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Original Research

Spatial-Temporal Evolutionary Characteristics and Its Driving Mechanisms of China's Logistics Industry Efficiency under Low Carbon Constraints

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Abstract

As a pillar industry for national economic development and a key industry for carbon emission reduction in China, the logistics industry occupies a special place in the low carbon economy. In order to understand the spatial and temporal evolutionary characteristics and driving mechanisms of the efficiency of China's logistics industry, and to decipher the development path of the traditional logistics industry, this study selects the efficiency of China's provincial logistics industry as the research object. The study finds that the efficiency of China's logistics industry is at a low level of development and tends to fluctuate upwards, with the provinces with higher efficiency values concentrated in the eastern region; the level of economic development, the level of information technology, government logistics regulation and environmental regulations can significantly improve the efficiency of the logistics industry in the region, but energy intensity will have a negative impact on the efficiency of the logistics industry. In addition, the level of economic development of a region has a significant 'siphoning effect' on other regions, inhibiting the development of the logistics industry in other regions. Finally, based on the findings of the study, recommendations are made to promote the green development of logistics.

Keywords: low carbon economy, logistics industry efficiency, spatial Durbin model, siphon effect

Introduction

Due to global warming and increased environmental pollution, the development of a low-carbon economy has received widespread attention from various countries. The logistics industry is known as an accelerator of economic development and runs through all areas of social and economic activities. Its rapid development also consumes a large amount of energy and is a key industry in China's carbon emission reduction, occupying a special seat in the development of a low-carbon economy [1]. Establishing a low-carbon logistics development model to effectively reduce greenhouse gas emissions generated by economic

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growth is an important way to address climate and environmental issues [2]. Therefore, this study selects the efficiency of China's logistics industry under low-carbon constraints as the research object, in line with the call for high-quality development of the world economy, and the evaluation results obtained are of more practical reference value, which can provide a more comprehensive understanding of the development effectiveness of China's logistics industry and the source of power for the green development of China's logistics industry, as well as provide certain theoretical followings for countries around the world to formulate corresponding policy measures, so as to promote the logistics industry's This will promote the efficient and high-quality development of the logistics industry.

Driven by the low carbon economy, logistics efficiency has also been widely studied by scholars from different countries. At present, the concept of "logistics efficiency" still lacks a unified definition in the international arena, and the current research is usually concerned with the economic efficiency of logistics, i.e. the ratio of input factors to output factors in the logistics industry [3, 4]. The research on logistics efficiency is also mainly composed of several aspects, such as logistics efficiency evaluation, low carbon logistics efficiency and logistics efficiency influencing factors. For logistics efficiency evaluation, Chinese scholars have mostly focused on macro-level evaluation in areas along the Belt and Road [5, 6] and the Yangtze River Economic Belt [7, 8]. International studies, on the other hand, have concentrated more on the micro level such as port logistics [9-11] and enterprise logistics [12-13]. In terms of the choice of evaluation methods, there are two main methods for calculating total factor productivity depending on whether a production function needs to be set: parametric and non-parametric methods. The parametric method is represented by stochastic frontier analysis (SFA) [14, 15]. However, as parametric methods require strict assumptions, data envelopment analysis (DEA), first proposed by Charnes et al. in 1978, has been recognised by scholars in various countries and applied in various fields [16]. For example, international research has seen scholars refine data envelopment analysis to assess the efficiency of logistics systems in European countries [17, 18]. Chinese scholars have also applied data envelopment analysis extensively, combining DEA with Bayesian correction methods to evaluate regional logistics efficiency [19,20]. For low-carbon logistics efficiency, Chinese scholars mainly focus on the development of the logistics industry in a low-carbon context [21, 22], while international studies are more likely to explore the evaluation of logistics efficiency after carbon emissions are incorporated into the efficiency evaluation system [23]. Many scholars have also attempted to summarise the factors influencing logistics efficiency in several directions, with Chinese scholars summarising drivers such as infrastructure development, industrial structure, information technology level and foreign direct investment [24, 25], while international studies have taken a more comprehensive approach, taking into account factors such as environmental sustainability and economic development level [26, 27].

Although previous researchers have made certain research results in the field of low-carbon logistics research, enriching the research area, research methods and influence factors, there are still deficiencies in the following aspects: (1) in the evaluation of logistics efficiency. Many studies only consider the economic output, and few articles consider the output of social services and carbon emissions. In addition, most studies do not take into account the impact of subjectivity in the selection of evaluation indicators on the accuracy of the evaluation results, resulting in a certain gap between the evaluation results and the objective reality. (2) In terms of influencing factors. Relevant studies have paid little attention to the influence of the spatial autocorrelation of the efficiency of the logistics industry on the research results, usually using ordinary regression models for analysis. And in some articles that use spatial econometric models for analysis, the use of spatial adjacency matrix is the most common, but it can only explain the impact produced by spatially adjacent regions, and the choice of spatial econometric models is also more subjective, without considering the gap between the economic significance of different models.

In view of the above shortcomings, this study considers both economic and social service outputs in the output indicators, incorporates carbon emissions into the non-desired output indicators, and uses principal component analysis to deal with the evaluation indicators, based on which the Super-SBM method is introduced to measure the efficiency of China's provincial logistics industry under low-carbon constraints. At the same time, four common spatial econometric models are constructed using a spatial distance matrix, and the most appropriate model is selected according to its effectiveness to explore the driving mechanism of the green development of China's logistics industry.

Material and Methods

Variable Descriptions and Data Sources

The logistics industry is an important industry that integrates a number of sectors, including transport, storage, information and services. As there are no statistics on the logistics industry in the statistical yearbook, this study draws on the practice of most scholars to define the logistics industry in terms of the transport, storage and postal industry. Considering the fact that the statistical bureau only used the "transportation, storage and postal industry" in 2003, the starting year of this study is 2003, so as to establish an evaluation index system for the efficiency of China's logistics industry under the low carbon constraint.

Input indicators: capital input uses fixed asset investment in the transport, storage and postal sector as investment flows and uses Zhang's perpetual inventory method to estimate the capital stock [28]. Labour input is expressed in terms of the number of employees in the transport, storage and postal industry. Infrastructure inputs are reflected by road mileage, railway mileage and postal network points. Energy inputs are measured by converting the main fuels consumed in the development of the logistics industry into standard coal, based on the criteria of energy reference calorific value and standard coal conversion factor in the China Energy Statistics Yearbook.

Desired output: The output of the transport, storage and postal sector, processed by the GDP deflator, is taken as the economic output of the logistics industry. At the same time, the social turnover of goods is used to measure the output of the social services side of the logistics industry development process.

Non-desired output: expressed through the emissions generated during the development of the logistics industry. where CO_2 emissions are measured with reference to the IPCC (2006) estimates for CO_2:

$$CO_2 = \sum_{i=1}^{n} E_i \times CF_i \times CC_i \times COF_i \times (44/12) \quad (1)$$

where i is the type of energy, E_i is the consumption of i energy, CF_i is the calorific value of i energy, CC_i is the carbon content of i energy, COF_i is the oxidation factor of i energy and $CF_i \times CC_i \times COF_i \times (44/12)$ represents the emission factor of an energy source. In this paper, the eight main energy sources consumed by the logistics industry are selected as the main indicators for the calculation of carbon emissions in the logistics industry, and their relevant data are shown in Table 1.

Among them, Hong Kong, Macao, Taiwan and Tibet are not included in the scope of the regions selected for this study due to the lack of data on them. The indicator data are obtained from the China Statistical Yearbook, China Population and Employment Statistical Yearbook and China Energy Statistical Yearbook.

Research Methods

The choice of logistics efficiency evaluation method directly affects the accuracy of the evaluation results, so a suitable evaluation method needs to be used to judge the correctness of logistics decisions [29]. The traditional DEA model is mainly a radial DEA model, and there is a certain lack of consideration for the slack problem [30]. Moreover, most of the current studies have not processed the indicators before the evaluation of logistics efficiency, which cannot avoid the influence of the subjectivity of indicator selection on the evaluation results, making the evaluation results have certain bias. In summary, this study uses principal component analysis (PCA) to reduce the dimensionality of the input indicators by referring to the practice of Põldaru and Roots [31], and then adopts the Super-SBM model to obtain the evaluation results of logistics efficiency after obtaining comprehensive and objective indicators, and finally uses the spatial econometric model to carry out the analysis of the influencing factors of logistics efficiency. The specific framework is shown in Fig. 1.

Principal Component Analysis

Principal component analysis is one of the most commonly used statistical analysis methods in research. It can reduce the dimensionality of variables according to their linear combination and transform them into another set of independent data, so as to achieve the purpose of simplifying the original data and revealing the relationship between variables [32]. Therefore, the problem of overlapping information between indicators can be effectively solved by principal component analysis, avoiding the influence of subjectivity in the selection of indicators on the evaluation results. The calculation process of principal component analysis is as follows.

(1) Data normalization. X_{ij} denotes the observed value of indicator j in region i and X^*_{ij} is the value of the indicator after normalization.

(2) Calculate the covariance matrix $(X^*_{ij})_{n\times 6}$ and find the eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \lambda_6 \geq 0$ of the covariance matrix and the corresponding eigenvectors $\mu_1, \mu_2, \ldots, \mu_6$.

(3) Calculate the contribution of variance E. $E = \sum_{k=1}^{m} \lambda_k / \sum_{n=1}^{6} \lambda_n$, generally with a cumulative variance contribution of not less than 80%.

(4) Extraction of the first m major components. $y_k = \sum_{j=1}^{6} \mu_{kj} x_j$ (k = 1, 2, ..., m).

(5) To find the composite evaluation value of an indicator. The composite evaluation value of an indicator is calculated using the sum of the variance contribution rate and the indicator weighting factor $F = \sum_{k=1}^{m} a_k y_k$, where a_k is the variance contribution rate of the kth principal component and y_k is the kth principal component.

Given the magnitude differences between input and output variables obtained after the PCA treatment, the following formula was used for this study.

Table 1. Standard coal conversion factors and emission factors for major energy sources.

	Raw coal	Crude oil	Petrol	Paraffin	Diesel	Fuel oil	Liquefied petroleum gas	Natural gas
Standard coal conversion factor	0.7143	1.4286	1.4714	1.4714	1.4571	1.4286	1.7143	1.215
CO_2 emission factor	2.0553	3.0651	2.9848	3.0967	3.1605	3.2366	3.1663	1.9963

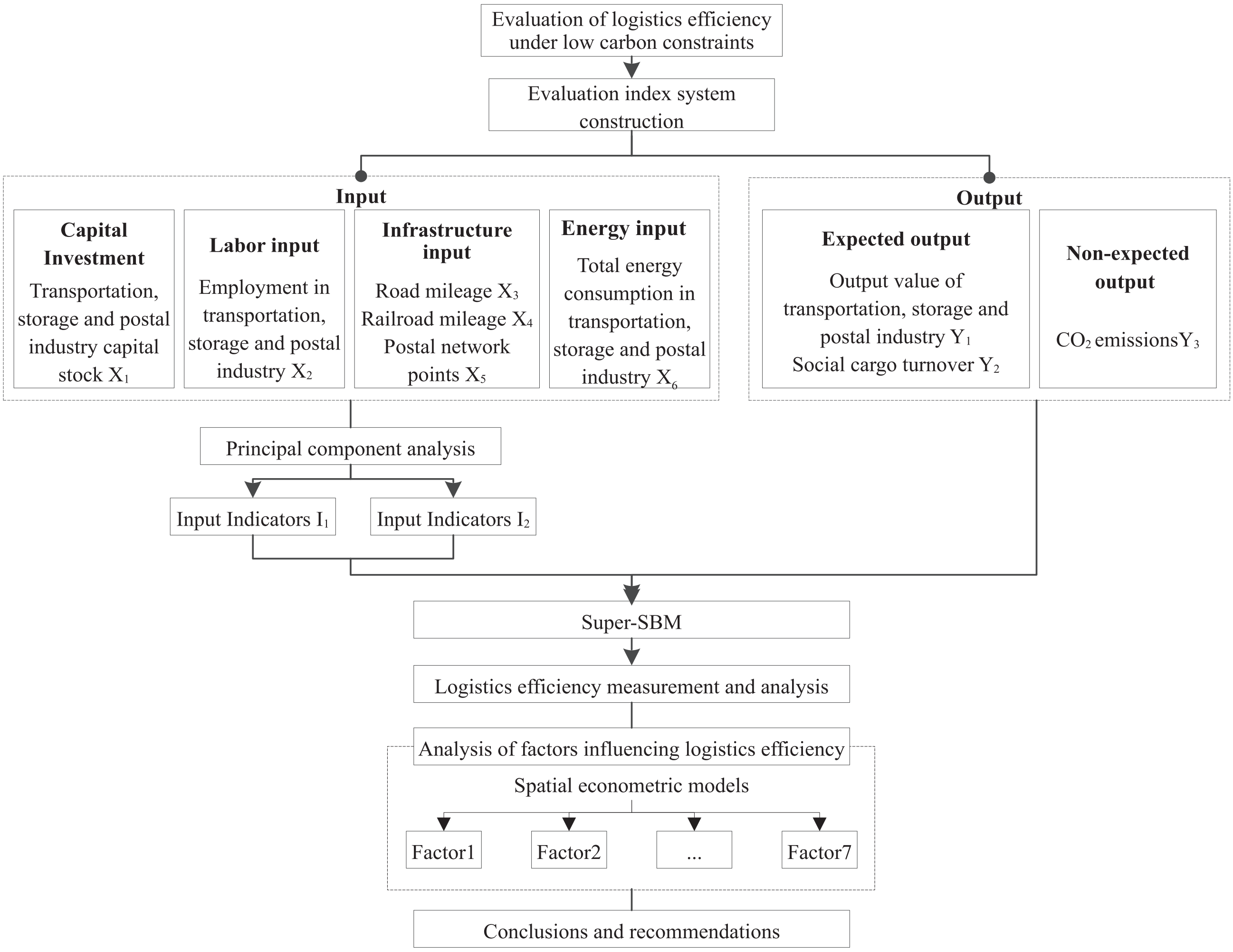

Fig. 1. Research framework.

$$X_{ij}^{*}=0.1+\frac{X_{ij}-\min_j(X_{ij})}{\max_j(X_{ij})-\min_j(X_{ij})} \tag{2}$$

$$Y_{ij}^{*}=0.1+\frac{Y_{ij}-\min_j(Y_{ij})}{\max_j(Y_{ij})-\min_j(Y_{ij})} \tag{3}$$

Where X^{*}_{ij} and Y^{*}_{ij} are the input and output variables obtained through standardisation, respectively, X_{ij} denotes the new input variable obtained using principal component analysis, and Y_{ij} denotes the initial output variable. After processing using the above method, both input and output variables take values ranging from 0.1 to 1 and are used as the final input and output variables.

Super-SBM Model

Data Envelopment Analysis (DEA) is one of the most widely used methods in efficiency analysis. Compared to other methods of evaluating efficiency, DEA has many advantages in terms of low error and simplicity of algorithms. However, the radial DEA model measures the inefficiency of a decision unit on the basis of proportional changes in inputs and outputs, without paying much attention to the slack improvement of the inefficient decision unit, resulting in a certain degree of deviation between the measured results and the objective reality. The efficiency measures can be ranked to avoid multiple efficiency values of 1. The expressions are as follows.

$$\min\rho=\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{-}}{x_{ij}}}{1+\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{+}}{y_{rk}}+\sum_{i=1}^{q_2}\frac{s_i^{b-}}{b_{ik}}\right)}$$

Subject to

$$\begin{gathered}\sum_{j=1,\ j\neq k}^{n}x_{rj}\lambda_j-s_i^{-}\leq x_{ik}\\ \sum_{j=1,\ j\neq k}^{n}y_{ij}\lambda_j+s_i^{+}\geq y_{rk}\\ \sum_{j=1,\ j\neq k}^{n}b_{ij}\lambda_j-s_i^{b-}\leq b_{ik}\\ \lambda,\ s^{-},\ s^{+},\ s^{b-}\geq 0\end{gathered}$$

$$i=1,2,\cdots,m;r=1,2,\cdots,q_1;t=1,2,\cdots,q_2;j=1,2,\cdots,n(j\neq k) \tag{4}$$

where ρ is the efficiency value of the evaluated unit, m denotes the number of input variables, q_1 and q_2 are the number of desired and undesired outputs respectively, s_l^-, s_l^+ and s_l^{b-} correspond to the slack variables of inputs (x_i), desired outputs (y_i) and undesired outputs (b_r) respectively, and x_{ik} and y_{ik} are the input vector and output vector of the decision unit respectively.

Spatial Measurement Models

According to the First Law of Geography, any spatial unit is dependent on other spatial units to a certain extent, i.e. there is spatial correlation. Of course, this correlation must also exist in the study of regional logistics. If a common panel data model is used, without taking into account the impact of spatial correlation, wrong conclusions may be drawn. In order to accurately investigate the key factors driving the green development of China's logistics industry, this study refers to the methods used by Bai Junhong and other scholars in spatial economics research [33], and constructs four common spatial econometric models to analyse the factors influencing the efficiency of the logistics industry. The common spatial econometric models include the spatial Durbin (SDM) model, the spatial crossover (SAC) model, the spatial autoregressive (SAR) model and the spatial error (SEM) model, and their expressions are as follows.

$$Y=\alpha+\delta WY+X\beta+WX\theta+\varepsilon \tag{5}$$

$$Y=\alpha+\delta WY+X\beta+\mu \tag{6}$$

$$Y=\alpha+\delta WY+X\beta+\varepsilon \tag{7}$$

$$Y=\alpha+X\beta+\mu \tag{8}$$

where Equation (5) is the spatial Durbin model, Equation (6) is the spatial crossover model, Equation (7) is the spatial autoregressive model, and Equation (8) is the spatial error model. Y is the efficiency of the logistics industry as measured by the Super-SBM model, X represents the factors influencing logistics efficiency, α denotes the constant term, δ denotes the spatial lag term coefficient, W denotes the spatial weight matrix, β denotes the regression coefficient, λ denotes the spatial error term coefficient, both ε and μ are perturbation terms that obey independent distributions and $\varepsilon\in(0, \sigma^2 I_n)$ When there is no interaction in the spatial Durbin model, i.e. θ in the spatial Durbin model takes a value of 0, or λ in the spatial crossover model takes a value of 0, it can be reduced to a spatial autoregressive model. Similarly, when θ, δ and β in the spatial Durbin model satisfy the relation: $\theta = -\delta\beta$, or when δ in the spatial crossover model takes a value of 0, it can be reduced to a spatial error model.

Results and Discussion

The Chronological Evolution Character of the Efficiency of the Logistics Industry

This study measured the efficiency values of China's provincial logistics industry from 2007-2018 using MAX-DEA software, as shown in Table 2 and Table 3. It can be found that the efficiency of the logistics industry in 2018 in most regions has improved compared to the initial year but is still below 1, indicating that China's logistics industry has started to move towards a green development stage, however, in fact the logistics industry in most regions has not reached an efficient production state when carbon emissions are taken into account. This is due to the fact that the traditional logistics industry's sloppy development approach has resulted in wasted energy and increased carbon emissions, thus slowing down the development of the logistics industry to a certain extent.

Fig. 2 shows more visually the change in the mean value of China's provincial logistics industry efficiency by year, and the picture shows that China's logistics industry efficiency showed a fluctuating upward trend from 2007-2018, which can be roughly divided into three stages: growth-decline-growth. The first stage was the growth stage from 2007 to 2012, where the efficiency of the logistics industry increased more significantly, from 0.511 in 2007 to 0.593 in 2012, a growth rate of about 16%; the second stage was the decline stage from 2012 to 2016, where, except for a small increase in the efficiency value in 2014, all other years showed a downward trend, from 0.593 in 2012 0.593 in 2012 to 0.540 in 2016, a decrease of nearly 9%; the third stage is the growth phase again from 2016-2018, during which the efficiency of China's logistics industry continued to resume its growth trend, with the efficiency value increasing from 0.540 in 2016 to 0.575 in 2018, a growth rate of 6.5%.

The increase in efficiency in China's logistics industry is due to the effective implementation of many policies to support the development of the logistics industry. 200 billion was invested in 2008 to apply to energy saving and emission reduction projects, and in recent years the Chinese government has attached great importance to the development of green logistics, introducing important policy documents such as the Special Action Plan for Reducing Costs and Increasing Efficiency in the Logistics Industry (2016-2018), which has promoted the deep integration of new generation information technology intelligent equipment and The deep integration of the logistics industry has effectively reduced energy consumption and carbon emissions in the logistics industry, providing strong support to promote cost reduction and efficiency enhancement and high-quality development of the logistics industry. In contrast, the decline in the increase in total social logistics costs in 2013, the reduced stimulus effect of the economy, the slowdown in the growth rate

Table 2. Results of measuring the efficiency of China's provincial logistics industry from 2007 to 2012.

DMU	2007	2008	2009	2010	2011	2012
Inner Mongolia	0.503	0.578	0.614	0.626	0.634	0.644
Guangxi	0.423	0.471	0.465	0.481	0.490	0.516
Chongqing	0.419	0.434	0.451	0.441	0.450	0.455
Sichuan	0.331	0.351	0.324	0.344	0.354	0.354
Guizhou	0.466	0.469	0.475	0.469	0.462	0.462
Yunnan	0.384	0.381	0.364	0.340	0.331	0.338
Shaanxi	0.423	0.418	0.431	0.439	0.440	0.479
Gansu	0.545	0.580	0.571	0.575	0.583	0.603
Qinghai	0.565	0.575	0.571	0.579	0.578	0.585
Ningxia	0.513	0.556	0.560	0.576	0.582	0.594
Xinjiang	0.470	0.491	0.518	0.522	0.503	0.526
Shanxi	0.501	0.453	0.445	0.476	0.468	0.487
Anhui	0.542	0.769	0.721	0.720	0.705	0.710
Jiangxi	0.475	0.569	0.559	0.559	0.568	0.620
Henan	0.484	0.626	0.617	0.626	0.638	0.685
Hubei	0.336	0.367	0.375	0.475	0.425	0.458
Hunan	0.397	0.454	0.438	0.479	0.467	0.545
Beijing	0.409	0.396	0.406	0.415	0.434	0.407
Tianjin	1.144	0.562	0.915	0.962	0.952	0.900
Hebei	0.757	0.779	0.815	0.875	0.875	1.005
Shanghai	0.803	0.795	0.752	0.839	0.872	0.877
Jiangsu	0.529	0.580	0.621	0.675	0.783	1.016
Zhejiang	0.532	0.535	0.556	0.621	0.668	0.682
Fujian	0.537	0.531	0.509	0.511	0.507	0.517
Shandong	0.541	0.709	0.666	0.688	0.721	0.666
Guangdong	0.392	0.399	0.389	0.398	0.444	0.530
Hainan	0.519	0.474	0.477	0.494	0.509	0.525
Liaoning	0.471	0.510	0.529	0.564	0.607	0.633
Jilin	0.459	0.486	0.485	0.487	0.488	0.510
Heilongjiang	0.468	0.524	0.496	0.506	0.447	0.461

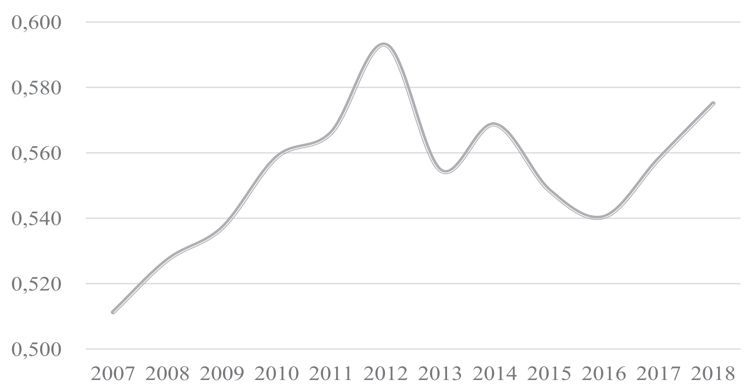

Fig. 2. Change in the average value of efficiency in China's logistics industry from 2007 to 2018.

Table 3. Results of measuring the efficiency of China's provincial logistics industry from 2013 to 2018.

DMU	2013	2014	2015	2016	2017	2018
Inner Mongolia	0.678	0.671	0.674	0.760	0.809	0.864
Guangxi	0.529	0.508	0.489	0.471	0.460	0.459
Chongqing	0.381	0.401	0.377	0.374	0.383	0.414
Sichuan	0.410	0.343	0.360	0.279	0.278	0.298
Guizhou	0.439	0.431	0.389	0.367	0.365	0.360
Yunnan	0.335	0.321	0.310	0.295	0.278	0.260
Shaanxi	0.479	0.464	0.440	0.479	0.495	0.480
Gansu	0.529	0.537	0.508	0.488	0.503	0.510
Qinghai	0.541	0.554	0.540	0.522	0.506	0.497
Ningxia	0.563	0.550	0.539	0.528	0.518	0.524
Xinjiang	0.462	0.480	0.408	0.434	0.439	0.459
Shanxi	0.468	0.480	0.448	0.457	0.477	0.514
Anhui	0.699	0.708	0.635	0.630	0.601	0.610
Jiangxi	0.536	0.557	0.531	0.513	0.493	0.522
Henan	0.556	0.555	0.521	0.513	0.550	0.496
Hubei	0.437	0.445	0.416	0.374	0.375	0.371
Hunan	0.456	0.474	0.421	0.412	0.405	0.398
Beijing	0.405	0.399	0.383	0.369	0.372	0.372
Tianjin	0.719	0.765	0.712	0.687	0.700	0.741
Hebei	0.988	1.011	1.001	0.898	1.006	1.003
Shanghai	0.799	0.900	0.908	0.868	0.913	1.179
Jiangsu	0.946	0.955	1.001	0.923	1.006	0.880
Zhejiang	0.670	0.698	0.696	0.716	0.723	0.787
Fujian	0.479	0.507	0.516	0.527	0.554	0.554
Shandong	0.560	0.584	0.577	0.603	0.714	0.748
Guangdong	0.551	0.691	0.696	0.794	0.902	0.947
Hainan	0.456	0.525	0.489	0.472	0.454	0.456
Liaoning	0.649	0.647	0.650	0.633	0.640	0.671
Jilin	0.492	0.483	0.437	0.446	0.437	0.455
Heilongjiang	0.428	0.414	0.384	0.380	0.387	0.425

of the industry's value added and the accelerated adjustment of business models and structures may have contributed to the short-term decline in the efficiency of the logistics industry. With effective policies and proper guidance from the Chinese government, the development trend of China's green logistics industry will remain positive in the future.

Spatial Distribution Characteristics of the Efficiency of the Logistics Industry

In order to visualise the spatial distribution of the efficiency of China's provincial logistics industry and to compare the spatial differences in the efficiency of China's provincial logistics industry, this study calculates the average value of the efficiency of the logistics industry in each province and, combined with the natural interruption point grading method, divides the resulting average value of efficiency into five levels, namely: low efficiency level (0.328~0.415), lower efficiency level (0.415~0.488), medium efficiency level (0.488~0.600), higher efficiency level (0.600~0.671) and high efficiency level (0.671~1). Then, according to the classified levels, the spatial distribution map of the efficiency of China's provincial logistics industry was drawn using ArcGIS software, as shown in Fig. 3.

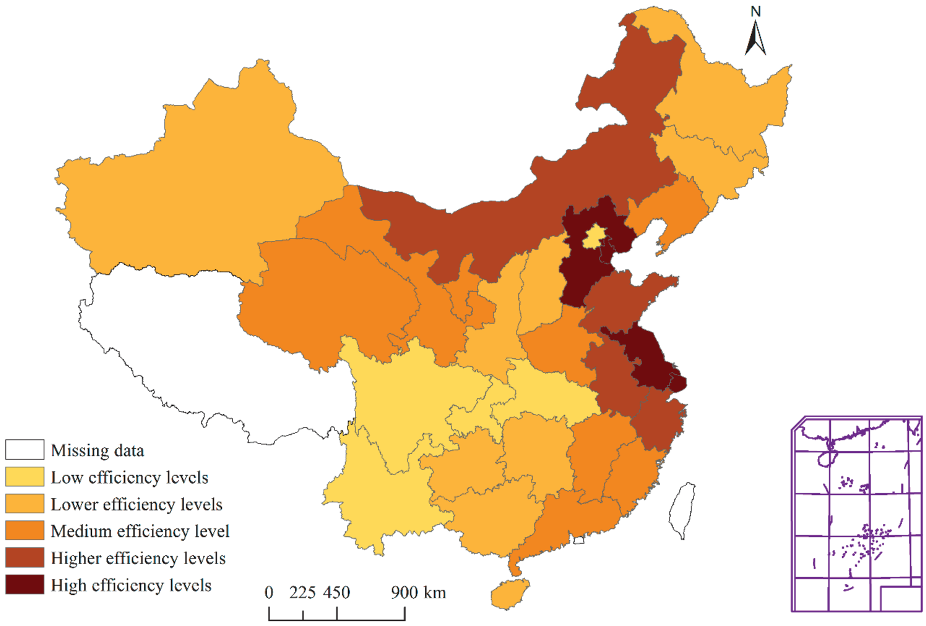

Fig. 3. Spatial distribution of provincial logistics industry efficiency averages in China, 2007 to 2018.

Combined with Fig. 3, it can be seen that there are 16 regions in which the efficiency of the logistics industry is at a medium-high level or above, accounting for more than 50% of the total, and nearly half of the regions are relatively backward in terms of the efficiency level of the logistics industry. Among them, the regions with logistics industry efficiency at high and above levels are Hebei, Shanghai, Jiangsu, Tianjin, Inner Mongolia, Anhui, Zhejiang and Shandong, showing a concentrated distribution, Hebei, Shanghai, Jiangsu and Tianjin belong to the high efficiency level, and the above regions, except Inner Mongolia and Anhui, all belong to the eastern region with better economic development, indicating that the economic promotion of the eastern region makes the logistics activities in the region more The above regions, with the exception of Inner Mongolia and Anhui, all belong to the eastern region with better economic development. The regions in the medium efficiency level include Liaoning, Guangdong, Henan, Qinghai, Ningxia, Gansu, Jiangxi and Fujian, showing a multi-point distribution, with distribution in all four major regions of China. The remaining regions are all at the lower and lower levels of logistics industry efficiency, with the western region accounting for the majority, at 50%, showing that the logistics industry in the western region is developing more slowly, with a mismatch between inputs and outputs, and there is more room for improvement. Interestingly, Beijing, which is part of the eastern region, is also among the regions with low efficiency levels, which may be related to the city's high population density, traffic congestion, low degree of distribution "intensification", low on-board rates and usage rates, and high operating costs.

In order to better compare the differences between regional logistics efficiency, this study refers to the way the economic regions were divided by the National Bureau of Statistics in 2011, and divides the 30 selected provincial areas into four major regions, namely the west, central, east and northeast, and plots the changes in the mean value of logistics industry efficiency in each region, as shown in Fig. 4. It can be seen that the efficiency of the logistics industry in the four regions shows a trend of gradual increase from west to east. Among them, the eastern region has the highest logistics industry efficiency, with an annual average value of 0.674, which is about 22% higher than the national average (0.553). The average value of logistics efficiency in the central region (0.518) is slightly higher than that in the northeast (0.505), but both are below the national average and still have a large gap with the eastern region. The western region is the least efficient of the four regions in terms of logistics industry, with an average value of 0.476 throughout the year, making the logistics industry less developed than the other regions.

The above analysis shows that the efficiency of China's provincial logistics industry and the level of economic development show a similar spatial distribution, with high-efficiency areas concentrated in the eastern region and low-efficiency areas more in the central and western regions, and the spatial distribution is not yet balanced, which to a certain extent indicates that there is a certain link between the level of economic development and the development of the logistics industry. The economy of the eastern region is more developed than that of the central and western regions, which makes the logistics facilities in the eastern region more perfect, and at the same time concentrates most of the international logistics channel resources, the central and western regions need to carry out foreign trade through the eastern region for transit, which also makes the coastal region logistics

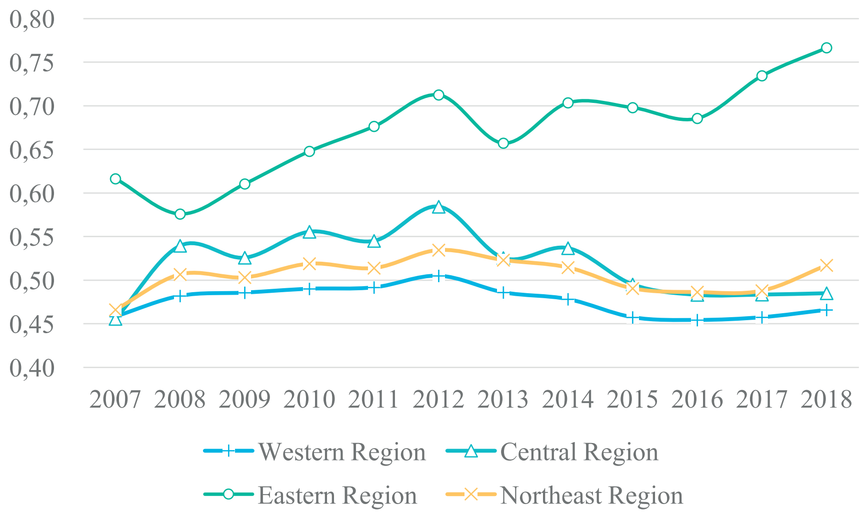

Fig. 4. Trends in the efficiency of the logistics industry in the four major regions of China.

industry more and more strong, and gradually pull the gap with the central and western regions, to achieve the coordinated development of regional logistics industry is also a problem that needs to be solved urgently The coordinated development of the regional logistics industry is also an issue that needs to be addressed.

The Mechanisms Driving Efficiency in the Logistics Industry

Based on the existing studies, this study constructs a system of indicators on the factors influencing the efficiency of China's provincial logistics industry from four perspectives: economic environment, industrial environment, policy environment and environmental regulation, respectively. To avoid abnormal fluctuations in the data, regional GDP is logarithmically processed, as shown in Table 4. The data of the indicators are obtained from China Statistical Yearbook, China Environmental Statistical Yearbook and China Energy Statistical Yearbook.

In the current study, the spatial adjacency matrix is usually selected for regression analysis, but the degree of mutual influence of economic activities between different regions is somewhat different, and the spatial adjacency matrix cannot differentiate the degree of influence. Therefore, in this study, the spatial distance matrix was chosen to explore the driving mechanism of efficiency in the logistics industry. In addition, the LM and Robust LM tests for the SEM and SAR models showed that both rejected the original hypothesis at the 5% level, confirming the spatial error and spatial lag effect that the research model has, and enabling the establishment of the corresponding spatial econometric model. In terms of the selection of fixed and random effects for the SAR, SEM and SDM models, the Human test results showed that the initial hypothesis of using random effects could not be accepted by all three models at the 5% level, so all four models constructed were set as fixed effects models.

The regression results are shown in Table 5. It can be found that the spatial term coefficients δ or λ of

Table 4. Content of the Logistics Industry Efficiency Impact Factor Indicator System.

Variable type	Variable name	Variable symbols	Operation method
Explained variables	Efficiency in the logistics industry	Eft	Super-SBM model solution results
Explanatory variables	Economic development level	GDP	Regional GDP
	Degree of external openness	Open	Total imports and exports / Regional GDP
	Logistics industry structure	Struct	Logistics output / Regional GDP
	Logistics energy intensity	Energy	Logistics energy consumption / Logistics industry output
	Level of informatization	Mobile	Total mobile calls / Number of people
	Government logistics regulation	Trans	Total transport expenditure / Total fiscal expenditure
	Environmental pollution control intensity	Poll	Investment in environmental pollution control / Regional GDP

Table 5. Spatial econometric model regression results.

Variables	SAR	SEM	SAC	SDM
δ or λ	0.3567*** (0.004)	0.6329*** (0.000)	0.8001*** (0.000)	0.2201* (0.091)
lnGDP	0.0989*** (0.000)	0.1144*** (0.000)	0.1160*** (0.000)	0.1234*** (0.000)
Open	0.0387 (0.116)	0.0388* (0.096)	0.0282 (0.197)	-0.0218 (0.347)
Struct	0.0104* (0.051)	0.0025 (0.643)	0.0004 (0.937)	0.0018 (0.725)
Energy	-0.0322*** (0.007)	-0.0527*** (0.000)	-0.0529*** (0.000)	-0.0518*** (0.000)
Mobile	-0.0014*** (0.000)	-0.0009*** (0.010)	-0.0001 (0.802)	0.0009** (0.020)
Trans	0.0064*** (0.001)	0.0039* (0.089)	0.0032 (0.149)	0.0031* (0.100)
Poll	0.0009 (0.401)	0.0007 (0.556)	0.0002 (0.856)	0.0024** (0.032)
*W * lnGDP*	/	/	/	-0.0996*** (0.000)
*W * Open*	/	/	/	-0.0084 (0.461)
*W * Struct*	/	/	/	0.0006 (0.798)
*W * Energy*	/	/	/	-0.0173 (0.002)
VMobile	/	/	/	0.0003 (0.308)
*W * Trans*	/	/	/	0.0011 (0.304)
*W * Poll*	/	/	/	0.0007 (0.312)
Rs-q	0.2445	0.2667	0.3358	0.3944
Log-likelihood	493.0467	505.1660	513.9744	518.5558

***, **, * indicate significant at 1%, 5% and 10% levels respectively

all four models passed the significance test at the 10% level, indicating that there is a significant positive spatial correlation between the efficiency of China's provincial logistics industry. Combined with the regressions of the models, the Rs-q and Log-likelihood values of the SDM model among the four models are greater than those of the other models, indicating that the SDM model has the best fitting effect. At the same time, the Wald and LR tests on the SDM model revealed that Wald_spatial log, LR_spatial log, Wald_spatial error and LR_spatial erro all rejected the original hypothesis of θ = 0 and θ = δβ at the 5% level, indicating that the SDM model could not be reduced to a SAR and SEM model. Therefore, logistics a more comprehensive understanding of the factors on the efficiency of the logistics industry role mechanism, the next will be the SDM model regression results of the effect decomposition, decomposition results are shown in Table 6.

As can be seen from Table 6, the direct effect of the level of economic development on the efficiency of China's logistics industry is significantly positive, while the indirect effect is negative, indicating that the level of economic development can significantly promote the efficiency of the logistics industry in the region, but also has a significant "siphon effect" on other regions, attracting talents and resource elements of the logistics industry from other regions to This will attract talents and resources from other regions to gather in economically developed regions, thus inhibiting the development of logistics industry in other regions. In terms of the total effect, the level of economic development, after taking into account the spatial interaction, can still effectively improve the efficiency of the regional logistics industry. The coefficients of the direct and total effects of energy intensity in logistics are both negative

Table 6. SDM model effect decomposition results.

Variables	Direct effects		Indirect effects		Total effect	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
lnGDP	0.1216***	11.8708	-0.1009***	-6.0114	0.0207**	2.2687
Open	-0.0225	-1.0049	-0.0080	-0.7047	-0.0305	-0.9708
Struct	0.0023	0.4638	0.0006	0.2633	0.0029	0.4203
Energy	-0.0517***	-4.4825	-0.0173	-1.2413	-0.0690***	-3.2145
Mobile	0.0009**	2.4095	0.0003	1.1984	0.0012**	2.4056
Trans	0.0032*	1.7080	0.0010	1.0780	0.0042*	1.6907
Poll	0.0023**	2.1446	0.0007	0.9721	0.0030**	2.0518

***, **, * indicate significant at 1%, 5% and 10% levels respectively

and pass the significance test, indicating that the inhibiting effect of energy intensity on the efficiency of logistics industry is more obvious. The direct and total effects of information level are both significant and positive, confirming the role of information level in promoting the green development of logistics industry. The results of the direct and total effects of government logistics regulation show that the intensity of government logistics regulation has a significant positive impact on the efficiency of the logistics industry and is an effective way to improve the efficiency of the regional logistics industry. The direct and total effects of the intensity of environmental pollution control both pass the significance test at the 5% level and both have a positive effect on logistics efficiency, but because the existing environmental regulation is relatively rigid and ignores the phenomenon of regional differentiation, it is difficult to play a role in promoting green logistics in other regions. This suggests that the effect of the intensity of environmental pollution control on the efficiency of the logistics industry is more reflected in the region.

Therefore, this study makes the following recommendations for the green development of the logistics industry: (1) strive to improve the level of economic development and give full play to the role of the economy in promoting the logistics industry; (2) uphold the concept of green development, strengthen low-carbon and energy-saving technological innovation, and promote the transformation and upgrading of high-energy-consuming and low value-added industries; (3) increase investment in information infrastructure, support the innovation and promotion of logistics technology, and guide enterprises to make use of advanced information technology and logistics technology; (4) play the role of government regulation and control, increase financial support, and create a good logistics environment; (5) strengthen environmental pollution control and promote the formation of a special bill on environmental regulation.

Conclusions

This study found that the efficiency of the logistics industry in most regions of China has not reached an effective state, and the overall efficiency of the logistics industry is still at a low level, with more room for improvement. Among them, the chronological evolution of the efficiency of China's logistics industry from 2007 to 2018 shows a fluctuating trend of growth-decline-growth, reflecting that the green development of the logistics industry is to a certain extent influenced by some uncertain factors. In addition, the spatial distribution of logistics industry efficiency is still uneven, with provinces with higher efficiency values concentrated in the economically developed eastern regions and provinces with lower efficiency levels more often in the central and western regions, showing a similar distribution to the level of economic development.

After further analysis of the factors influencing the efficiency of China's logistics industry, this paper concludes that a region's level of economic development, information technology, government regulation of logistics and environmental regulations can significantly improve the efficiency of the logistics industry in that region, while energy intensity can have a negative impact on the efficiency of the logistics industry.

Therefore, each country can realize the green development of the logistics industry by upgrading the level of economic development and information technology, playing the role of economic promotion and government regulation, upholding the concept of green development and promoting environmental regulation to form a special bill and other series of measures.

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Conflict of Interest

The authors declare no conflict of interest.

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