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Evaluation of Local Green Supply Chain Performance Using a Three-Phase Data Envelopment Analysis (DEA) Model and Malmquist Efficiency Framework

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ABSTRACT: *Regional synergistic development and low-carbon economy are China's current themes of regional economic development. Based on the background of low-carbon development, the relevant data of the Ningbo metropolitan area from 2017 to 2022 are selected, and the three-stage DEA model and Malmquist model are used to measure the low-carbon logistics efficiency of Ningbo metropolitan area region from static and dynamic dimensions, respectively. The results show that regional economic development, residents' consumption and research and development expenditures have a certain impact on the measurement of low-carbon logistics efficiency in Ningbo metropolitan area. From the static perspective, the low-carbon logistics efficiency of Ningbo metropolitan area has reached the ideal state. Still, the overall low-carbon logistics efficiency of Ningbo metropolitan area has not reached the optimal state. There is still room for upward mobility, mainly due to the fact that the scale of the logistics industry has room for upgrading. From a dynamic point of view, technological progress promotes the development of low-carbon logistics efficiency.*

Subject Categories and Descriptors: [C.2 COMPUTER-COMMUNICATION NETWORKS] Data communications [E.2 DATA STORAGE REPRESENTATIONS]

General Terms: Data Envelopment Analysis, Malmquist Efficiency Framework, Green Supply Chain Performance

Keywords: Ningbo metropolitan area, Three-stage DEA model, Malmquist model, Low-carbon logistics efficiency

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1. Introduction

In recent years, China's logistics industry has been developing rapidly, but behind the significant increase in the value added of the logistics industry, there are problems such as rapid energy consumption and serious pollution of the natural environment. Due to the current logistics industry energy consumption, low operational efficiency, increasing demand for the characteristics of the logistics industry has gradually become the focus of carbon emission reduction, in order to ensure the sustainable development of the logistics industry, to meet the "14th Five-Year Plan" period of the new requirements for the development of the logistics industry to promote the transformation and upgrading of the logistics industry, to get rid of the original high-energy consumption, the road of sloppy development, and to vigorously develop the green, efficient and low carbon logistics become an inevitable choice. Low-carbon logistics has become an inevitable choice. However, the logistics industry has become a major industry in China's energy consumption and carbon emissions (Wang et al., 2018). Doing a good job in the field of logistics to reach the carbon peak, carbon neutral is the logistics industry to achieve sustainable development is incumbent upon the responsibility of the logistics industry, but also China's economic high-quality development of an important issue. This study takes Ningbo metropolitan area as the research object, and promoting the green development of logistics industry in Ningbo metropolitan area is an important and realistic initiative for the green development of economy and the construction of ecological civilization. Analyzing the low-carbon logistics efficiency in Ningbo metropolitan area and exploring the differences and influencing factors of low-carbon logistics efficiency between Ningbo metropolitan area can help to explore the potential of low-carbon development of regional logistics, promote the green development of the coastal city cluster, and enhance the quality of ecological environment.

The efficient operation of logistics is the foundation and guarantee of regional economic development, and the synergistic development of logistics can effectively drive the effective flow of other factors of production, thus realizing the synergistic development of regional economy. However, the rapid development of the logistics industry is often accompanied by excessive energy consumption, serious pollution of the natural environment and other issues. Under the new economic development model, in order to realize the sustainable development of Ningbo metropolitan area, low-carbon logistics has become an inevitable choice. The synergistic development of Ningbo metropolitan area is an important strategic initiative in China, and it is of great significance for the logistics industry in Ningbo metropolitan area to realize low-carbon sustainable development by measuring the low-carbon logistics efficiency of Ningbo metropolitan area, studying the development of low-carbon logistics in Ningbo metropolitan area, and putting forward countermeasures and suggestions accordingly.

2. Literature Review

In recent years, domestic academic research on logistics efficiency mainly involves the national, provincial and industry levels, while most foreign scholars choose to start from the industry level, such as railroads, aviation and shipping. At present, the main methods for measuring logistics efficiency are parametric and non-parametric methods. In terms of parametric methods, Iris & Lam (2019) used stochastic frontier analysis (SFA) to conduct an empirical study on the logistics efficiency of listed logistics companies in different regions. Tamak et al. (2019) used stochastic frontier model as an analytical framework to conduct a comprehensive measurement of logistics efficiency in China. Cao & Deng (2019) used SFA model to measure the logistics efficiency of the five northwestern provinces of the Silk Road Economic Belt. In terms of nonparametric methods, Markovits-Somogyi & Bokor (2014) evaluated the logistics efficiency of 12 provinces in western China and analyzed their spatial structure by using the super-efficiency DEA method. Liu (2022) calculated the efficiency of the logistics industry in 30 regions under carbon constraints based on the super-efficiency DEA model. Tang & Tang (2018) utilized the DEA model to evaluate and analyze the logistics efficiency of Guangdong province Evaluating and analyzing the logistics efficiency of Guangdong Province, revealing the current situation and pattern of logistics efficiency in Guangdong Province. Gong & Jing (2019) analyzed the logistics efficiency of the Yangtze River Economic Belt by using the DEA-Malmquist index model, and put forward relevant suggestions based on its current situation. Zhang et al. (2014) measured and analyzed the efficiency of the logistics industry of the western region of China based on the three-phase DEA model after eliminating the influence of the external environment and the stochastic factors. The efficiency of the logistics industry in 30 provinces in China was measured and analyzed. Liu & Yang (2019) used the Malmquist-Luenberger index method to measure the efficiency of the logistics industry in 30 provinces in China, including the undesired outputs. Tang et al. (2018) used the DEA and Malmquist index model based on the provincial panel data of China's logistics industry to Measurement.

The study of low-carbon logistics efficiency has been widely emphasized by scholars. For example, Ramos et al. (2022) calculated the efficiency of the logistics industry under low carbon constraints and explained the influence of environmental variables on the low carbon logistics efficiency in each region. Cui & Varatharajan (2021) revealed the spatial evolution characteristics and influencing factors of the low carbon logistics efficiency in 30 regions, and researched the relationship between the industrial structure and the low carbon logistics efficiency, and pointed out that the industrial structure adjustment has an impact on the low carbon logistics efficiency. Some scholars have measured the low-carbon logistics efficiency of regions or industries. Zheng et al. (2021) used the traditional DEA model to measure the logistics efficiency values of Beijing, Tianjin and Hebei provinces and cities respectively, analyzed the reasons and put forward countermeasure suggestions. Khan (2021) used the ML model to measure the green total factor productivity of the logistics industry in 13 cities, and analyzed the impact of environmental regulation on the green total factor productivity. Although the research on logistics efficiency has achieved certain results, there are fewer studies on logistics efficiency measurement from an overall perspective while considering carbon constraint indicators. At present, research on low-carbon logistics mainly focuses on inter-provincial panel data. Data Envelopment Analysis (DEA) is widely used in the study of efficiency values. In the first stage of the three-stage DEA method, the DEA- bcc model is used to measure efficiency. However, this efficiency measure can only reduce the inputs and outputs of radial regulation in the same proportion, which is prone to produce multiple evaluation indicators with DEA efficiency value of 1. It is impossible to evaluate and rank them. Zhang et al. (2020), Strale (2019), and Radha et al. (2020)

all proposed a three-stage super-efficient SBM-DEA model (super-efficient SBM model with three-stage DEA methodology). The basic principle of the model is as follows: in the first stage, the ultra-efficient SBM model is used to measure the efficiency value instead of the traditional DEA-BCC model, which avoids the defects of the traditional method. The external disturbances of the low-carbon logistics efficiency are analyzed by using stochastic frontier analysis (SFA). And in the third stage, based on the adjusted input and output values, the ultra-efficient SBM model to measure the efficiency value again, and get the low-carbon logistics efficiency value that excludes the interference of environmental factors and random error terms.

Current research on efficiency measurement of logistics industry has achieved certain results, but the efficiency evaluation values obtained from most of the researches may have certain errors due to the fact that the traditional DEA method ignores the influence of the external environment and stochastic factors. Meanwhile, most of the studies on regional logistics efficiency have been conducted from an economic perspective. Low-carbon indicators such as energy and carbon emissions have not been fully considered. Therefore, on the basis of previous research results, this study chooses the three-stage DEA non-parametric method under the constraint of low-carbon indicators to construct the logistics efficiency analysis framework of Ningbo metropolitan area and measure the logistics efficiency of the three cities in Ningbo metropolitan area. On the one hand, it avoids the risk of wrong function setting due to the pre-estimation of the production function form by parametric method; on the other hand, it can eliminate the influence of environmental factors and random errors on the empirical results. Finally, on the basis of three-stage DEA static analysis, Malmquist model is applied to conduct dynamic analysis and put forward relevant suggestions to promote the sustainable development of low-carbon logistics in Ningbo metropolitan area. It has important theoretical and practical guidance value.

3. Methodology

Based on the existing literature, this study selects the relevant data of Ningbo metropolitan area in China from 2018 to 2022, and adopts the three-stage DEA model and Malmquist model to measure and analyze the low-carbon logistics efficiency of Ningbo metropolitan area in China from the static dimension and dynamic dimension, respectively. The three-stage DEA model is a measurement from the static spatial dimension, and the traditional DEA model ignores the influence of environmental factors and random variables on the results, and the results may be underestimated or overestimated, while the three-stage DEA model can effectively eliminate the influence of environmental factors on the efficiency model, and can objectively and scientifically present the real low-carbon logistics efficiency. Therefore, the three-stage DEA model is chosen to statically measure the low-carbon logistics efficiency of Ningbo metropolitan area in China.

3.1 Three-stage DEA analysis Method

Data envelopment analysis (DEA) is widely used in the calculation of efficiency, including the determination of tax collection and management efficiency. The three-stage DEA analysis method is formed after Fried's improvement, and a method for eliminating disturbance terms such as environmental factors is proposed to make the calculation of efficiency values more accurate.

The first stage: traditional DEA efficiency analysis. Using DEAP2.1 software, because in tax collection and management, the input of tax authorities is easy to control, so in the DEA model, input-oriented, rather than output-oriented, in the case of variable returns to scale, DEA-BCC model is selected to measure the initial tax collection and management efficiency value. The model is expressed as Eqs. (1)-(4).

$$\min\theta-\varepsilon(\hat{e}^T S^- + e^T S^+) \tag{1}$$

s.t.

$$\sum_{j=1}^{n} X_j\lambda_j + S^- = \theta X_0 \tag{2}$$

$$\sum_{j=1}^{n} X_j\lambda_j - S^+ = Y_0 \tag{3}$$

$$\lambda_j..0, S^-, S^+..0 \tag{4}$$

Among them, θ represents the effective value of efficiency, and the value range is [0, 1]. ε is non-Archimedean infinitesimal. $\hat{e}^T$ and e^T are single-valued vector spaces. $j=1,2...n$ denotes the decision making unit DUM. *X, Y* represents the input and output variables of DUM respectively. S^- and S^+ represent the slack variables in the second stage, which means output deficit and input redundancy respectively. θ represents the comprehensive efficiency value of the decision-making unit. λ denotes the weight.

If $\theta=1, S^-=S^+=0$, the decision-making unit is DEA effective. $\theta=1, S^-\neq 0,$ or $S^+\neq 0$, then the decision making unit is weak DEA effective. If $\theta<1$, the decision making unit is non-DEA efficient.

The second stage: SFA regression. Using Frontier 4.1 software and stochastic frontier analysis (SFA regression), the quantitative relationship between slack variables and input variables is measured. By quantifying environmental factors, the revised input variable value is obtained after eliminating the influence of environmental variables. The model is expressed as Eq. (5).

$$S_{ik} = f(Z_k, \beta^i) + V_{ik} + U_{ik} (i=1,2...m; k=1,2...n) \tag{5}$$

Among them, S_{ik} is the slack variable of the k^{th} input in the ith decision unit, Z_k is the environment variable, β^i is the coefficient of the environment variable, and $V_{ik} + U_{ik}$ is the mixed error term.

The third stage: the adjusted DEA efficiency analysis. In the second stage, DEAP 2.1 software is used to bring the constant output data and the input variable data excluding the influence of environmental factors into the DEA-BCC model to calculate the efficiency value, so as to obtain a more accurate tax collection and management efficiency value.

3.2. Malmquist index

The Malmquist index is a linear operation by setting a distance function, with multiple output and input variables. The distance function is defined by the method of directional output and input. Given the input variable matrix, the output distance function is defined as the optimal proportional term of the output variable matrix. In this study, the directional output variable is used to analyze the technological innovation efficiency of Chinese industrial enterprises. The distance function of the output variable is expressed as Eq. (6).

$$D_0(x,y)=\inf\{\delta:(x,y/\delta)\in p(x)\} \quad (6)$$

In the Eq. (6), the variables x and y are the input and output variable matrices respectively. is the possibility set of production efficiency. δ is the representative variable of the directional output efficiency index. Through nonlinear operation, it can be concluded that if y outside the set $p(x)$, then the function value will be greater than 1. If y it is at the boundary of the set $p(x)$, then the function value is equal to 1. If y it is contained in the set $p(x)$, then the value of the function will be less than 1. From t-1 to t period, the function expression of Malmquist index is shown as Eq. (7).

$$M_0\left(x_t,y_t,x_{t-1},y_{t-1}\right)=\left(\frac{D_0^{t-1}\left(x_t,y_t\right)}{D_0^{t}\left(x_{t-1},y_{t-1}\right)}\times\frac{D_0^{t}\left(x_t,y_t\right)}{D_0^{t}\left(x_t,y_t\right)}\right)^{1/2} \quad (7)$$

In the Eq. (7), $\left(x_{t-1},y_{t-1}\right)$ and $\left(x_t,y_t\right)$ represent the input and output vectors of t-1 and t periods. D_0^t and D_0^{t-1} represent two distance functions, then the output-oriented Malmquist can be expressed as Eq. (8).

$$M_0^{t-1}\left(x_t,y_t,x_{t-1},y_{t-1}\right)=\frac{D_0^{t-1}\left(x_t,y_t\right)}{D_0^{t-1}\left(x_{t-1},y_{t-1}\right)} \quad (8)$$

Based on this, the expression of the production efficiency M index of period based on the technical level of period is t-1 as Eq. (9).

$$M_{t-1,t}=\left(\frac{D_t^u(x_t,y_t)}{D_{t-1}^u(x_{t-1},y_{t-1})}\times\frac{D_{t-1}^u\left(x_{t-1},y_{t-1}\right)}{D_t^c\left(x_{t-1},y_{t-1}\right)}/\frac{D_t^u\left(x_t,y_t\right)}{D_t^u\left(x_t,y_t\right)}\right)\times\left(\frac{D_{t-1}^c\left(x_{t-1},y_{t-1}\right)}{D_t^c\left(x_{t-1},y_{t-1}\right)}\square\frac{D_{t-1}^c\left(x_t,y_t\right)}{D_t^c\left(x_t,y_t\right)}\right)^{1/2} \quad (9)$$

In the Eq. (9), $D^c\left(x,y\right)$ and $D^u(x,y)$ represent the distance function under the condition of constant returns to scale and variable returns to scale respectively. $\frac{D_t^u(x_t,y_t)}{D_{t-1}^u(x_{t-1},y_{t-1})}$ represents PTEC. $\frac{D_{t-1}^u\left(x_{t-1},y_{t-1}\right)}{D_t^c\left(x_{t-1},y_{t-1}\right)}$ represents SBC. The technical level change TC is $\frac{D_{t-1}^c\left(x_{t-1},y_{t-1}\right)}{D_t^c\left(x_{t-1},y_{t-1}\right)}\square\frac{D_{t-1}^c\left(x_t,y_t\right)}{D_t^c\left(x_t,y_t\right)}$, and the value of technical efficiency change EFFC = PTEC * SEC. When $M_{t-1,t}>1$, the production efficiency increases. When $M_{t-1,t}=1$, the production efficiency is fixed. When $M_{t-1,t}=1$, the efficiency decreases.

If the M index of any two years is calculated, for the input-output vector (x_t,y_t) of year t, four different distance functions are required: $D_0^{t-1}(X_{t-1},Y_{t-1})$, $D_0^{t-1}(X_t,Y_t)$, $D_0^t(X_{t-1},Y_{t-1})$ and $D_0^t(X_t,Y_t)$. The mathematical models of these distance functions calculated by DEA are shown as Eqs. (10)-(17).

$$(D_0^{t-1}(X_{t-1},Y_{t-1}))^{-1}=\max_{\theta\lambda}\theta \quad (10)$$

$$s.t.\begin{cases}-\theta y_{i,t-1}+Y_{t-1}\lambda..0,\\ x_{i,t-1}-X_{t-1}\lambda..0,\\ \lambda..0.\end{cases} \quad (11)$$

$$(D_0^t(X_t,Y_t))^{-1}=\max_{\theta\lambda}\theta \quad (12)$$

$$s.t.\begin{cases}-\theta y_{i,t}+Y_t\lambda..0,\\ x_{i,t}-X_t\lambda..0,\\ \lambda..0.\end{cases} \quad (13)$$

$$(D_0^t(x_{t-1},y_{t-1}))^{-1}=\max_{\theta\lambda}\theta \quad (14)$$

$$s.t.\begin{cases}-\theta y_{i,t-1}+Y_t\lambda..0,\\ x_{i,t-1}-X_t\lambda..0,\\ \lambda..0.\end{cases} \quad (15)$$

$$(D_0^{t-1}(X_t,Y_t))^{-1}=\max_{\theta\lambda}\theta \quad (16)$$

$$s.t.\begin{cases}-\theta y_{i,t-1}+Y_{t-1}\lambda..0,\\ x_{i,t}-X_t\lambda..0,\\ \lambda..0.\end{cases} \quad (17)$$

3.3. Index Selection

According to the development characteristics of the logistics industry in Ningbo metropolitan area, based on the principle of representativeness and data availability, the logistics efficiency analysis index is selected on the basis of consulting relevant literature. The input indexes are selected from the perspective of the three production factors of people, goods and goods, and are measured by the number of logistics industry employees, logistics industry fixed asset investment and logistics mileage. Since it is to measure the efficiency of low-carbon logistics, carbon dioxide emissions constrained by low carbon are added. The output indexes are selected from the perspectives of economic and social benefits. Economic benefits are measured by the output value of the logistics industry, and social benefits are measured by freight volume and cargo turnover. The environmental indexes are selected from four perspectives: economic level, consumption level, science and technology level and government support, which are measured by regional GDP, per capita consumption expenditure, R&D expenditure and financial expenditure of logistics industry. The index data of Ningbo, Zhoushan and Taizhou are directly or indirectly derived from China Statistical Yearbook and Zhejiang Statistical Yearbook. The overall index data of Ningbo metropolitan area draws on the processing methods of some scholars and is obtained by adding the index data of the three places (Table 1).

4. Results Analysis

4.1. Results of traditional DEA analysis in the first stage

Using the obtained index data, the DEAP2.1 analysis software is used to select the BCC model, and the comprehensive efficiency, pure technical efficiency and scale efficiency values of the low-carbon logistics industry in Ningbo metropolitan area without eliminating environmental factors and random interference errors are obtained (Table 2).

From the perspective of comprehensive efficiency, the comprehensive efficiency of Ningbo in 2021 is 0.994, which does not reach the production frontier, and the annual comprehensive efficiency of the remaining years is 1, which reaches the production frontier; the comprehensive efficiency of Zhoushan City in 2019 and 2021 was 0.991 and 0.991, respectively, which did not reach the

Index types	Index name (unit)	Index description
Input index	Number of employees in the logistics industry (per)	Including railway, road, water, aviation and pipeline transportation, multimodal transport, transportation agency, loading and unloading handling and warehousing industry, postal industry, the number of employees, the original data added to the calculated results
	The total investment in fixed assets of the logistics industry (billion RMB)	Transportation, warehousing, postal industry investment in fixed assets
	Logistics mileage (km)	Transportation, warehousing, postal industry investment in fixed assets
	CO_2 emissions (million tons)	Represents low carbon constraints
	Gross logistics industry production value (billion RMB)	Gross production value of transportation, warehousing and postal services
Output index	Freight volume (million tons)	Total freight volume of railways, highways, waterways, civil aviation and pipelines
	Turnover of goods (billions of tons of kilometers)	Total freight turnover of railways, highways, waterways, civil aviation and pipelines
	Regional GDP (billions RMB)	The regional economic level
	Per capita consumption expenditure of residents (RMB)	The regional consumption level
Environment variable	R&D expenditure (billion RMB)	The level of regional science and technology
	Logistics industry fiscal expenditure (billion dollars)	The government support, with regional transportation expenditure instead

Table 1. Index of low carbon logistics efficiency

Name	Minimum value	Maximum value	Mean value	Standard deviation	median
Total water resources (billion cubic meters)	23257	32466	27773	2531	27958
Water resources per capita (Cubic meter per person)	1729	2339	2048	161	2060
Total water supply (billion cubic meters) Total water use (billion cubic meters)	5320	6183	5920	223	6016
Per capita water consumption (Cubic meter per person)	5320	6183	5920	223	6016
Number of wastewater treatment facilities (sets)	412	454	437	13	442
Total industrial wastewater discharge (10,000 tons)	65128	106832	86355	12882	86355
Industrial wastewater discharge standard (10,000 tons)	2122527	2768702	2506383	174371	2506383
Chemical oxygen demand emissions from industrial wastewater (10,000 tons)	1892891	2803780	2402731	255591	2402731
Ammonia nitrogen emissions from industrial wastewater (10,000 tons)	286	555	416	83	416
Domestic sewage discharge (10,000 tons)	3	53	21	17	21
Chemical oxygen demand emissions in domestic sewage (10,000 tons)	2470115	5762299	4095114	1042822	4095114
Ammonia nitrogen emissions from domestic sewage (10,000 tons)	803	887	841	18	838
Total planted area (10,000 hectares)	89	103	98	4	99
Total investment in environmental pollution control (100 million RMB)	360	912	613	144	600
Investment in industrial pollution control (ten thousand RMB)	1628	13342	7402	3779	8254
	2218281	9976511	5525777	2002774	5004573

Table 2. The first stage DEA analysis of low carbon logistics efficiency results

production frontier. The annual comprehensive efficiency of the remaining years was 1, which reached the production frontier. The comprehensive efficiency of Taizhou in 2019 and 2020 was 0.992 and 0.989, respectively, which did not reach the production frontier. The annual comprehensive efficiency of the remaining years was 1, which reached the production frontier. In terms of the average value of comprehensive efficiency, Taizhou is relatively low at 0.9962. Secondly, Zhoushan is 0.9964, Ningbo is 0.9988, Ningbo, Zhoushan and Taizhou are close to the production frontier. Combined with the average value of pure technical efficiency and scale efficiency, the reason why the comprehensive efficiency of Beijing-Tianjin-Hebei region is DEA strong and effective comes from the high scale efficiency of low-carbon logistics.

From the perspective of pure technical efficiency, the pure technical efficiency of low-carbon logistics in Ningbo,

Item	Particular year	Technical benefit TE	Scale efficiency SE (k)	Comprehensive benefit OE (θ)	Relaxation variable S-	Relaxation variable S	Validity
Ningbo	2018	1	1	1	0	0	DEA strong efficiency
Ningbo	2019	1	1	1	0	0	DEA strong efficiency
Ningbo	2020	1	1	1	0	0	DEA strong efficiency
Ningbo	2021	0.995	1	0.994	0.012	248.246	NON-DEA effective
Ningbo	2022	1	1	1	0	0	DEA strong efficiency
Zhoushan	2018	1	1	1	0	0	DEA strong efficiency
Zhoushan	2019	0.992	0.999	0.991	0.18	1.527	Non-DEA effective
Zhoushan	2020	1	1	1	0	0	DEA strong efficiency
Zhoushan	2021	0.996	0.995	0.991	0.354	3.963	Non-DEA effective
Zhoushan	2022	1	1	1	0	0	DEA strong efficiency
Taizhou	2018	1	1	1	0	0	DEA strong efficiency
Taizhou	2019	0.994	0.999	0.992	0.026	8.816	Non-DEA effective
Taizhou	2020	0.99	0.999	0.989	0.07	0	Non-DEA effective
Taizhou	2021	1	1	1	0	0	DEA strong efficiency
Taizhou	2022	1	1	1	0	0	DEA strong efficiency

Variable	The relaxation variable of the number of employees in the logistics industry	Logistics industry total investment in fixed assets slack variables	Logistics mileage relaxation variable	Carbon dioxide emissions relaxation variable
Constant	17.281**(2.703)	-3.020(-0.723)	-0.786**(-4.431)	-0.028(-0.292)
Regional GDP	29.057**(11.165)	27.562**(16.209)	-0.914**(-12.657)	0.130**(3.342)
Per capita consumption expenditure of residents	-0.001**(-3.076)	0.000**(3.326)	0.000**(3.893)	0.000(0.613)
R&D expenditure (billion RMB)	-0.004(-0.539)	0.115**(24.747)	0.005**(27.162)	0.010**(94.817)
Logistics industry financial expenditure	-0.000(-0.539)	0.011**(24.747)	0.001**(27.162)	0.001**(94.817)
Gamma	0.981**	0.998**	0.995**	1**
Sigma-squared	132.103**	1105.995**	481.529**	5062.611**
LR	8.8**	8.4**	9.3**	14.1**

Note: *p<0.05, **p<0.01.

Table 3. Model regression results

Zhoushan and Taizhou is close to the production frontier, and most of the annual efficiency value is 1. The production frontier is DEA effective, indicating that the logistics resources of Ningbo, Zhoushan and Taizhou are fully utilized. From the perspective of scale efficiency, the pure technical efficiency of low-carbon logistics in Ningbo, Zhoushan and Taizhou is close to the production frontier. In most years, the efficiency value is 1, which reaches the DEA strong efficiency of the production frontier, indicating that the scale of logistics industry in Ningbo, Zhoushan and Taizhou is gradually reasonable.

4.2. The second stage of SFA model regression

In order to eliminate the impact of environmental factors on the efficiency of low-carbon logistics, the SFA regression model is used. The dependent variables are the number of employees in the logistics industry, the total investment of fixed assets in the logistics industry, the logistics mileage and the carbon dioxide emissions. The independent variables are regional economic level, consumption level, science and technology level, government-supported regional GDP, per capita consumption expenditure, R&D expenditure and logistics industry financial expenditure. With the help of Frontier4.1 software for SFA regression, if the regression coefficient is positive, the increase of the environmental variable value will cause the redundancy of the input variable to cause waste, and the regression coefficient is negative, indicating that the increase of the environmental variable value will reduce the input variable and reduce the waste. The model regression results are shown in Table 3.

The gamma value is greater than 0.5 and passes the significance test at the level of 1% (Table 3). The LR one-sided likelihood ratio test effectively rejects the OLS estimation results, so it can be concluded that the SFA estimation results are credible. The gamma values are all above 0.98, infinitely close to 1, indicating that the internal ineffective management greatly affects the slack variables, and the influence of the random error term is negligible. SFA regression analysis shows that the external environment has a significant effect on the slack variables

Item	Particular year	Technical benefit TE	Scale efficiency SE (k)	Comprehensive benefit OE (θ)	Relaxation variable S-	Relaxation variable S	Validity
Ningbo	2018	1	1	1	0	0	DEA strong efficiency
Ningbo	2019	1	1	1	0	0	DEA strong efficiency
Ningbo	2020	1	1	1	0	0	DEA strong efficiency
Ningbo	2021	0.998	0.999	0.998	2992.745	226.161	Non-DEA effective
Ningbo	2022	1	1	1	0	0	DEA strong efficiency
Zhoushan	2018	1	1	1	0	0	DEA strong efficiency
Zhoushan	2019	1	1	1	0	0	DEA strong efficiency
Zhoushan	2020	1	1	1	0	0	DEA strong efficiency
Zhoushan	2021	1	1	1	0	0	DEA strong efficiency
Zhoushan	2022	1	1	1	0	0	DEA strong efficiency
Taizhou	2018	1	1	1	0	0	DEA strong efficiency
Taizhou	2019	1	1	1	2.654	7.302	Non-DEA effective
Taizhou	2020	1	1	1	0	0	DEA strong efficiency
Taizhou	2021	1	1	1	0	0	DEA strong efficiency
Taizhou	2022	1	1	1	0	0	DEA strong efficiency

Table 4. Results of the third stage DEA analysis

of the input factors of the logistics industry in Ningbo metropolitan area, so the adjustment of the input variables is particularly important.

4.3. Results of the third stage DEA analysis

From the analysis of the second stage, it can be seen that the environmental variables have different effects on different input slack variables. The effect of environmental factors leads to a large deviation in the performance of low-carbon logistics efficiency, so the input variables need to be adjusted. The adjusted input variables are analyzed by DEA again, and compared with the first stage. If the efficiency value increases, the environmental factors have a negative impact. If the efficiency value decreases, the environmental impact has a positive impact (Table 4).

By comparing the data of Table 2 and Table 4, it can be seen that after data adjustment, except for Ningbo City in 2021 and Taizhou City in 2019, Ningbo City, Zhoushan City and Taizhou City in 2018 and 2022. The comprehensive efficiency, pure technical efficiency and scale efficiency of low-carbon logistics are all 1, which is DEA effective. It shows that the low-carbon logistics efficiency of each of the three cities in Ningbo has achieved the optimal output of the current input, the logistics resources are fully utilized, and the logistics scale is gradually reasonable. The calculation results of comprehensive efficiency, pure technical efficiency and scale efficiency of low-carbon logistics have different degrees of change before and after adjustment. Among them, all the comprehensive efficiency values of Ningbo, Zhoushan and Taizhou have been improved to varying degrees, indicating that environmental factors have a negative effect on the efficiency of low-carbon logistics in Ningbo, Zhoushan, Taizhou and Ningbo. This is because the location advantage of Ningbo metropolitan area is significant, and the level of government support and science and technology is relatively leading. However, in the case of diminishing returns to scale, the positive external environment will not promote the development of logistics. The value of logistics efficiency does not rise but falls, and other values also change to a certain extent, which fully shows that environmental factors have a certain impact on the measurement of low-carbon logistics efficiency.

4.4. Malmquist analysis results

The three-stage DEA model belongs to the static analysis model, which cannot identify the dynamic changes of the measurement unit and cannot reveal the reasons for its changes. In order to further illustrate the dynamic development trend of low-carbon logistics efficiency in Ningbo metropolitan area, the input data and the original output data adjusted in the second stage are selected, and the Malmquist model is run by DEAP2.1 to obtain Table 5.

Time phasing	DMU	Technical Efficiency (EC)	Technology Progress (TC)	Pure Technical Efficiency (PEC)	scale efficiency (SEC)	Total factor productivity (TFP)
	Taizhou	1	0.9823	1	1	0.9823
2018->2019	Ningbo	1	null	1	1	null
	Zhoushan	1	0.9739	1	1	0.9739
	Taizhou	1	1.0023	1	1	1.0023
2019->2020	Ningbo	1	null	1	1	null
	Zhoushan	1	0.9832	1	1	0.9832
	Taizhou	1	1.0239	1	1	1.0239
2020->2021	Ningbo	1	null	1	1	null
	Zhoushan	1	1.0672	1	1	1.0672
	Taizhou	1	1.1257	1	1	1.1257
2021->2022	Ningbo	1	null	1	1	null
	Zhoushan	1	1.067	1	1	1.067

Table 5. Analysis results of Malmquist model

It can be seen from Table 5 that from 2018 to 2022, the total factor productivity of low-carbon logistics in Taizhou and Zhoushan showed a downward trend. The changes of pure technical efficiency and scale efficiency were both 1, and the trend was stable, while the technological progress showed an upward trend, indicating that the rising trend of technological progress of low-carbon logistics led to the increase of total factor productivity of low-carbon logistics. From 2018 to 2022, the total factor productivity of low-carbon logistics in Ningbo tends to be stable. The technical efficiency, pure technical efficiency and scale efficiency are all 1, and the trend is stable, indicating that there is no problem in the allocation of technology investment in the whole logistics industry and there is no diseconomies of scale.

5. Conclusions

This study uses the three-stage DEA model and the Malmquist model to measure the low-carbon logistics efficiency of Ningbo, Taizhou and Zhoushan in Ningbo metropolitan area from 2014 to 2019. The results show that:

(1) The external environment has a certain impact on the measurement of low-carbon logistics efficiency. By comparing the efficiency values of low-carbon logistics before and after eliminating environmental factors, except that individual values remain unchanged at the efficiency frontier value of 1, the remaining efficiency values have different degrees of change, thereby improving the efficiency of low-carbon logistics. High-tech truly empowers the logistics industry to effectively reduce the waste of investment resources and effectively improve the efficiency of low-carbon logistics. Excessive government support will cause waste of personnel and assets, resulting in reduced efficiency of low-carbon logistics.

(2) From the perspective of static space, the low-carbon logistics efficiency of the three places in Ningbo metropolitan area is high. From the adjusted data, it can be seen that the comprehensive efficiency, pure technical efficiency and scale efficiency of low-carbon logistics in Ningbo, Taizhou and Zhoushan in 2018 and 2019 all reach the production frontier, indicating that the logistics resources are optimized and the synergy of the logistics industry is high.

(3) From the perspective of dynamic time, technological progress promotes the development of low-carbon logistics efficiency. Large-scale investment has improved the technical level of the logistics industry, thus promoting the growth trend of low-carbon logistics total factor productivity in Ningbo metropolitan area.

Declarations of interest
None

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None

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