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Retraction

Retracted: Public Sector Performance Assessment Based on DEA Model: The Case of Environmental Policy

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

References

[1] R. Zhang, "Public Sector Performance Assessment Based on DEA Model: The Case of Environmental Policy," *Security and Communication Networks*, vol. 2022, Article ID 7240379, 12 pages, 2022.

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Research Article

Public Sector Performance Assessment Based on DEA Model: The Case of Environmental Policy

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The contradiction between economic development and environmental protection is a core issue that plagues developing countries. The Chinese government has continuously implemented different environmental policies to alleviate the contradiction between economic development and environmental protection, but how they will perform remains unknown. Therefore, this paper revises the classical DEA model and then empirically evaluates the efficiency of environmental policies in 31 Chinese provinces from 2015 to 2020. It is found that the environmental efficiency of each local government has steadily improved, and the provincial differences show a trend of continuous reduction. However, when decomposed, the technical efficiency gap among provinces is large, and the scale efficiency even shows a downward trend. This paper also adopts the Malmquist index for dynamic analysis of environmental efficiency, and the research findings have important theoretical value for scientific formulation of environmental policies.

1. Introduction

Socioeconomic development is accompanied by increasingly serious environmental problems, and some regions are pursuing short-term economic growth at the expense of resources and the environment, causing enormous pressure on the ecological environment, which in turn leads to the deterioration of human living environment. Water pollution, air pollution, land desertification, acid rain, extreme weather, and other environmental problems have emerged, such as the increasingly serious problem of haze, which has caused great inconvenience to people's production and life. The important reason for such problems is that the previous sloppy economic growth mode of pursuing economic development unilaterally and the wrong development concept of polluting first and treating later have caused irreversible process of environmental destruction. Environmental problems have become a major obstacle to the sustainable development of China's economy and society. The government is the main body of environmental governance, and environmental governance is an important part of national governance; along with the increasing severity of environmental problems, governments at all levels have begun to pay attention and focus on how to achieve a balance between economic development and environmental protection [1]. The report of the 18th National Congress of China has elevated the construction of ecological civilization to a national macrostrategy, and the report of the 19th National Congress emphasizes that "green water and green mountains are the silver mountain of gold." At present, China has proposed a carbon neutral strategy, striving to reach the peak of carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060. Various local governments have put environmental governance in the forefront, but how effective it will be is not yet known, and a scientific and systematic study is urgently needed. More importantly, environmental governance is the primary task of the governmental public sector and an important part of evaluating the performance of the governmental public sector.

Scientific performance evaluation methods are a key part of implementing government performance evaluation of low-carbon governance. Scholars emphasize that government performance evaluation should choose different methods according to different evaluation purposes and result users [2, 3]. Among them, the DEA method shows unique advantages in evaluating the efficiency of public administrations and organizations and is widely used by scholars in the evaluation of government governance performance and energy and environmental efficiency [4–6], and scholars believe that the DEA method is an effective method that can combine information on the main services (outputs) and inputs provided by government service providers for measurement. However, the classical DEA model relies too much on the chosen indicators for efficiency evaluation and is slightly inadequate in dynamic evaluation capability. Therefore, this paper constructs a local government low-carbon governance performance evaluation index system from the perspective of local government low-carbon governance performance, using a combination of nonradial DEA method, RAM model and Malmquist index, and evaluates local government low-carbon governance performance statically and dynamically, with a view to providing the government with environmental governance formulation. It is intended to provide theoretical references for the government to make environmental governance decisions.

2. Methodology

In order to integrate energy, carbon emissions, and economic growth into the framework of efficiency analysis, we first need to construct a production possibility set that contains both desired and undesired outputs [7, 8]. In the literature, normal products are often defined as desired outputs, and pollutants emitted as byproducts of industrial production, such as waste gas and waste water, are defined as undesired outputs [9, 10]. Scholars refer to the technological structure of the relationship between outputs, including pollutant byproducts, and factor resource inputs as environmental technology [11]. Environmental technology is broken down by output, but the impact of input breakdown on the technology structure relationship is not considered. As the material basis for pollutant production, energy does not fit directly into the construct of best practice facets as do other resources [12]. Therefore, we further disaggregate production inputs into energy elements and common elements such as capital, equipment, and labor. Assume that each region uses N common inputs $x = (x1, \ldots, xN) \in R_N^+$ and M energy inputs $e = (e1, \ldots, eN) \in R_M^+$, which gets P desired outputs $y = (y1, \ldots, yN) \in R_P^+$ and I undesired outputs $b = (b1, \ldots, bN) \in R_I^+$. The production possibility set is simulated as

$$T = \left\{(x, e, y, b):\ (x, e) \text{ can produce } (\mathrm{y}, \mathrm{b}), x \in R_+^N, e \in R_+^M\right\}. \tag{1}$$

Assuming that the input and output vectors for each province are $J\,(xtj, etj, ytj, btj)$ at each period $t = 1, \ldots, T$, and $j = 1, \ldots, J$, we use the DEA extension model-RAM model to construct the optimal practice frontier (or reference technology) for China and compare the production of each province with the optimal practice frontier to measure the change in efficiency.

2.1. Efficiency Model Based on Desired Output. Scholars were the first to produce optimal practice bounds by constructing a nonparametric linear convex surface [13]. Since then, DEA methods represented by the CRS model based on constant payoffs to scale and the VRS model with variable payoffs to scale have followed the definition of technical efficiency, measuring the ability to achieve maximum output given various input factors or minimize inputs for a given level of output [14, 15]. The horizontal and vertical axes in Figure 1 are represented as two input factors $x1$ and $x2$, respectively, and SS represents the optimal production possible frontier that can be achieved without efficiency losses. The technical efficiency of decision unit j is equal to OJ'/OJ. In fact, the inefficiency of decision unit j consists of a combination of excess JJ' of input factors due to technical inefficiency and slack variables CJ' due to improper input factors, i.e., input factor X1 while maintaining the same output can continue to decrease from point J' to point C. The true efficiency of decision unit A should be OJ'/(JC + OJ'). Therefore, the traditional DEA ignores the interfactor allocation efficiency due to the radial limitation.

The RAM model characterizes TE based on the slackness of inputs and outputs with respect to the projection of the efficiency frontier and allows for free variation in the amount of input and output factors, instead of requiring the input and output factors to vary in the same proportion as in the traditional DEA solution [16, 17]. At the same time, the RAM model does not require the choice of calculating efficiency values from the input perspective or from the output perspective. More importantly, each input-output variable is summed in the objective function of the RAM planning model in a structure that allows for independent efficiency measures of desired or undesired outputs as well as integration of desired and undesired output efficiencies in the same model architecture. In addition, since the RAM constraints are equated, the slack in each element represents the difference between the current use of that element and the use in the optimal state of technology, facilitating the resolution of the sources of inefficiency. Assume that the jth province in period $t\ (j = 1, \ldots, J)$ has input and normal output slack relative to the production frontier projection of $S_n^x \geq 0, \forall_n; S_p^y \geq 0, \forall_p$. Thus, the efficiency model based on undesired output is [18]

$$\max\left\{\left(\sum_{n=1}^{N} R_n^x s_n^x + \sum_{p=1}^{P} R_p^y s_p^y\right) \middle| \begin{array}{c} \sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_{nj}, \forall n; \sum_{j=1}^{J} y_{pj}\lambda_j - s_p^y = y_{pj}, \forall p; \\ \sum_{j=1}^{J} \lambda_j = 1, \lambda \geq 0, \forall j; s_n^x \geq 0, \forall n; s_p^y \geq 0, \forall p; \end{array}\right\}. \tag{2}$$

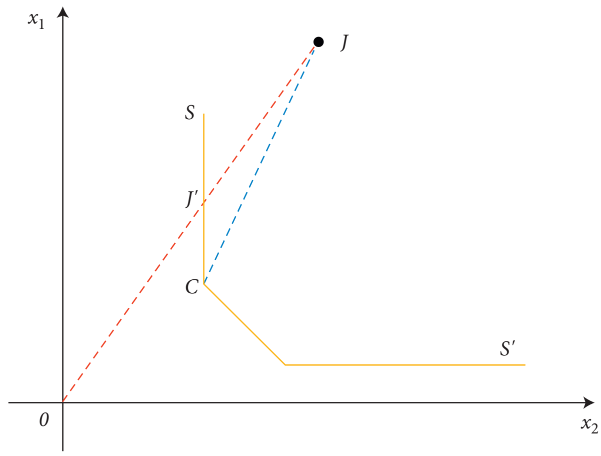

Figure 1: Traditional DEA model.

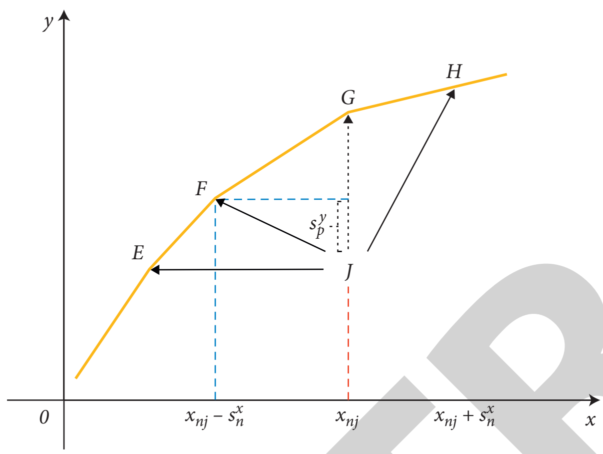

Figure 2: RAM efficiency (1).

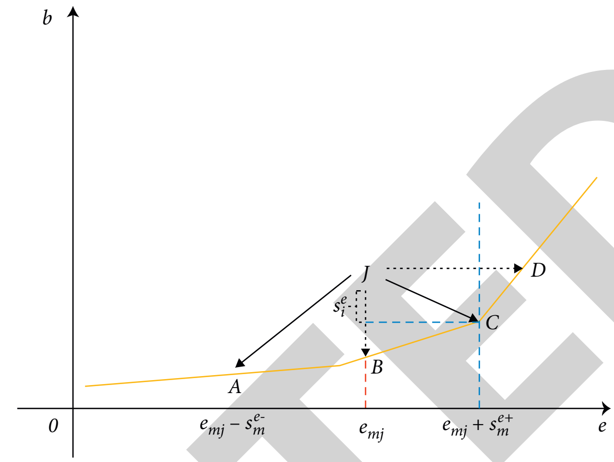

Figure 3: RAM efficiency (2).

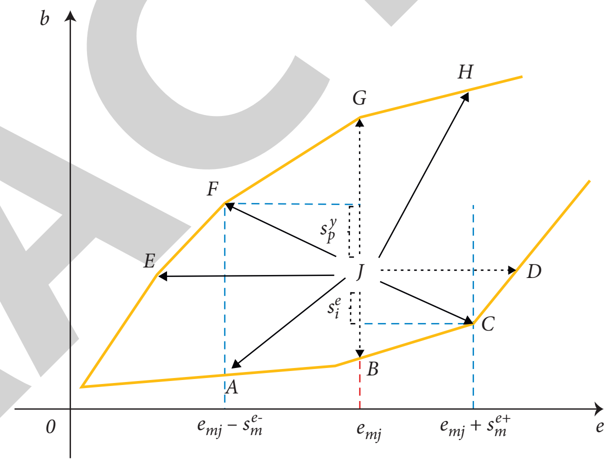

Figure 4: RAM joint efficiency.

The adjustment interval for slack (S_n^x, S_p^y) is defined based on the calculation of the extreme differences [max(*xnj*)-min(*xnj*)] and [max(*ypj*)-min(*ypi*)] for each input-output in all evaluated provinces.

$$R_n^x = \frac{1}{(N+P)\left[Max\left(x_{nj}\right) - Min\left(x_{nj}\right)\right]}, \tag{3}$$

$$R_p^y = \frac{1}{(N+P)\left[Max\left(y_{pj}\right) - Min\left(y_{pj}\right)\right]}. \tag{4}$$

From the definition of relaxation it follows that (S_n^x, S_p^y) lies between zero and the extreme difference.

$$0 \le s_n^{x\,*} = x_{nj} - \sum_{j=1}^{J} x_{nj}\lambda^* \le R_n^x, \tag{5}$$

$$0 \le s_p^{y\,*} = \sum_{j=1}^{J} y_{pj}\lambda^* - y_{pj} \le R_p^y, \tag{6}$$

where $*$ denotes the state in which the model achieves an optimal solution. x is the weight of the cross-sectional observation of the maximum relative efficiency possible in reality for each province when the model achieves an optimal solution. Let $\sum_{j=1}^{J}\lambda_j^t$, combined with the constraint that the weight variable λ_j^t is nonnegative, express the production technology as a variable payoff of scale, then the objective function value of linear programming to maximize the degree of inefficiency satisfies max(-) ∈ [0, 1], and the RAM economic efficiency indicator for province j in period t can be transformed into

$$0 \le \theta_p = 1 - \left(\sum_{n=1}^{N} R_n^x s_n^{x\,*} + \sum_{p=1}^{P} R_p^y s_p^{y\,*}\right) \le 1. \tag{7}$$

$\theta_p \in [0, 1]$ satisfies the boundedness of efficiency values with monotonic orderability. When all input slack and output slack are equal to zero, the objective function value is equal to zero, at which point $\theta_p = 1$, indicating that the region is located on the optimal practice boundary and reaches the technically efficient Pareto optimum. The principle of the economic efficiency model can be explained in Figure 2. In Figure 2, the horizontal axis denotes the input x, the total draw denotes the desired output y, and the arc EFG constitutes the optimal practice boundary of economic efficiency. For a province j, the current input-output point J of that province in the solution process needs to be projected along the JF direction, when economic output y tends to increase while input x tends to

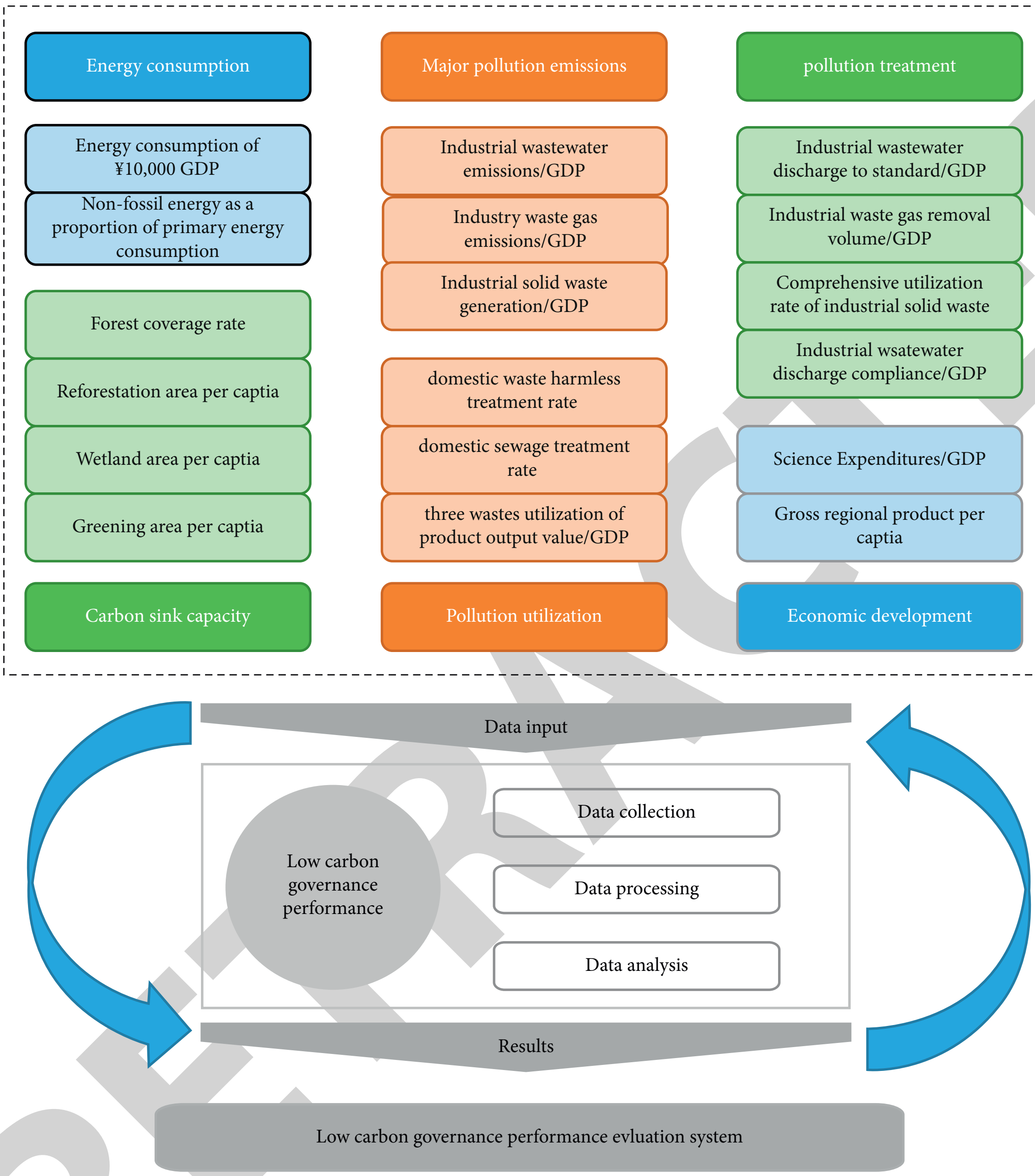

Figure 5: Local government low-carbon governance performance evaluation system.

decrease, and thus efficiency improves. The JH direction is an inefficient projection, when economic output y tends to increase, but the output increase is due to the increase in input factor x, not due to efficiency improvement.

2.2. Environmental Efficiency Model Based on Nondesired Outputs. Further environmental factors are incorporated into the model. The slack variable S_i^b is to represent the excess emissions of the ith pollutant. Combined with the negative sign constraint in front of the slack variables, this satisfies the inverse expectation that the production process tends to expand economic output and reduce environmental pollution. Traditional DEA treats energy as a common input due to perspective constraints [19–21]. The expansion of energy consumption is judged as a deterioration of efficiency, which leads to the fact that energy efficiency does not reflect the productivity impact of intersubstitution between energy factors and other factors or between different energy factors [22]. Scholars using nonradial DEA measures of energy efficiency have found a mixed effect, i.e., an increase in alternative energy use may lead to a contraction of a larger number of inputs of other types of energy, holding other inputs and outputs constant, and an expansion of a certain type of energy consumption does not necessarily indicate a deterioration in efficiency but may instead imply an improvement in efficiency. We construct energy slack variables S_m^{e-} and S_m^{e+} and combine the positive and negative sign constraints in front of the slack variables in the equation constraint to make them indicate two projection directions

Table 1: Low-carbon governance efficiency in China from 2015 to 2017.

Region	2015			2016			2017		
	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guizhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Xizang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.967	1.000	0.967	0.993	1.000	0.993	0.951	1.000	0.951
Shanxi	0.968	0.977	0.991	1.000	1.000	1.000	1.000	1.000	1.000
Neimenggu	0.880	0.902	0.975	0.861	0.872	0.987	0.873	0.875	0.998
Liaoning	0.752	0.816	0.921	0.722	0.808	0.894	0.884	0.900	0.981
Jilin	0.732	0.735	0.996	0.779	0.779	1.000	0.714	0.751	0.950
Heilongjiang	0.716	0.746	0.959	0.710	0.751	0.945	0.735	0.766	0.959
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Fujian	0.936	1.000	0.936	0.943	1.000	0.943	0.935	1.000	0.935
Jiangxi	0.879	0.884	0.994	0.911	0.911	1.000	0.900	0.913	0.987
Shandong	0.911	1.000	0.911	0.937	1.000	0.937	1.000	1.000	1.000
Henan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hubei	0.813	0.823	0.987	0.858	0.861	0.996	0.819	0.855	0.958
Hunan	0.814	0.815	1.000	0.927	0.929	0.998	0.935	0.937	0.998
Guangxi	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hainan	0.738	0.739	0.998	0.827	0.835	0.991	0.765	0.799	0.958
Chongqing	0.718	0.759	0.945	0.763	0.874	0.872	0.762	0.891	0.855
Sichuan	0.940	0.941	0.999	0.888	0.894	0.993	0.937	0.937	1.000
Yunnan	0.855	0.864	0.990	0.939	1.000	0.939	0.984	1.000	0.984
Shaanxi	0.842	0.880	0.957	0.825	0.872	0.945	0.847	0.888	0.953
Gansu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Qinghai	0.901	0.986	0.910	0.944	1.000	0.944	0.937	0.986	0.951
Ningxia	0.714	0.757	0.940	0.762	0.795	0.958	0.783	0.807	0.971
Xinjiang	0.911	0.986	0.924	0.888	1.000	0.888	0.969	0.970	1.000
Mean	0.903	0.923	0.978	0.919	0.941	0.975	0.927	0.944	0.980

of energy expansion and contraction; i.e., we define the environmental efficiency model for nondesired outputs as

$$\max\left\{\begin{array}{c}\left(\sum_{n=1}^{N}R_n^x s_n^x+\sum_{m=1}^{M}R_m^e\left(s_m^{e+}+s_m^{e-}\right)+\sum_{i=1}^{I}R_i^b s_i^b\right)\mid\sum_{j=1}^{J}x_{nj}\lambda_j\\ +s_n^x=x_{nj},\forall n;\sum_{j=1}^{J}e_{mj}\lambda_j-s_m^{e+}+s_m^{e-}=e_{mj},\forall m;\\ \sum_{j=1}^{J}b_{ij}\lambda j+s_i^b=b_{ij},\forall i;\sum_{j=1}^{J}\lambda_j=1,\lambda_j\geq 0,\forall j;\\ s_n^x\geq 0,\forall n;s_m^{e+}\geq 0,s_m^{e-}\geq 0,\forall m;s_i^b\geq 0,\forall i\end{array}\right\}. \tag{8}$$

When limiting the nondesired output to carbon emissions an environmental emitter, the RAM carbon environmental efficiency (CE) indicator for province j in period t is obtained as follows:

$$0\leq\theta_E=1-\left(\sum_{n=1}^{N}R_n^x s_n^{x*}+\sum_{m=1}^{M}R_m^e\left(s_m^{e+*}+s_m^{e-*}\right)+\sum_{i=1}^{I}R_i^b s_i^{b*}\right)\leq 1. \tag{9}$$

Figure 3 represents the environmental efficiency model. Assuming that input factor energy is applicable, the horizontal axis represents energy e and the vertical axis represents nondesired output b. For a province j, the point J corresponds to carbon emission cj and energy consumption emj. Since the energy mixing effect is considered, the RAM carbon environmental efficiency has two effective projection directions JA and JC, and accordingly the optimal practice boundary of environmental efficiency extends from the arc BC to CD. During the projection along the JA direction to the optimal boundary, both energy consumption and carbon emission tend to decrease. In the projection along JC direction towards the optimal boundary, the consumption of certain energy sources tends to increase but causes a decrease in carbon emissions due to the presence of the mixing effect.

2.3. Joint Efficiency Model Based on Dual Output. Economic efficiency (PE) assumes that there is no environmental control and pursues economic efficiency while ignoring environmental pollution, while carbon environmental efficiency (CE) meets the reverse expectation that the production process tends to reduce environmental pollution through the improvement of energy use and the optimal allocation of other factors of production, and its efficiency connotes the implementation of energy-saving and carbon-reducing environmental controls. The use of PE or CE alone

Table 2: Low-carbon governance efficiency in China from 2018 to 2020.

Region	2018			2019			2020		
	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
Jiangsu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.0000	1.000
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.0000	1.000
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guizhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Xizang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	0.938	1.000	0.938	0.942	1.000	0.942
Hebei	0.791	0.852	0.928	0.941	1.000	0.941	0.912	0.913	0.999
Shanxi	0.777	0.989	0.786	1.000	1.000	1.000	0.978	1.000	0.978
Neimenggu	0.764	0.858	0.891	0.925	1.000	0.925	0.810	0.856	0.947
Liaoning	0.912	0.912	1.000	0.875	0.884	0.990	1.000	1.000	1.000
Jilin	0.594	0.751	0.791	0.755	0.875	0.862	0.690	0.725	0.952
Heilongjiang	0.590	0.771	0.765	0.773	0.774	0.999	0.739	0.777	0.951
Zhejiang	1.000	1.000	1.000	0.988	1.000	0.988	0.960	1.000	0.960
Fujian	1.000	1.000	1.000	0.904	1.000	0.904	1.000	1.000	1.000
Jiangxi	0.804	0.915	0.878	0.870	0.882	0.987	0.831	0.877	0.947
Shandong	0.976	1.000	0.976	0.948	1.000	0.948	1.000	1.000	1.000
Henan	0.933	0.968	0.964	1.000	1.000	1.000	0.900	0.901	0.999
Hubei	0.680	0.817	0.832	0.799	0.800	0.999	0.859	0.861	0.998
Hunan	0.748	0.870	0.859	0.861	0.890	0.968	0.834	0.844	0.988
Guangxi	0.998	1.000	0.998	0.993	1.000	0.993	1.000	1.000	1.000
Hainan	0.622	0.809	0.769	0.741	0.773	0.959	0.790	0.812	0.973
Chongqing	0.628	0.845	0.743	0.715	0.738	0.968	0.716	0.771	0.929
Sichuan	0.722	0.918	0.787	0.897	0.904	0.993	0.821	0.884	0.929
Yunnan	0.783	0.948	0.825	0.908	0.912	0.995	0.897	0.897	0.999
Shaanxi	0.755	0.915	0.825	0.895	0.898	0.996	0.810	0.913	0.888
Gansu	0.949	1.000	0.949	1.000	1.000	1.000	1.000	1.000	1.000
Qinghai	0.866	0.936	0.925	0.872	0.879	0.992	0.758	0.829	0.914
Ningxia	0.672	0.799	0.841	0.805	0.816	0.987	0.794	0.806	0.986
Xinjiang	0.846	0.951	0.890	0.908	1.000	0.908	0.882	0.888	0.994
Mean	0.852	0.930	0.910	0.913	0.936	0.975	0.901	0.921	0.977

as indicators of economic development is clearly one-sided, so it is necessary to integrate them in a unified framework. The joint efficiency model is as follows:

$$\max \left\{ \begin{array}{c} \left(\sum_{n=1}^{N} R_n^x s_n^x + \sum_{m=1}^{M} R_m^e \left(s_m^{e+} - s_m^{e-} \right) + \sum_{p=1}^{P} R_p^y s_p^y + \sum_{i=1}^{I} R_i^b s_i^b \right) | \\ \sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_{nj}, \forall n; \\ \sum_{j=1}^{J} e_{mj}\lambda_j - s_m^{e+} + s_m^{e-} = e_{mj}, \forall m; \sum_{j=1}^{J} y_{pj}\lambda_j - s_p^y = y_{pj}, \forall p; \\ \sum_{j=1}^{J} b_{ij}\lambda_j + s_i^b = b_{ij}, \forall i; \\ \sum_{j=1}^{J} \lambda_j = 1,\ \lambda_j \geq 0, \forall j;\ s_n^x \geq 0, \forall n;\ s_m^{e+} \geq 0,\ s_m^{e-} \geq 0, \forall m; \\ s_p^y \geq 0, \forall p;\ s_i^b \geq 0, \forall i \end{array} \right\}. \tag{10}$$

The planning model of equation (10) considers both desired and undesired outputs, and accordingly, two optimal practice bounds can be constructed, one for carbon emissions and the other for economic growth. The joint efficiency can measure the degree of coupling between economic growth and energy-saving and carbon-reduction control, which reflects the low-carbon economy model of

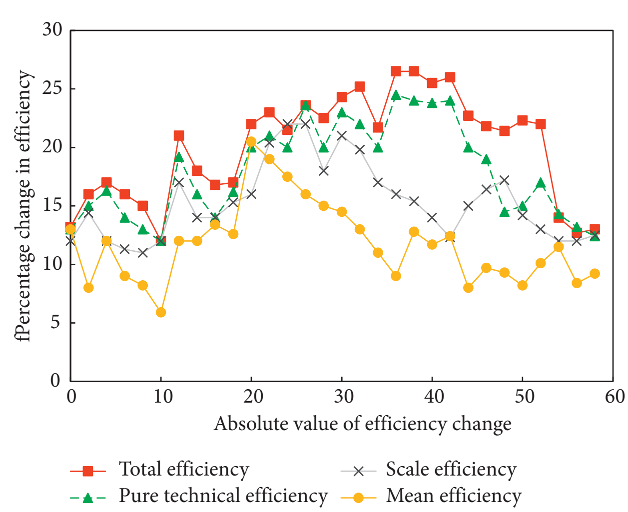

Figure 6: Trend change in efficiency distribution (TE, PTE, SE).

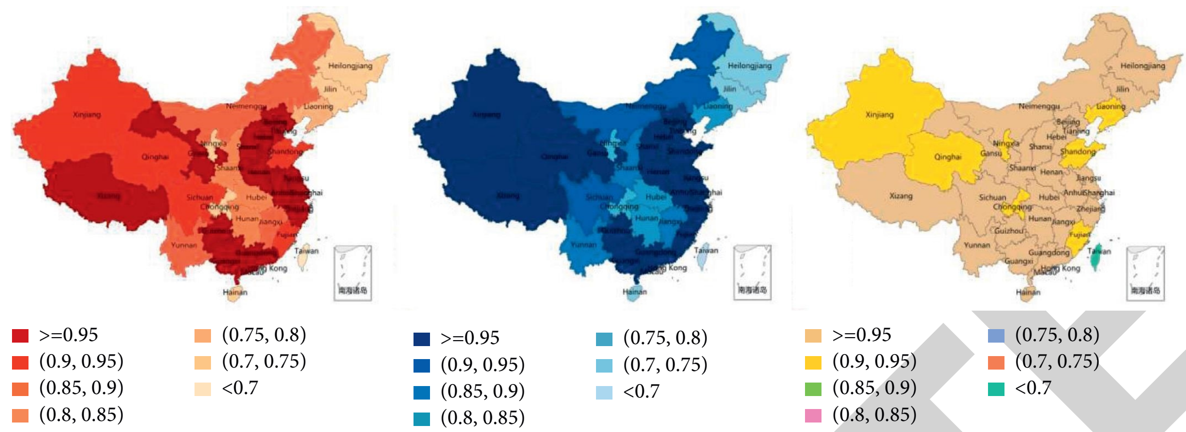

Figure 7: 2015 low-carbon governance efficiency in China (TE, PTE, SE).

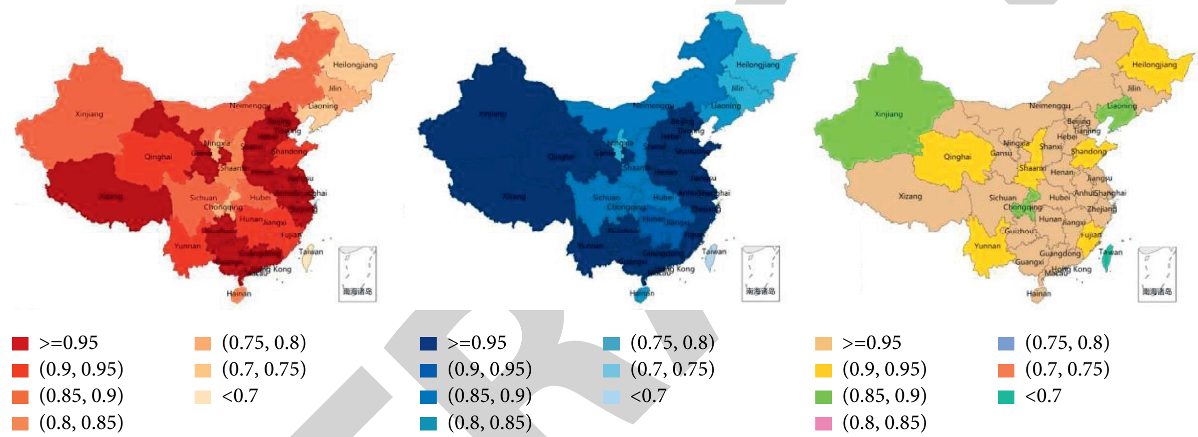

Figure 8: 2016 low-carbon governance efficiency in China (TE, PTE, SE).

win-win situation between economic and social development and ecological protection. At this point, the joint efficiency index of province j at time t can be calculated by the following equation:

$$0 \leq \theta_U = 1 - \left(\sum_{n=1}^{N} R_n^x s_n^{x*} + \sum_{m=1}^{M} R_m^e \left(s_m^{e+*} + s_m^{e-*} \right) + \sum_{p=1}^{P} R_p^y s_p^{y*} + \sum_{i=1}^{I} R_i^b s_i^{b*} \right) \leq 1. \tag{11}$$

This is because the existence of two optimal practice bounds that the efficiency projection of the decision unit in the joint efficiency model changes from the unilateral projection under the economic efficiency model and the environmental efficiency model to the bilateral projection. In Figure 4, the horizontal axis represents energy e and the vertical axis represents both normal output y and carbon emissions c. The arc ABCD represents the optimal practice boundary for carbon emissions and the arc EFG represents the optimal practice boundary for economic growth. The low-carbon economy model cannot unilaterally pursue economic growth at the expense of the environment, nor can it achieve carbon reduction at the expense of economic growth. Specifically, province J can improve economic efficiency along the JF direction, when normal output increases from *ypj* to *ypj*+ S_i^b while the energy consumption level decreases from *emj* to *emj*- S_m^{e-}. Second, the province J can improve the carbon environmental efficiency along the JC and JA projection directions. jC direction implies management improvement, which improves the energy use efficiency by optimizing the energy structure or applying low-carbon technology equipment, when the energy consumption level increases from *emj* to *emj*+ S_m^{e+}, but the carbon emission is reduced. ja direction is a natural emission reduction, which any region can achieve without management improvement by limiting. The JA direction is a natural reduction in energy consumption and carbon emissions that can be achieved in any region.

In sum, the revised DEA model can provide more accurate information and can also better predict the efficiency of low-carbon environmental governance policies.

2.4. Malmquist Index. Malmquist index is able to measure the dynamic efficiency of the environmental policy, which makes up for the shortage of traditional DEA models that can only analyze static efficiency. (x^t, y^t) denotes the input and output quantities in period t, $D_c^t(x^t, y^t)$ denotes the

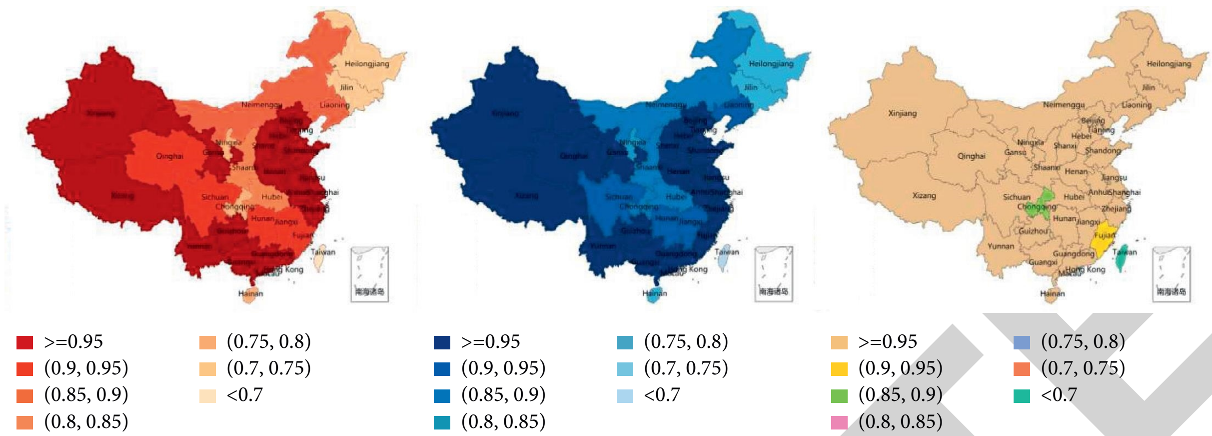

Figure 9: 2017 low-carbon governance efficiency in China (TE, PTE, SE).

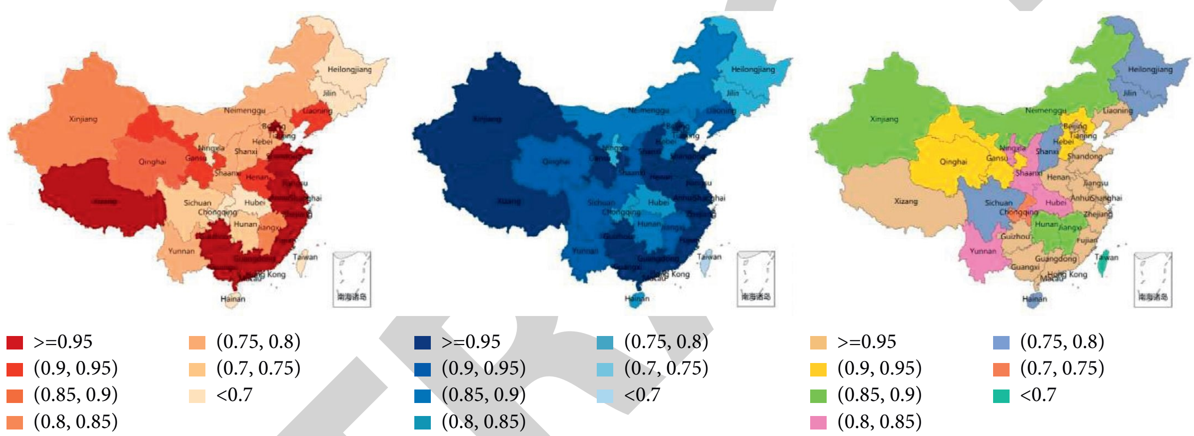

Figure 10: 2018 low-carbon governance efficiency in China (TE, PTE, SE).

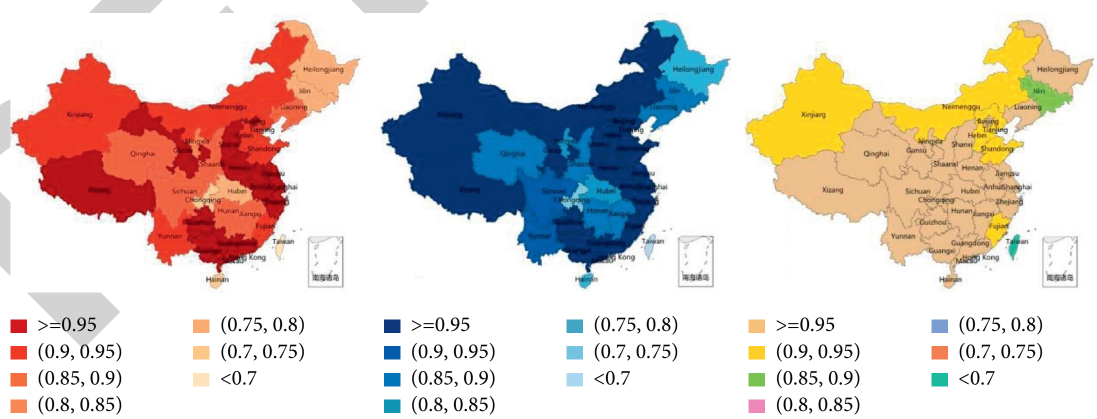

Figure 11: 2019 low-carbon governance efficiency in China (TE, PTE, SE).

output distance function under the technical conditions in period t, M^t denotes the value of change in efficiency from period t to period $t+1$ under the technical conditions in period t, and (x^{t+1}, y^{t+1}) denotes the input and output quantities in period $t+1$, $D_c^{t+1}(x^{t+1}, y^{t+1})$ denotes the output distance function under the technical conditions in period $t+1$, and M^{t+1} denotes the value of change in efficiency from period t to period $t+1$ under the technical conditions in period $t+1$. The Malmquist index formula is as follows [23]:

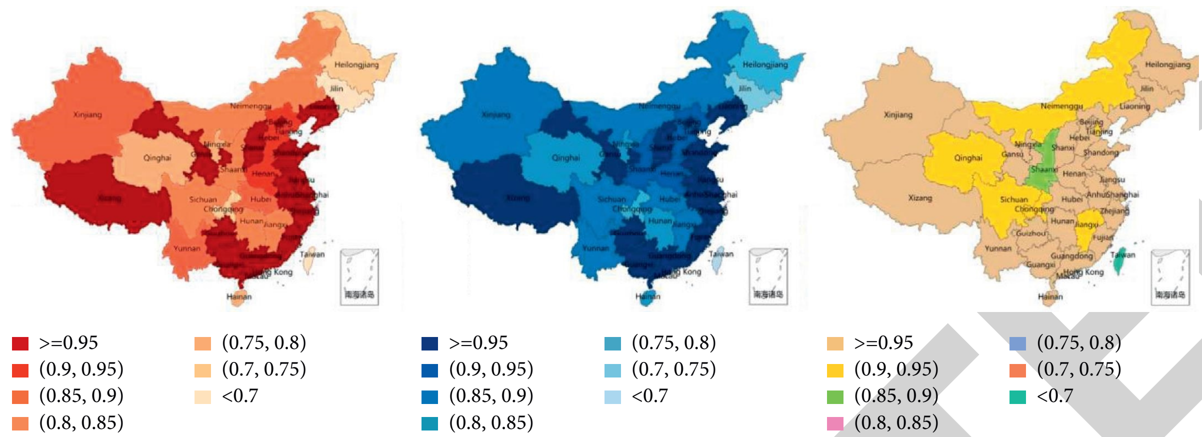

Figure 12: 2020 low-carbon governance efficiency in China (TE, PTE, SE).

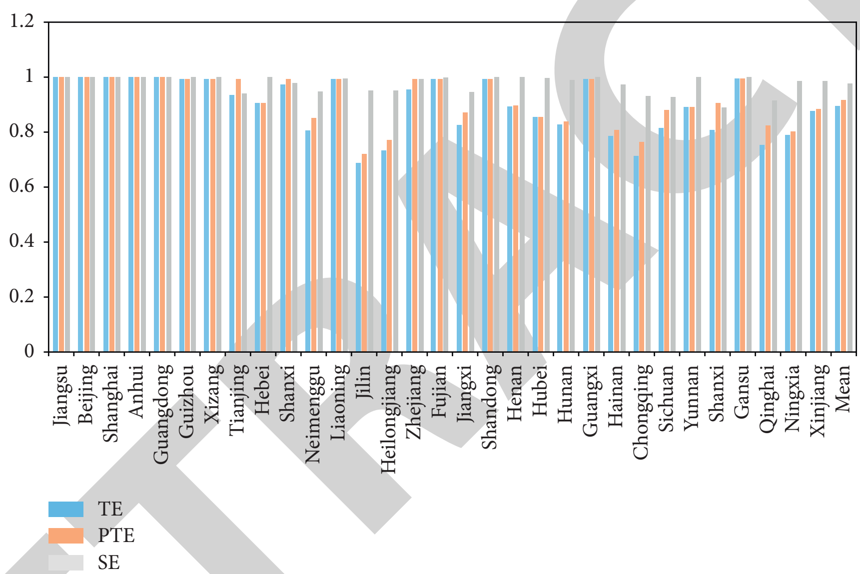

Figure 13: The efficiency values from in 2020.

$$
\begin{aligned}
TFP &= M^{t+1}\left(x^{t+1}, y^{t+1}, x^{t}, y^{t}\right) \\
&= \left(M^{t} \times M^{t+1}\right)^{\frac{1}{2}} \\
&= \left[\frac{D_c^{t}\left(x^{t+1}, y^{t+1}\right)}{D_c^{t}\left(x^{t}, y^{t}\right)} \times \frac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t}, y^{t}\right)}\right]^{\frac{1}{2}}.
\end{aligned}
\tag{12}
$$

When $TFP > 1$, it indicates an upward trend; when $TFP = 1$, it indicates no change; and when $TFP < 1$, it indicates a downward trend. Assuming constant returns to scale, TFP can be further decomposed into technical efficiency change ($EFFCH$) and technical progress change ($TECH$). Assuming variable returns to scale, EFFCH can be decomposed again into pure technical efficiency change ($PECH$) and scale efficiency change ($SECH$). Therefore, the TFP is calculated as

Table 3: The Malmquist index and its decomposition from 2015 to 2020.

Period	EFFCH	TECH	PECH	SECH	TFP
2015–2016	1.0024	0.9328	1.0029	0.9996	0.9349
2016–2017	1.0104	0.9061	1.0038	1.0063	0.9152
2017–2018	0.9140	1.0957	0.9849	0.9277	0.9955
2018–2019	1.1111	0.8570	1.0226	1.0863	0.9438
2019–2020	0.9682	1.0459	0.9708	0.9976	1.0109
Mean	1.0012	0.9675	0.9970	1.0035	0.9601

$$TFP = EFFCH \times \mathrm{TECH} = PECH \times SECH \times \mathrm{TECH}. \tag{13}$$

2.5. Index System Construction. Based on the extensive literature review, we selected energy consumption, major pollution emissions, pollution control and utilization, carbon sink capacity, and economic development as our index system. Figure 5 shows the index system this paper used, energy consumption. It is the goal of local governments to

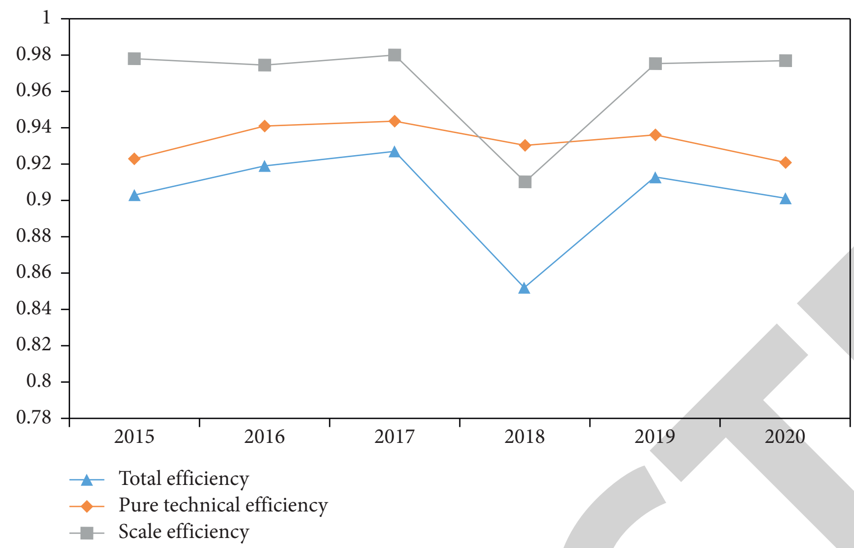

Figure 14: The mean efficiency values from 2015 to 2020.

achieve more economic output with less energy consumption by formulating relevant policies to guide, control, and regulate the behavior of social agents such as enterprises and the public, and it is used to reflect the government's function of promoting energy efficiency. Therefore, two main indicators are chosen for this dimension: energy consumption per 10,000 Yuan of GDP (equivalent value) and the share of nonfossil energy in primary energy consumption [24].

Major pollution emissions: The rapid development of China's economy over the past three decades is mainly attributed to the energy- and labor-intensive industrial sector, which has not only increased the emissions of various greenhouse gases such as carbon dioxide, but also led to serious environmental pollution. The industrial sector will inevitably play an important role in promoting a low-carbon, resource-efficient, and environment-friendly society in China. The environmental performance of industry is considered to be an important criterion for evaluating the environmental performance of local governments. Therefore, this indicator layer mainly selects industrial "three waste" emission indicators, including industrial wastewater emission, industrial gas emission, and industrial solid waste generation [25].

Pollution control and utilization: This is the ability of local governments to remove and utilize pollutants by investing certain human and financial resources to guide, control, and regulate the behavior of enterprises and the public and other social entities. The indicators of industrial "three wastes" emission in (2) correspond to the indicators of industrial "three wastes" pollution control and utilization adopted in this part, mainly including industrial wastewater discharge compliance, industrial waste gas removal, industrial solid waste comprehensive utilization rate, "three wastes" comprehensive utilization products output value, and "three wastes" comprehensive utilization products output value, with (4) carbon sink capacity, the value of the "three wastes" comprehensive utilization products, the domestic sewage treatment rate, the domestic waste harmless treatment rate [26].

Carbon sink capacity: This is the ability of local governments to store atmospheric greenhouse gases in biological carbon pools through land use adjustment and forestry measures. "Carbon sink" is the deposit of "carbon" in nature, and the largest deposit of "carbon" on Earth is forest vegetation. Therefore, in this paper, the indicators of green area per capita in built-up areas, wetland area per capita, afforestation area per capita in the current year, green coverage rate in built-up areas, and forest coverage rate are chosen to measure this function of local governments to enhance carbon sink capacity [27].

Economic development: The ultimate goal of low-carbon governance is to achieve sustainable economic development, and since technological progress is one of the determinants or controlling factors of a low-carbon economy, carbon productivity is also determined by the level of technology. Therefore, drawing on the research results of previous scholars, this paper selects the gross regional production value per capita, scientific expenditure, and the number of employees in science and technology services to measure the ability of local governments to promote economic development [28].

3. Results and Discussion

As shown in Tables 1 and 2, the total efficiency (TE) of low-carbon governance in Jiangsu, background, injury, Anhui, Guangdong, Guizhou, and Tibet is basically 1, reaching DEA effective. Tianjin, Zhejiang, Shandong, Henan, Guangxi, and Gansu are slightly less efficient. Jilin and Heilongjiang have lower total efficiency, with an average value below 0.72 and an annual minimum value less than 0.60. Figure 6 illustrates the trends in total efficiency, pure technical efficiency, and scale efficiency.

Overall, the provinces do not differ much and the gap tends to narrow gradually. In terms of pure technical efficiency (PTE), Jiangsu, Beijing, Tianjin, Shanghai, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Guangxi, Guizhou, Tibet, and Gansu all reached DEA effective. Hebei, Shanxi, and Henan out of technical efficiency are slightly inferior. The national pure base efficiency reached 0.933, indicating that the provincial governments in China operate at a high level of efficiency in low-carbon governance. In terms of scale efficiency (SE), Jiangsu, Beijing, Injury, Anhui, Guangdong, Guizhou, and Tibet all reach 1 per year, and the average value of scale efficiency of 23 provinces is above 0.95, indicating that the scale of low-carbon governance inputs in China has reached the optimal scale (Figures 7-12).

As shown in Figure 13, the total efficiency in Jilin and Chongqing is the lowest across the whole provinces. Jiangsu, Beijing, Shanghai, Anhui, and Guangdong have the highest efficiency getting the effective DEA.

Based on the measurement and analysis of government low-carbon governance TE, the evolutionary path of government low-carbon governance efficiency over time is further examined by Malmquist index and its decomposition, and the measurement results are shown in Table 3. The mean value of TFP is 0.9601, which indicates that government low-carbon governance performance is at a slight decline level. From the dynamic decomposition results, both EFFCH and PECH are greater than 1, indicating that technical efficiency change and pure technical efficiency change are the main reasons for the government's low-carbon governance efficiency improvement (Figure 14).

4. Conclusions

Environmental issues have become a hot issue in the field of national governance in China and gradually received the attention and importance of governments at all levels. China has mentioned the construction of ecological civilization in the report of the 18th National Congress and the report of the 19th National Congress, and ecological civilization has become a national strategic choice. However, the success of environmental governance work depends on not only the quantity and strength of environmental governance resources invested, but more importantly, the effectiveness of the use of environmental governance resources. In other words, the issue of environmental governance has become the most important aspect in evaluating government efficiency. So, what is the low-carbon governance performance of each province in China? This paper selects 31 provinces in China, constructs a corresponding performance evaluation index system, and further analyzes the low-carbon governance performance of local governments systematically from both static and dynamic aspects using a modified DEA model and Malmquist index. The findings of the study have important policy implications for government environmental governance. Practically, the results indicate that provincial governments cannot rely entirely on increasing the scale of environmental protection investment to improve the efficiency of low-carbon governance but should instead adopt a series of measures and approaches to stimulate public awareness of environmental protection, encourage social forces and enterprises to participate in environmental governance, and form a collaborative development pattern of individual and collective protection. Currently, there is still a need to continue to increase the investment in environmental governance, improve the environmental protection policy system, and improve efficiency and completion of policy implementation. Theoretically, this paper constructs a methodologically revised DEA model and also more accurately estimates the efficiency of low-carbon governance. In addition, this paper is also the first paper to evaluate the performance of various local governments nationwide, and the study fully demonstrates the regional imbalance and inadequacy of low-carbon governance. Of course, there are some shortcomings in this paper. First, although the selection of indicators in this paper is based on a large amount of literature, some important factors may be overlooked, and a more comprehensive evaluation of the government's low-carbon governance performance cannot be made. Second, the time span of the paper is only 6 years, and environmental governance is a long-term task, and analyzing low-carbon governance performance from a longer time span may lead to more findings. Finally, the DEA model used in this paper still has room for improvement, such as a DEA model that integrates environmental efficiency and economic efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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