental governance	(0.48, 0.56]	(0.52, 0.013, 0.01)	(0.38, 0.43]	(0.405, 0.008, 0.01)	(0.90, 0.97]	(0.935, 0.012, 0.01)	(0.61, 0.67]	(0.64, 0.01, 0.01)
General efficiency of environmental governance	(0.3, 0.48]	(0.39, 0.03, 0.01)	(0.28, 0.38]	(0.33, 0.017, 0.01)	(0.74, 0.90]	(0.82, 0.027, 0.01)	(0.49, 0.61]	(0.55, 0.02, 0.01)
Less efficiency of environmental governance	(0.22, 0.3]	(0.26, 0.013, 0.01)	(0.23, 0.28]	(0.255, 0.008, 0.01)	(0.67, 0.74]	(0.705, 0.012, 0.01)	(0.43, 0.49]	(0.46, 0.01, 0.01)
Least efficiency of environmental governance	(0, 0.22]	(0.11, 0.037, 0.01)	(0, 0.23]	(0.115, 0.038, 0.01)	(0, 0.67]	(0.335, 0.112, 0.01)	(0, 0.43]	(0.215, 0.072, 0.01)

Table 8. Evaluation of integrated cloud parameters.

Region	Province	Indicator Cloud Parameters		
		Expectations	Entropy	Hyperentropy
East	Beijing	0.6385	0.4297	0
	Tianjin	0.5617	0.562	0
	Hebei	0.2575	0.0537	0
	Shanghai	0.001	0	0
	Jiang Su	0.1087	0.027	0
	Zhejiang	0.2133	0.0124	0.0124
	Fukushima	0.3149	0.0452	0.0338
	Shandong	0.1607	0.0459	0
	Guangdong	0.1367	0.0125	0.0063
	Hainan	1.5008	0.1616	0
	Average value	0.3893	0.0925	0
Central	Shanxi	0.415	0.0814	0
	An Hui	0.2054	0.0336	0.0068
	Jiangxi	0.5581	0.2055	0.0909
	Henan	0.2248	0.0502	0
	Hubei	0.3191	0.0379	0
	Huanan	0.265	0.0296	0.013
	Average value	0.3312	0.0471	0.0122
West	Inner Mongolia	1.0908	0.032	0.0123
	Guang Xi	0.2811	0.0326	0.0123
	Chong Qing	0.5553	0.2315	0.1028
	Shikawa	0.4953	0.1553	0.1183
	Guizhou	1.0173	0.147	0.0804
	Yunnan	0.9099	0.1973	0
	Shaanxi	0.7797	0.3423	0
	Gan Su	1.0932	0.0485	0
	Ningxia	0.7922	0.3435	0
	Qinghai	1.821	0.3749	0
	Xinjiang	0.1883	0.066	0
	Average value	0.8203	0.0782	0
National average		0.5521	0.068	0

(4) Evaluation of the environmental governance efficiencies of provinces from a national perspective. After comparing the cloud parameters of 27 provinces in the western region with the evaluation of the cloud parameters of the national scope, it was found that Hainan, Inner Mongolia, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, and Qinghai are provinces with high environmental governance efficiency. Beijing belongs to the province with a relatively high environmental governance efficiency, while Tianjin, Jiangxi, Chongqing, and Sichuan belong to provinces with average environmental governance efficiencies. Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Shanxi, Anhui, Henan, Hubei, Hunan, Guangxi, and Xinjiang are all provinces with low environmental governance efficiencies. From a national perspective, the environmental governance efficiencies of the 27 provinces show a “big difference between high and low, with the middle being small” and “low efficiency in the eastern and central regions, with instability in the western region”. There are large differences in the environmental governance efficiencies among provinces, and there is still much room for improvement and upgrading overall. Considering the allocation of expected value, entropy, and super entropy, it can be concluded that the environmental governance efficiencies of Jiangxi and Chongqing best represent the overall situation of environmental governance efficiency in the national scope.

4. Discussion

Currently, studies have been conducted on the measurement of environmental governance efficiency in China's provinces with different results. One main finding has been that the highest governance efficiency is in the eastern region, the second in the central region, and the third in the western region, as measured in the study by Xuemei Lu and Xiaoqing Zhang (2019) [34]. The study by Guoxian Bao and Bin Guan (2019) [5] concluded that the difference in environmental governance efficiencies between the eastern, central, and western regions is not significant, with the eastern. The study by Liu, Bingxi and Wang, Baoshun et al. (2016) concluded that there is a relatively serious efficiency loss in environmental governance, and the governance efficiency value is wavy and deteriorating [13]. The study by Ren, W. and Zhang, Z. et al. (2020) also concluded that the eastern region has the highest eco-efficiency, followed by the central region, and the gap between the central and western regions is gradually decreasing, but the overall environmental management efficiency is low [35]. There is a lack of research on environmental management efficiency from the inter-provincial perspective in China and the conclusions obtained are highly variable. The only consensus conclusion is that China's environmental governance efficiency is still at a relatively low level. In this regard, it is necessary to improve the efficiency of environmental governance in China and to scientifically measure the efficiency of environmental governance in each province of China. In order to scientifically measure environmental governance efficiency, the following improvements have been made in this study.

Firstly, compared to existing DEA model literature, this study adopts the third-stage super-efficiency SBM model, which is a more scientifically rigorous method for measuring efficiency within the DEA model. Additionally, this study incorporates cloud model analysis to provide a more comprehensive investigation of the DEA model results. This approach combines DEA calculations with cloud model evaluation, which represents an innovative attempt to integrate research methods. Secondly, to ensure a more scientific and reliable selection of input and output indicators, this study incorporates the three-dimensional theory into the selection of input indicators. The production environment, living environment, and ecological environment are used as dimensions to select input indicators. To enhance the reliability of the study, output variables are divided into expected and unexpected outputs. Finally, this study examines panel data from 27 provinces between 2003 and 2020. The results are more reliable and have practical significance, providing better recommendations and suggestions for improving China's environmental governance efficiency.

In summary, the main academic value of this research lies in the construction of an indicator system based on the three dimensions of production, living, and ecological environments. This approach considers the three major sources of environmental pollution and damage, providing a more comprehensive and objective selection of indicators. By combining the third-stage SBM model with cloud model analysis, this study accurately measures environmental governance efficiency, enabling a more in-depth analysis of the development status, trends, and prospects of environmental governance efficiency in various provinces and regions. Cloud model analysis provides an advantage over traditional graph and chart analysis by providing more comprehensive and objective results, enabling a more accurate assessment of the stability of environmental governance efficiency development in different provinces and regions.

The main management significance and social impact of research lie in the in-depth measurement and evaluation of environmental governance efficiency; calculations of the real level, changing trend, and differences of environmental efficiency among provinces in China; and determinations of the space that contributes to the improvement of environmental governance policies. Research has found that environmental governance efficiency in the eastern region is influenced by its developed economic factors, that is, the region uses a large amount of financial, material, and human resources to improve infrastructure, but in essence, it still remains in a "high input, low output" state and has not truly improved its environmental governance efficiency. The overall environmental governance efficiency shows a situation where the western region is first, the eastern region is second, and the central region is third. The environmental governance efficiency of 27 provinces shows a "big at both ends, small in the middle" and "low efficiency in the eastern and central regions, and instability in the western region" situation, and the degree of difference in environmental governance efficiency among each province and city is large. In China's government-led public utilities construction work, there is still a long way to go to improve the efficiency of environmental governance.

At the same time, according to research results, there is a certain degree of fluctuation in the environmental governance efficiency of 27 provinces in China from 2003 to 2020, and the overall situation is characterized by a large degree of difference among provinces and great potential for improvement. Therefore, further research on environmental governance efficiency is worth exploring. In the future, research can explore the relationship between economic development and environmental governance efficiency from the perspective of economic development, whether there is an Environmental Kuznets Curve (EKC) relationship between the two, whether the degree of development of economic development and environmental governance efficiency has entered the turning point under the EKC relationship, explore in-depth the impact of government public value preferences and public policies on environmental governance efficiency, etc., which all have practical and theoretical significance and are worthy of in-depth research and exploration.

Finally, there is still room for further deepening research. Environmental governance efficiency can be differentiated between urban and rural areas, which would enable a more detailed understanding of the differences in environmental governance efficiency between cities and rural areas in each province and municipality. Similarly, it is possible to further include regions that were not covered in this study in order to more comprehensively measure China's environmental governance efficiency.

5. Conclusions and Recommendations

5.1. Research Findings

This study evaluated the environmental governance efficiency of 27 provinces and 3 geographical regions in China from 2003 to 2020 using a method combining a third-stage super-efficiency SBM model and cloud model. The following research conclusions have been obtained.

Firstly, the influence of random error factors and external environmental conditions on the efficiency of rural domestic sewage treatment in China are significant. Their existence underestimate the environmental governance efficiencies of the central and western regions of China and overestimate the environmental governance efficiency of the eastern region. Relatively speaking, the impact of external environmental factors on the redundancy of input varies. It can be found that for the redundancy of two input variables for the production environment, the factors that have a positive impact are mostly economic factors, while for the redundancy of input variables for the living environment and ecological environment, factors that have a positive impact not only include economic factors but also population factors. This indicates that the efficiencies of governance for the living environment and ecological environment are affected by both economic and population factors.

Secondly, after removing the influence of random errors and external environmental factors, it was found that the adjusted efficiency means of the central and western regions of China from 2003 to 2020 had significantly improved and the rankings of most provinces' governance efficiencies had increased. Except for the overall environmental governance efficiency and ranking of Hainan, the environmental governance efficiencies of most provinces in the eastern region showed a significant decrease. Among them, Shanghai's environmental governance efficiency decline was the most severe, indicating that the existence of external environmental factors and random factors had significantly overestimated the environmental governance efficiency of the eastern region of China.

Finally, from a regional perspective, the overall environmental governance efficiency still shows that the western region is first, the eastern region is second, and the central region is third. The environmental governance efficiency of the 27 provinces shows a "large at both ends, small in the middle" and "low efficiency in the eastern and central regions, and instability in the western region" state, with significant differences in efficiency levels among provinces. After removing the influence of random errors and external environmental factors, the number of provinces with effective governance has decreased from seven to five. Overall, China's environmental governance efficiency is still dominated by inefficiency, and improving environmental governance efficiency is an arduous and pressing task.

5.2. Suggestions for Countermeasures

According to the conclusions above, the following recommendations for relevant countermeasures are proposed:

(1) Steps should be taken to promote the growth of per capita GDP. Per capita GDP can play a positive role in improving the efficiency of production, living, and ecological environment governance. Public choice theory advocates for multi-subject co-governance, which can effectively improve environmental governance efficiency. Increasing the level of per capita GDP can not only improve people's material security, but also have a positive effect on enhancing people's willingness to participate in environmental governance;

(2) At the same time, it is necessary to change the government's orientation of blindly pursuing economic development. Although China's investment in environmental governance has increased year by year, its governance efficiency has not seen a significant improvement. This is largely due to the influence of the government's public value preferences. This is also why the scale of fiscal revenue, government size, and economic growth rate have a positive impact on redundant investment variables. The continuous increase in investment in environmental governance has been inefficiently used due to the government's value preferences for economic development. In response, the national government should introduce corresponding policies to strengthen supervision of local governments' environmental governance work;

(3) Environmental governance in different regions should be tailored to local economic foundations, major environmental issues, and other factors. It is not scientific to evaluate the environmental governance efficiency of different provinces. For the eastern and central regions, the focus should be on the government's transformation of development thinking, attaching more importance to the balanced and coordinated development between urbanization, industrialization, and the environment. As for the western region, due to its poor environmental conditions, environmental governance is more valued, but economic development in the western region should be strengthened to ensure sufficient material conditions such as infrastructure and equipment to meet the needs of environmental governance and achieve stable environmental governance efficiency.

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