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Super-SBM 및 Tobit 모델을 기반으로 한 중국지역 환경효율성 평가 및 영향요인 연구

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Evaluation of regional Eco-Efficiency and its influencing factors in China: Based on Super-SBM and Tobit model

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요 약 본 연구에서는 2011년부터 2021년까지 중국의 31개 성(省)급 행정구역을 연구 대상으로 삼았으며, 자본, 노동, 토지 및 자원 투입을 투입 변수로, GDP 및 녹색 범위를 예상 산출량으로, 폐수, 폐가스 및 고형 폐기물 등의 배출을 바람직하지 않은 산출물로 하고, 지역 환경효율성을 측정하기 위해 super-SBM 모형을 이용하였다. 외부 환경요인이 환경효율성에 미치는 영향을 분석하기 위해 토빗 회귀분석을 이용하였다. 그 결과 중국의 평균 환경효율성 수준은 낮았고 동부지역의 환경효율성은 다른 지역보다 높았으며 서부, 북동부 및 중부 지역에서 큰 차이가 있었다.

주제어 환경효율성, 지속가능성 평가, 초효율성, 토빗 모형, 중국의 31개 성

Abstract In this study, 31 provincial-level administrative regions in China from 2011 to 2021 were taken as the research objects, and the super-SBM model was used to measure the regional eco-efficiency with capital, labor, land and resource input as input variables, GDP and green coverage as the desirable outputs, and wastewater, waste gas and solid waste emissions as the undesired outputs. Tobit regression was used to analyze the effects of external environmental factors on eco-efficiency. The results showed that the average level of eco-efficiency in China was low, and the eco-efficiency in the eastern region was higher than that in other regions, and there were great differences in the western, northeast and central regions.

Key Words Eco-Efficiency, Sustainability assessment, Super-SBM, Tobit model, 31 province of China

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1. Introduction

As one of the world's most populous countries, China faces enormous environmental challenges. Large-scale industrialization and urbanization have led to severe problems such as air pollution, water pollution, and soil degradation. In recent years, the Chinese government has been increasing its investment in ecological governance and environmental protection, and governments at all levels have also continuously emphasized sustainable development, and formulated a series of ecological protection policies, including the construction of ecological civilization, emission reduction targets, and the formulation of environmental protection laws and regulations, in order to cope with environmental problems and pursue a balance between economic growth and environmental protection. From this point of view, eco-efficiency is the eternal theme of sustainable development, and how to accurately and systematically measure, evaluate and improve eco-efficiency has become the core issue.

After the report of the 18th National Congress of the Communist Party of China in 2012, the Chinese government put the construction of ecological civilization in a prominent position in the overall work, and the reports of the 19th and 20th National Congresses of the Communist Party of China once again elaborated on the specific goals of the construction of "Beautiful China" and further promoted green and low-carbon development. Therefore, in order to measure the changes of China's regional ecological environment in the past decade, this paper selects the data of each province from 2011 to 2021, takes 31 provincial-level administrative regions in China as the research object, constructs a scientific and reasonable input-output index system of eco-efficiency, and uses the undesirable Super-SBM model to calculate the eco-efficiency of each province. At the same time, the panel Tobit regression is used to analyze the impact of economic and social factors on regional eco-efficiency, and corresponding policy suggestions are put forward to promote economic growth and ecological balance from the perspective of optimizing resource use efficiency.

2. Theoretical Background

2.1 Eco-Efficiency

The concept of eco-efficiency was first proposed by Schaltegger and Sturm (1990) and refers to the efficiency with which ecosystems or human activities use resources to produce desired products or services and reduce adverse impacts on the natural environment [1]. Since then, many scholars have defined the meaning of eco-efficiency, and although the definitions vary, they all have in common how to maximize economic growth and resource efficiency while minimizing negative environmental impacts. At present, scholars' research on eco-efficiency mainly focuses on the definition of concepts, evaluation methods and specific applications. The relevant previous studies are shown in Table 1.

2.2 Efficiency evaluation and Super-SBM

Efficiency evaluation is a quantitative method used to measure and evaluate the level of output (or outcome) of an organization, business, project, or process under a given input condition to determine its resource utilization efficiency or technical efficiency. There are several methods of efficiency analysis, and one of the main methods is Data Envelopment Analysis (DEA). Charnes (1978) first proposed this DEA method to evaluate the efficiency of Decision Making Units (DMUs) [6]. However, the traditional DEA model is mainly based on radial perspective, which cannot eliminate the influence of relaxation variables, and the results may be wrong (Sun et al., 2021) [7]. In order to solve this problem, Tone (2001) proposed the Slacks-Based Measure (SBM) model. This method is a variant of DEA that is used to assess relative efficiency and take into account laxity or waste in decision-making

〈Table 1〉 Previous research on eco-efficiency

Author	Research interests	Main points
Schaltegger & Sturn (1990)	Definition of the concept of eco-efficiency	For the first time, eco-efficiency is quantitatively described as the ratio of economic value added to the environmental impact generated [1], bringing the environment and the economy into the same conceptual frame work.
Cramer & Loche (2001)		The definition of eco-efficiency should be carried out from the perspective of sustainable development, which mainly refers to the fact that human beings should control the ecological impact within the carrying capacity of the earth while meeting their own needs [2].
Huppes & Ishikawa (2005)		Eco-efficiency mainly describes the relationship between resource use and value production, and should reduce resource consumption and environmental pollution as much as possible on the basis of value creation [3].
Hahn, Figge, Liesen et al. (2010)		Eco-efficiency is the ratio between the added value of production and the added value of environmental impact, and is used to describe the relationship between value and environmental impact [4].
Matsumoto & Chen (2021)		The concept of eco-efficiency, as a practical tool for promoting sustainable development, is considered to play an increasingly important role in the study of reducing resource depletion and environmental degradation [5].
Aldieri et al. (2019)	Research on eco-efficiency evaluation methods	Eco-efficiency was measured in 10 European countries using a single ratio method using renewable energy as a percentage of total energy [6].
Mickwitz et al. (2006)		The index system method was used to measure regional ecological efficiency from three dimensions: economic, social, and natural [7].
Ganeghem et al. (2010)		Six environmental indicators were selected to measure the eco-efficiency of the steel industry using the indicator system method [8].
Dyckhoff & Allen (2001)		Using the data envelopment method, it is pointed out that the use of DEA to measure eco-efficiency can effectively avoid the problem of clarifying the weights of environmental performance indicators, and the measurement effect is relatively reasonable [9].
Gómez-Calvet, Conesa et al. (2016)		Based on the specific efficiencies of three air pollutants (carbon dioxide, sulfur dioxide, and nitrogen oxides), the eco-efficiency was measured using the relaxation free direction distance function in the data envelopment analysis framework [10].
Shah et al. (2020)		The data envelopment method was used to analyze the sustainability transformation of Ulsan metropolis in Korea under the 15-year eco-industrial development (EID) (2000-2015) [11].
Mirmozaffari et al. (2020)		The eco-efficiency of 24 cement companies from five developing countries was compared between 2014 and 2019 using the data envelopment method [12].
Moutinho & Madaleno (2021)		Using a data envelopment analysis (DEA), the ratio of GDP per capita to greenhouse gas emissions (GHG) is used to calculate the EU's Phase 1 eco-efficiency score in mid-27 years [13].
Rene (2007)	Research on eco-efficiency applications	Based on examples, the eco-efficiency of the mineral processing industry in Australia has been studied, and eco-efficiency is considered to be very important for environmental benefits [14].
Caiado et al. (2017)		The study of sustainable development from the perspective of eco-efficiency and the latest relationship between eco-efficiency and sustainable development have been constructed [15].
Ibáñez Forés et al. (2021)		The purpose of this study was to analyze how to ensure that Brazilian cities achieve medium- and long-term waste recycling based on the incorporation of feasible and available technologies using the LCA method [16].

units [8]. In the same year, Tone proposed the super-efficient SBM model to evaluate the effective DMUs of SBMs, so as to compensate for the lack of calculation of all DMU efficiency values. This model has also been widely used in the fields of management, economics, and operations research, and the relevant research results are shown in Table 2.

3. Research Design

3.1 Data Collection

This paper adopts the sampling method of census and selects 31 provincial-level administrative regions in Chinese mainland as the research sample, covering all

〈Table 2〉 Previous research on efficiency evaluation and SBM model

Author	Findings
Kim (2015)	The Non-Radial SBM and DEA Window models were used to compare and analyze the efficiency changes and efficiency stability of community credit cooperatives in different regions of Korea [20].
Jung (2022)	The DEA-SBM model was used to investigate the operational efficiency of the safety management system of 19 subsidiaries of Korean iron and steel enterprises, and improved measures to improve the safety management level were proposed [21].
Park (2016)	Using the DEA-SBM model and EM cluster analysis, the efficiency of the major suppliers in the automotive industry was analyzed using the three-year financial data and customer evaluation scores of 64 suppliers under the Automotive Chassis Parts Group as input-output variables [22].
Shi (2019)	The Super-SBM-DEA model and the Malmquist index were used to analyze the technical efficiency of China's cultural industry in detail, and a method to measure the efficiency of China's cultural industry was proposed [23].
Park (2015)	The efficiency of 13 tenants in the port logistics complex of Incheon Port and Busan Singang was analyzed using the CCR and BCC models, as well as the Super-SBM model, and the tenant operation efficiency of the port logistics hinterland was analyzed [24].
Zhao et al. (2022)	The SBM model was used to measure the agroecological efficiency of 31 provinces in China and analyze its spatial and temporal differences [25].
Sun et al. (2021)	The Super-SBM model was used to measure the ecological efficiency of provincial-level regions in China, and the Tobit regression model was used to reveal the internal driving factors [18].

provinces in Chinese mainland (except Hong Kong and Macao), with a total of 341 DMUs. In order to ensure the accuracy of the sample data, all input-output and influencing factor data were selected from the China Statistical Yearbook, China Environment Statistical Yearbook, China Energy Statistical Yearbook and China Fiscal Yearbook from 2011 to 2021.

3.2 Research models

3.2.1 SBM Model

In this paper, it refers to the Super-SBM model (Super Slacks-Based Measure) proposed by Tone (2001) [8], which is one of the DEA-derived models. Compared with the traditional DEA model, the undesirable outputs SBM model not only avoids the deviation caused by radial and angular measurements, but also considers the influence of undesired output factors in the production process, which can better reflect the essence of efficiency evaluation. Super-SBM further extends the traditional SBM model to more fully account for various efficiency levels and relaxation variables. Based on this, this study adopts a Super-SBM model based on non-radial and non-angular directions, and the basic form of the model is as follows:

$$\rho = min \frac{\frac{1}{q}\sum_{i=1}^{q}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{\mu_1+\mu_2}\left(\sum_{r=1}^{\mu_1}\frac{\bar{y}_r^g}{y_{r0}^g}+\sum_{l=1}^{\mu_2}\frac{\bar{y}_l^b}{y_{l0}^b}\right)}$$

$$\bar{x} \geq \sum_{i=1,\neq 0}^{n}\lambda_i x_i, \quad \bar{y}^g \leq \sum_{i=1,\neq 0}^{n}\lambda_i y_i^g$$

$$\bar{y} \geq \sum_{i=1,\neq 0}^{n}\lambda_i y_i^b, \quad \bar{x} \geq x_0, \quad \bar{y}^g \leq y_0^g, \ \bar{y}^b \geq y_0^b$$

$$\sum_{i=1,\neq 0}^{n}\lambda_i = 1, \ \bar{y}^g \geq 0, \lambda \geq 0$$

In the above formula, x、y^g、y^b represent the inputs of the decision-making unit, the desirable output terms and the undesired output terms, $\bar{x}$、$\bar{y}^g$、$\bar{y}^b$ represent the relaxation vectors of inputs, desirable outputs and undesired outputs, λ is the weight vector, and the subscript "0" in the model is the unit to be evaluated. The objective function value ρ is the eco-efficiency of the provincial-level administrative region, which is strictly monotonically decreasing with respect to, s^-、s^g、s^b. When $\rho \geq 1$, $\bar{x}$、$\bar{y}^g$、$\bar{y}^b$ are all 0, the decision-making unit is efficient; when $\rho < 1$, it indicates that the decision-making unit has an efficiency loss, and it is necessary to make corresponding improvements in input-output.

3.2.2 Tobit Model

Eco-efficiency is influenced by other factors in addition to the input-output indicators chosen. In order to understand the efficiency evaluation results more comprehensively, this paper constructs a regression model by taking the efficiency values obtained by the SBM model as the dependent variable and the influencing factors as the independent variables to explore the relationship between these efficiency values and various influencing factors. In addition, since the efficiency score calculated by the SBM model is limited to 0 to 1, a restricted dependent variable model, the Tobit model, is used for regression analysis [15]. The basic form of the model is as follows:

$$y_{it}^{*} = x_{it}\beta + \mu_i$$

$$y_{it} = \begin{cases} y_{it}^{*}, if \ \ y_{it}^{*} > 0 \\ 0, \quad if \ \ y_{it}^{*} \le 0 \end{cases}$$

Where y_{it} is the dependent variable i.e., the efficiency value, x_{it} is the independent variable i.e., the influencing factor, β is the parameter vector, y^{*}_{it} is the latent variable, perturbation term, μ_i Obeying the normal distribution of the mean is 0 and the variance is σ^2 where i and t represent the first i province and year i, respectively.

3.3 Variable Selection

3.3.1 Input and output variables

At present, scholars have made a rich attempt to select variables for eco-efficiency measurement, and the relevant previous research are shown in Table 3.

Referring to the existing prior research, this paper

〈Table 3〉 Previous research on input and output variables

Author	Inputs	Outputs (Desirable outputs; Undesirable outputs)	Models
Gómez-Calvet, Conesa et al. (2016) [10]	three air-pollutants (CO_2e, SO_2, NO_x): Nitrous Oxides (NO_x), Sulphur Dioxide (SO_2), Carbon Dioxide equivalent (CO_2e)	the Gross Domestic Product (GDP)	DEA
Shah et al. (2020) [11]	Land resources, Human resources, Energy resources	Gross Output	DEA
Moutinho et al. (2021) [13]	GFCF per capita, Labor per capita, Energy use/area, Electricity/area, Deviations temp	GDP per capita/(greenhouse gas emissions (GHG)/area)	DEA, FRM
Huang et al. (2014) [27]	Capital input(GFCF),Labor input(The total number of employees), Land input(The construction land area), Energy input(The total energy consumption)	The gross domestic product (GDP); Chemical oxygen demand (COD), Wastewater, Exhaust gas, SO_2, Dust, Solid waste, Smoke dust	GB-US-SBM
Zeng et al. (2021) [28]	Area of construction land, Number of people employed, Total water use, Energy consumption	GDP, Comprehensive utilization rate of solid waste, Urban green space area; SO_2, Smoke and dust emissions, Wastewater emissions	Super-SBM, Malmquist, Tobit
Sun et al. (2021) [18]	Investment in fixed assets, Regional water consumption, Urban floor area, Urban employment, Energy consumption	Regional GDP; Total Pollution Emissions Index	Super-SBM, Tobit
Chen (2022) [29]	Number of Jobs, Industrial and Agricultural Water Consumption, Energy Consumption, Agricultural Land, Construction Land	Revenue, Gross Domestic Product (GDP); Total Wastewater Discharge, Total Exhaust Gas Emissions, Solid Waste Generation	CCR, BCC, SEM, SAC, SDM, SLM
Ma et al. (2018) [26]	Total water use, Total energy consumption, Total number of persons employed in urban units, private enterprises and self-employed persons, Total investment in fixed assets, Area of urban construction land	Regional GDP, Green coverage area; Total industrial waste discharge, Total investment in environmental pollution control	Super-SBM, Malmquist, Tobit

GFCF: Gross fixed capital formation

〈Table 4〉 Indicators of input and output variables

Variable types	Variables	Description of the variables	Sign
Inputs	Capital input	Total Investment in Fixed Assets (100 million yuan)	I_1
	Labor input	Employed persons in urban units, private enterprises and self-employed persons (10,000 persons)	I_2
	Land input	Built-up area (km^2)	I_3
	Resource input	Electricity consumption (100 million kWh)	I_4
Desirable outputs	Economic benefits	Gross Domestic Product (100 million yuan)	O_1
	Environmental benefits	Green coverage rate of built-up area (%)	O_2
Undesirable outputs	Water pollution	Municipal sewage discharge (10,000 cubic meters)	O_3
	Air pollution	Sulfur dioxide emissions from exhaust gas (10,000 tons)	O_4
	Solid waste pollution	General Industrial Solid Waste Generation (10,000 tons)	O_5

selects capital input, labor input, land input and resource input as input indicators. At the level of capital investment, the academic community widely uses the fixed asset investment of the whole society to measure the investment amount of the current year, and this paper also follows this method. In terms of labor input, this paper measures labor input by the sum of urban employment, private enterprises, and self-employed people. The built-up area is used to measure land input. In terms of resource input, since electricity consumption has become the main form of energy consumption in China, it is a better choice to use electricity consumption as energy input, so the total electricity consumption is selected to represent the resource input. Since GDP represents the total value of all final goods and services produced in a given region over a certain period, it is possible to compare the economic performance between different regions. Therefore, at the output level, the GDP at constant prices and the green coverage rate of built-up areas in 2010 were selected as the desirable output indicators. In this paper, three indicators of urban sewage discharge, sulfur dioxide emissions in waste gas and general industrial solid waste generation were selected as undesired output indicators from the aspects of wastewater, waste gas and solid waste.

〈Table 5〉 Previous research on the influencing factors of eco-efficiency

Type / Previous research	Influencing factors									
	Ec	St	Fo	Po	Fi	Ur	En	Go	In	Le
Zeng et al. (2021) [28]	○	○		○			○	○		
Sun et al. (2021) [18]	○	○				○	○			
Chen (2022) [29]	○	○	○			○				
Ma et al. (2018) [26]		○		○			○			
Yang (2021) [30]	○	○	○	○			○	○		
Liu et al. (2020) [31]	○	○						○	○	
Zhou et al. (2018) [32]	○	○		○						○
Xue et al. (2021) [33]	○	○	○			○				○
Zhu et al. (2019) [34]	○	○		○			○	○		
Ren et al. (2020) [35]	○		○		○					○
Frequency	9	9	4	5	1	3	5	4	1	3

Ec: Level of economic development; St: Industrial structure; Fo: Utilization of foreign capital; Po: Population density; Fi: Financial development; Ur: Level of urbanization; En: Energy mix; Go: Government spending; In: Level of informatization; Le: Environmental legislation

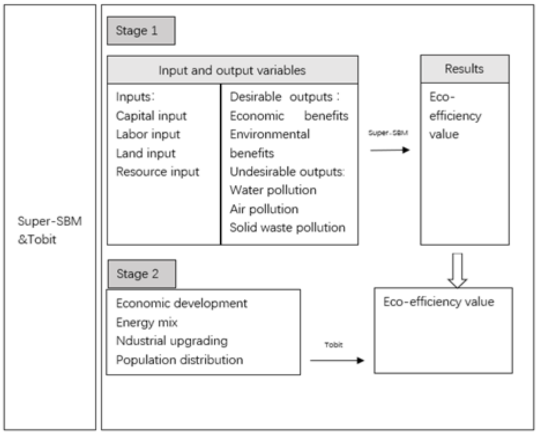
3.3.2 Influencing factor variables

There are many factors influencing the level of regional eco-efficiency, and from the existing research, the following factors are generally adopted by the academic community, as shown in Table 5.

From the analysis of the frequency of influencing factors, economic development can inject funds into strengthening regional environmental protection and ecological civilization construction; industrial structure represents regional resource allocation and consumption, which is closely related to resource consumption types and pollutant emissions; the use of fossil energy such as coal is the main cause of greenhouse gas emissions; population distribution makes labor, capital and other factors accumulate to space, which will also bring pressure to local resources and environment.

Therefore, in order to further explore the influencing factors of efficiency, this paper uses the Tobit regression model to analyze the impact of the following four related variables on eco-efficiency. The first is the factor of economic development, according to the existing economic theory, the level of economic development (Econ) is measured by GDP per capita. The second is the energy structure, which uses the proportion of total coal consumption in the total energy consumption of the region to represent the energy structure effect. The third is industrial upgrading, and the industrial structure is a direct factor affecting the ecological environment, which is measured by the proportion of the added value of the tertiary industry in the annual GDP of each province. The fourth is population distribution, with urban population density as a proxy variable. The selection and definition of variables are shown in Table 6.

In summary, this study uses the Super-SBM model to evaluate and compare the relative efficiency of eco-efficiency in China's provincial-level administrative regions. Then, the efficiency value obtained by SBM was taken as the dependent variable, and a series of economic and social factors expected to have an impact on the efficiency were selected as independent variables, and the Tobit model was used to test whether these factors had a significant impact on the ecological efficiency. A schematic diagram of the research model is shown in Figure 1.



[Fig. 1] Research model

4. Analysis of Results

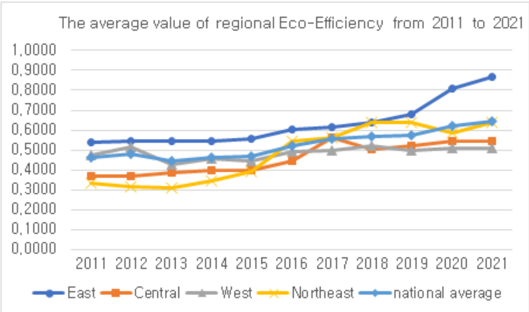
4.1 Eco-efficiency measurement and difference analysis

In this paper, the Super-SBM model was used to

〈Table 6〉 Influencing the selection of variables

Variable types	Variables	Definition of variables	Sign
Dependent variable	Local eco-efficiency	The efficiency value measured by Super-SBM	*EE*
Independent variable	Economicdevelopment	GDP per capita (RMB/person)	*PGDP*
	Energy mix	Coal consumption as a percentage of total energy consumption (%)	ES
	Industrial upgrading	Proportion of added value of tertiary industry in GDP (%)	TP
	Population distribution	Urban population density (people/ km^2)	PD

summarize the data of 31 provincial-level administrative regions in China to obtain the eco-efficiency values of each provincial-level region from 2011 to 2021, and the results were divided into eastern, central, western, and northeastern regions to calculate the mean distribution of the four major economic regions in China, as shown in Figure 2.



[Fig. 2] Trends in regional Eco-Efficiency in China from 2011 to 2021

In terms of the overall trends, the national average eco-efficiency has shown an upward trend year by year, which reflects the Chinese government's efforts in the construction of ecological civilization. However, the efficiency value is still below 1, indicating that there is still a long way to go to reduce environmental pollution, improve resource utilization efficiency and promote sustainable development. From the perspective of spatial distribution, the eco-efficiency gradually converges from east to west and from coastal to inland, and there are significant differences in eco-efficiency in different regions, as shown in Figure 1. In terms of the change trend, the eco-efficiency in the eastern region is higher than the national average and is at a high level, the eco-efficiency in the central and northeastern regions is gradually rising, which is basically consistent with the national trend, and the eco-efficiency in the western region is growing slowly and at a low level, which is also in line with the current situation of China's economic development.

The eco-efficiency of the eastern region continued to increase from 2011 to 2021, reaching 0.8651, showing a positive trend. This is due to the fact that the eastern region usually has a higher level of economic development, more resources and technology inputs, and more investment in environmental protection and sustainable development projects, so it is more eco-efficient. The eco-efficiency of the Tohoku region has improved significantly over the past few years, especially since 2016, due to more ecological protection and sustainable development measures taken by the region, such as the government's policy to revitalize the Tohoku region. The average eco-efficiency in the central and western regions is relatively low and fluctuates greatly over the entire time period. This is due to the fact that the central region has experienced rapid economic growth over the past decade, but the pace of environmental protection measures and technological upgrades has not kept pace with economic growth. The relatively low level of economic development and poor geographical conditions in the western region have limited resource input and technological upgrading.

4.2 Analysis of the causes of eco-efficiency loss

If the redundancy rate of the input item is >0, the rate of reduction of input needs is > that the redundancy rate of output needs to increase, and if the redundancy rate of undesirable output items >0 indicates the rate of reduction of undesirable outputs. In this study, the mean redundancy rate from 2011 to 2021 in the sample period was used as an example to analyze the causes of the loss of regional eco-efficiency in China from the perspective of input and output, and then to clarify the direction of improvement.

From Table 7, it can be seen that from the input level, Guizhou, Chongqing, Qinghai and Yunnan provinces have higher capital redundancy rates among input factors, indicating that these provinces are overly

Table 7 Input-output redundancy rate of Eco-Efficiency in 31 provinces in China from 2011 to 2021

Region	Province	Input redundancy rate (%)				Output redundancy rate (%)				
		I_1	I_2	I_3	I_4	O_1	O_2	O_3	O_4	O_5
Eastern region	Beijing	6.66	5.26	9.76	8.80	-6.92	35.35	6.32	90.34	41.96
	Tianjin	3.11	2.77	0.13	3.98	-3.48	1.05	0.01	45.40	6.27
	Hebei	23.72	0.00	0.00	9.60	-0.74	364.94	0.00	78.52	28.65
	Shanghai	0.00	0.00	1.00	0.95	-2.28	0.00	2.02	23.93	1.37
	Jiangsu	0.00	0.00	1.05	23.10	-0.42	783.74	0.00	80.42	3.07
	Zhejiang	20.89	5.13	21.21	35.63	-0.02	354.51	0.00	85.91	0.00
	Fujian	1.29	2.25	5.24	9.68	-1.06	55.80	0.00	74.06	19.35
	Shandong	0.00	0.00	11.97	4.56	-0.72	356.11	0.00	82.94	3.65
	Guangdong	5.41	0.66	18.62	37.79	0.00	1311.96	12.79	66.76	0.00
	Hainan	41.82	3.83	26.42	41.23	-0.25	0.00	7.93	75.51	17.83
	average	10.29	1.99	9.54	17.53	-1.59	326.35	2.91	70.38	12.22
Central region	Shanxi	19.39	15.57	19.01	22.86	0.00	237.44	0.00	88.41	62.84
	Anhui	22.46	9.57	6.80	29.73	0.00	760.77	0.00	80.68	51.10
	Jiangxi	12.49	12.09	22.80	10.68	0.00	139.19	0.00	90.34	69.35
	Henan	3.71	0.00	1.02	6.88	-1.44	346.81	0.00	85.77	5.15
	hubei	17.07	4.05	2.24	17.54	0.00	1093.04	0.86	80.97	34.89
	Hunan	27.75	0.92	0.22	6.49	-0.37	233.71	0.63	84.98	43.18
	average	17.14	7.03	8.68	15.70	-0.30	468.49	0.25	85.19	44.42
Western region	Inner Mongolia	13.94	0.00	11.12	0.24	-1.88	25.06	0.00	73.03	5.62
	Guangxi	32.17	17.06	0.91	47.37	0.00	538.34	4.03	87.73	62.87
	Chongqing	56.26	19.84	45.75	16.39	0.00	90.40	0.00	95.86	41.37
	Sichuan	4.49	0.63	3.98	5.79	0.00	891.77	0.00	79.20	2.84
	Guizhou	59.48	47.74	37.06	59.19	0.00	36.32	0.00	97.45	78.10
	Yunnan	43.99	18.71	21.99	45.10	0.00	226.47	1.05	92.44	76.11
	Tibet	4.79	3.90	5.34	0.48	-1.86	-7.89	2.90	10.18	13.86
	Shaanxi	25.31	3.63	1.53	19.35	0.00	220.04	0.00	90.85	55.96
	Gansu	36.48	33.14	52.34	55.71	0.00	0.00	1.95	94.36	57.18
	Qinghai	45.47	15.97	1.04	67.56	-0.36	0.00	2.81	75.15	83.15
	Ningxia	22.95	30.56	46.06	84.66	0.00	0.00	18.01	97.62	88.68
	Xinjiang	31.72	45.34	45.53	76.23	0.00	57.38	4.25	96.68	78.52
	average	31.42	19.71	22.72	39.84	-0.34	173.16	2.92	82.54	53.69
Northeast region	Liaoning	5.35	0.00	6.79	18.12	-1.05	511.76	4.25	79.16	44.33
	Jilin	18.21	27.42	27.90	7.30	0.00	332.45	0.00	90.03	57.67
	Heilongjiang	0.16	11.55	29.97	15.98	0.00	378.29	3.69	90.55	63.51
	average	7.91	12.99	21.56	13.80	-0.35	407.50	2.65	86.58	55.17

Note: The values marked in gray indicate the maximum redundancy rate of input-output indicators in each province.

dependent on capitalized assets industries and ignore other more flexible and efficient industries. Provinces such as Guizhou, Xinjiang, Gansu and Ningxia have higher rates of labor input redundancy, which are more dependent on labor-intensive industries and usually use large amounts of labor but have relatively low output. These regions may be more focused on traditional agriculture or primary industries, lacking advanced technology, automated production methods, skills and knowledge training to improve production efficiency. In terms of land input redundancy, Gansu, Ningxia, Chongqing, and Xinjiang provinces are relatively high, and urban planning and land use in these provinces may not be efficient enough, resulting in redundancy of land resources. Provinces such as Ningxia, Xinjiang, Qinghai and Guizhou may be overly reliant on energy-intensive industries, lack energy efficiency improvement measures and cleaner production technologies, and have an energy mix that favors the use of traditional and unclean energy, resulting in high energy waste.

From the perspective of desirable output, the redundancy rate of GDP in each province is not greater than zero, indicating that there is basically no shortage of GDP output. In terms of green coverage, Guangdong, Hubei, Sichuan and Anhui are obviously insufficient, especially Guangdong and Hubei. Therefore, these provinces should focus on protecting wetland ecosystems, strengthening urban greening planning, and increasing the positive impact of vegetation cover on air quality and ecosystems.

From the perspective of undesirable output, air pollution and solid waste pollution are the main pollutants that damage the regional ecological environment in China, and they are also important factors affecting eco-efficiency. Except for Tibet, air pollution redundancy is generally high, with an average air pollution redundancy rate of 79.52%.

in China, indicating that serious air pollution problems exist in all regions. Local governments should strictly supervise, optimize the industrial structure, strengthen policy incentives, improve the energy structure, raise environmental awareness, and encourage enterprises to take the initiative to reduce emissions to reduce air pollutant emissions. The provinces with high redundancy of solid waste pollution are Ningxia, Qinghai, Xinjiang and Guizhou, which may lack effective solid waste management measures, low waste reuse and recycling rates, low technical level, and insufficient environmental awareness of enterprises and residents, resulting in higher solid waste pollution. Ningxia and Guangdong provinces with significantly higher water pollution redundancy may be due to the fact that their urban wastewater treatment systems are not sufficient to cope with the growing demand for sewage discharge, and sewage treatment technology is not advanced or inefficient. In addition, specific industries and urbanization are also related to urban sewage discharge, such as Guangdong's well-developed manufacturing industry and high degree of urbanization, which bring greater pressure on water pollution.

In general, these input and output redundancies may be due to different policies and practices in different regions in terms of resource allocation, industrial structure, labor market and technological level. Therefore, this paper will further analyze the influencing factors of eco-efficiency.

4.3 Analysis of influencing factors of eco-efficiency

In this paper, the eco-efficiency values of 31 provinces in China from 2011 to 2021 were taken as the dependent variables, and the 4 influencing factors in Table 8 were used as explanatory variables.

In our study, the overall validity of the model was analyzed, and it can be seen from Table 8 that the likelihood ratio test p-value was less than 0.05, which indicated that the original hypothesis was rejected, that is, the explanatory variables put in the model construction were valid, and the model construction was meaningful.

The specific results can be analyzed:

From the national average, economic development, industrial upgrading and population distribution have a positive and significant impact on the national

Table 8 Tobit regression analysis results

Independent variables	Nationwide	East	Central	West	Northeast
PGDP	0.163** (9.347)	0.196** (7.943)	-0.004 (-0.109)	0.061** (3.871)	0.041 (1.084)
ES	0.015 (1.095)	-0.052 (-1.787)	-0.016 (-0.848)	0.053** (3.339)	-0.273** (-6.527)
TP	0.060** (3.816)	-0.017 (-0.526)	0.096** (3.722)	0.059** (3.738)	0.110** (3.369)
PD	0.023* (2.244)	0.085** (5.647)	0.113** (7.320)	-0.013 (-0.871)	0.137** (5.090)
log(Sigma)	-1.712** (-44.697)	-1.874** (-27.800)	-2.122** (-24.384)	-1.833** (-29.789)	-2.327** (-18.907)
Likelihood ratio test	$\chi^2(5)$=189.325, p=0.000	$\chi^2(5)$=125.279, p=0.000	$\chi^2(5)$=53.320, p=0.000	$\chi^2(5)$=72.263, p=0.000	$\chi^2(5)$=52.605, p=0.000
McFadden R^2	-18.503	4.989	-1.349	-1.945	-7.16
Dependent variable: *EE*					

*p<0.05, **p<0.01,The z-value is inside the parentheses

eco-efficiency, and the energy structure variables do not pass the significance test. The results highlight the key role of economic development, industrial upgrading, and population distribution in improving the country's eco-efficiency. However, due to the great differences in regional characteristics, resource distribution, economic development level and environmental policies, the external factors affecting the eco-efficiency of the four major economic regions in China are also different.

4.3.1 Eastern region

The impact coefficient of per capita GDP and urban population density on eco-efficiency is significantly positive, and has passed the significance test at least 5% level, while the proportion of added value of tertiary industry in GDP and energy structure have no significant impact on eco-efficiency in eastern China. As a relatively economically developed region in China, the eastern region has a high per capita GDP, a dense urban population and a diversified economic structure, which jointly promote the improvement of eco-efficiency. More resources are available in the region for environmental protection and technological innovation, resulting in improvements in environmental protection and resource efficiency.

4.3.2 Central region

The influence coefficient of the added value of the tertiary industry in GDP and urban population density on the eco-efficiency of the central region is significantly positive, and the per capita GDP and energy structure do not pass the significance level test. These results indicate that the relatively diversified industrial and population agglomeration effects in the central region are conducive to more efficient use of resources and environmental management, and improve eco-efficiency. Therefore, the central region should be encouraged to optimize and upgrade the industrial structure and develop to a cleaner, low-carbon, and high-value-added industry. Through scientific and rational urban planning and management, the improvement of urban population density is combined with sustainable development measures such as urban greening, which will help to improve the eco-efficiency of the region.

4.3.3 Western region

The level of economic development, energy structure and industrial upgrading have a positive and significant impact on the eco-efficiency of the western region, but population density has no significant impact on the eco-efficiency. The western region is rich in material resources, including energy resources. Positive measures in economic development, industrial upgrading and energy structure have led to the improvement of the overall eco-efficiency of the region.

The western region has a lower population density than the eastern region, which means that there is relatively less population pressure, which reduces the pressure on resources and the environment, so that the population density does not have a significant impact on eco-efficiency.

4.3.4 Northeast region

Industrial upgrading and population density have a significant positive impact on eco-efficiency in Northeast region, the proportion of coal consumption in total energy consumption has a significant negative impact on eco-efficiency, and per capita GDP has no significant impact on eco-efficiency. This reflects the positive results achieved in the development of services and urbanization in the Northeast region, which contributes to the improvement of eco-efficiency. However, the energy structure is still dependent on highly polluting forms of energy, such as coal, which may lead to large emissions and environmental pollution, which will adversely affect the ecological environment.

5. Conclusion

In this study, we took the panel data of 31 provinces in China from 2011 to 2021 as the research object, used the SBM model to measure the eco-efficiency, and used Tobit regression to test the impact of external environmental factors on the eco-efficiency. The results show that the average eco-efficiency of the 31 provinces in China during the statistical period is 0.526, which is at a low development level. From the regional perspective, the eco-efficiency is in the east> west> the northeast > the middle, and the eastern region has a more developed economic structure and industrial system, as well as a higher level of urbanization and environmental management measures, which promote the use of clean energy and reduce pollution emissions, so as to achieve a more sustainable and efficient ecological environment. Because of its dependence on resource-intensive industries, excessive exploitation of natural resources, irrational energy structure, and relatively lagging environmental protection policies, the western region has neglected ecological construction and has low eco-efficiency. The Northeast region is affected by heavy industry pollution, high-carbon energy dependence, problems with old industrial bases, resource depletion, difficulty in economic restructuring and population outflow, resulting in high environmental pressure. The central region has low eco-efficiency due to its high energy-intensive industries and relatively weak level of environmental management and technological innovation. From the perspective of local space, Shanghai, Tianjin, Fujian, Beijing and other provinces have better eco-efficiency, which may be inseparable from their geographical location, higher economic development level, better environmental protection policies and more optimized industrial and energy structure. The average eco-efficiency of Tibet is also relatively high, which is due to special reasons such as its relatively low degree of industrialization, low population density, and abundant ecological resources. However, the growth of regional eco-efficiency is relatively slow, the differences between regions are significant, and there is still a trend of uncoordinated and multipolar regional development. In addition, the results of influencing factor analysis show that the level of economic development, industrial upgrading and population density have a positive effect on the national eco-efficiency, but the influencing factors vary greatly in different regions.

In order to improve eco-efficiency, gradually narrow regional differences, and promote national sustainable development, the following suggestions are put forward: First, implement the strategy of sustainable development, promote the efficient use of resources and green economic growth through the combination of economic development and ecological protection, and achieve a win-win situation of economic and eco-efficiency. Second, we should speed up the adjustment of the energy structure, promote the increase in the proportion of clean energy, and reduce the dependence on highly polluting energy, so as to reduce environmental pollution and improve the eco-efficiency of the region. Third, promote industrial upgrading, encourage the development of high-tech and high value-added industries, reduce excessive exploitation of resources, and promote industries to be more environmentally friendly and sustainable, which will help improve eco-efficiency. Fourth, scientific planning and urbanization management should prevent excessive population gathering, reduce the consumption of land resources and environmental burdens, and create conditions for the improvement of regional eco-efficiency.

There are still some shortcomings in this study: first, in the selection of data, only four indicators with a greater impact on ecological efficiency are selected as influencing factors, but there are still some indicators with greater influence in different regions, which deserve more in-depth discussion. Second, when measuring the eco-efficiency value, the dynamic change and transfer law of the efficiency value have not been taken into account. Therefore, the next step of the research is to further expand the time range of the data, seek more scientific and perfect measurement indicators, construct a dynamic transfer model and a spatial regression model of ecological efficiency, and evaluate the provincial ecological efficiency in China in a more comprehensive way.

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