Spatial analysis of logistics ecological efficiency and its influencing factors in China: based on super-SBM-undesirable and spatial Dubin models

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Abstract

Improving the logistics ecological efficiency (LEE) has become a significant part of ensuring a sustainable development and tackling environmental pollution. Previous studies in the logistics industry seldom considered air pollutants and the association of spatial information. Therefore, innovatively considering SO₂, NOₓ, and PM, this study adopted the super-SBM-undesirable model to calculate the LEE of 30 provinces in China from 2005 to 2019 and, thereafter, developed information-based matrix to explore its influencing factors by using the spatial Dubin model. The results indicated that (1) the overall LEE was low with the average of 0.657, presenting a three-stage trend of “decreasing first, then rising, and later stable,” and significant regional differences with the decreasing gradient pattern of the “Eastern-Central-Western.” (2) A spatial directionality distributed from the northeast to southwest and a significant spatial autocorrelation were observed. (3) The LEE had a significant positive spillover effect. Industrial structure, urbanization level, environmental regulation, and technological innovation level had a positive impact on the local LEE, and industrial structure displayed the most promoting effects. Energy intensity, economic level, energy structure, and opening level had a significant effect on the local LEE with varying degree of inhibition. Local energy intensity and environmental regulation had a positive influence on the LEE in neighboring areas, while local opening level had inhibiting effects. In addition, policy recommendations for enhancing the LEE were made.

Keywords Logistics ecological efficiency • Air pollutants • Spatial information association • Spatial directionality • Spatial autocorrelation • Super-SBM-undesirable • Spatial Dubin model

Introduction

After decades of high-speed development, China is now the world’s second largest economy. However, the bearing pressure of China’s resources and environment has approached a critical value with respect to the economic growth (Khan 2019; Zhao et al. 2020). As a supporting, strategic, and leading industry of economic development (Egilmez and Park 2014; Liang et al. 2019; Zaman and Shamsuddin 2017), China’s logistics industry has experienced a rapid development since the release of the “Logistics industry Adjustment and Revitalization Plan” by the Chinese State Council in 2009. According to the China Statistics Bureau, the cumulative value of transportation, warehousing, and postal industries, which are closely related to the logistics industry, increased from 1652.24 billion yuan in 2009 to 4280.21 billion yuan in 2019, accounting for an average of 9.39% of the national GDP per year. However, behind the rapid growth of China’s logistics industry, a host of resources and energy
inputs abound. The energy consumption in the logistics industry increased from 24,460 tons of standard coal in 2009 to 43,909 tons in 2019, accounting for an average of 8.44% in comparison to the total energy consumed in China. Under the energy characteristics of “more coal, less oil and less gas” in China, a large amount of petrochemical energy consumed by China’s logistics industry has caused a severe environmental pollution (Halldórsson et al. 2010; Liang et al. 2019; Tang et al. 2018; Zaman and Shamsuddin 2017). Mobile source pollution, closely related to the logistics industry, has become an important source of environmental pollution in China (Ministry of Environmental Protection of the People’s Republic of China 2020) and had resulted in pollutants including sulfur dioxide (SO₂), nitrogen oxides (NOₓ), and particulate matter (PM), which are culprits of air pollution (Liu et al. 2019; Rodriguez-Rey et al. 2021; Sun et al. 2019).

The “high energy consumption, high emissions and high pollution” development mode of China’s logistics industry cannot concur with the requirements of protecting the ecological environment. Under the current technical conditions, environmental pollutants are still an inseparable and undesired output of the logistics industry (Rashidi and Cullinane 2019; Tang et al. 2018). It has been demonstrated that environmental problems cannot be solved by halting the economic growth. The stagnation of economic growth will result in serious economic and social problems and will not address environmental pollution (Huang 2016). China’s logistics industry must consider economic growth and ecological environment protection and also reduce the environmental impact of the logistics industry to the barest minimum; in other words, it must minimize the emissions of environmental pollutants and achieve a higher ecological efficiency (eco-efficiency) under the given economic output conditions.

Logistics eco-efficiency (LEE) is a key indicator for assessing the sustainability level of a logistic industry and was first proposed by Zhou et al. (2015). Based on comprehensive and scientific principles (Caiado et al. 2017), the LEE is defined as the ratio of its inputs (resource and energy) to outputs (economic and environmental). This can be used as an effective tool to measure the economic and ecological benefits of the logistics industry. Some scholars have considered carbon dioxide (CO₂) in the estimation of the LEE in China (Long et al. 2020; Zhou et al. 2015). Yet, the measurement of LEE is still lacking in accuracy, owing to the limitation of data on the emission of other pollutants. In addition, compared with the manufacturing and construction industry, the logistics industry has a strong spatial mobility in its operation process, with the spatial mobility of air pollutants relating to the logistics industry being stronger (Long et al. 2020). It is worth noting that the spatial dependence is comprehensively affected by geography, economy, and information in the logistics industry, which is an emerging composite service industry that integrates the transportation, warehousing, and information industries (Zhang et al. 2015). Therefore, as a prerequisite to improving the LEE in China, it is important to accurately measure the LEE by reasonably judging the environmental pollutant outputs of the logistics industry and also explore its driving factors from a multi-dimensional spatial perspective, which is of great significance towards realizing the sustainable development of China’s logistics industry and addressing environmental pollution issues.

The major innovations include the following: (1) This paper classified the environmental pollutants produced in the operations of logistics industries, e.g., SO₂, NOₓ, and PM, and constructed the eco-efficiency measurement index system of logistics industries based on the super-SBM-undesirable model. (2) The four spatial weight matrices—spatial adjacency, spatial distance, economic distance, and information distance—were built to explore the influencing factors of LEE, using the space-time double fixed spatial Dubin model. (3) Environmental and energy issues were taken into account while exploring the impact factors of the LEE and not just economic and social factors.

Figure 1 presents an overview of this study. The subsequent sections are ordered as follows: “Literature review” presents relevant literature. The methods and selection of related indicators are introduced in the “Research methods and indicators” section. The “Empirical analysis of LEE” section analyzes the overall and spatial features of LEE in China. The “Spatial effect analysis of factors in LEE” identifies influencing factors. The conclusions and suggestions are finally presented in the “Conclusions and policy recommendations” section.

**Literature review**

**Connotation and appraisal method of the LEE**

The logistics efficiency of considering eco-environmental constraints has gradually attracted the attention of scholars both in China and abroad. The existing literature employs different expressions, namely energy efficiency (Zhang et al. 2015), environmental efficiency (Fan et al. 2017), green efficiency (Liang et al. 2019), sustainable efficiency (Rashidi and Cullinane 2019; Tan et al. 2019; Tang et al. 2018), and ecological efficiency (Zhou et al. 2015; Long et al. 2020). However, since majority of them only consider the impact of CO₂ or carbon emissions on the ecological environment, the connotations of these concepts are relatively similar. As an instance, Fan et al. (2017) took carbon emissions as unexpected outputs to evaluate the environmental efficiency of the Chinese logistics industry; Long et al. (2020) treated CO₂ as the undesired output, and the logistics ecological efficiency of 11 provinces in the Yangtze economic belt from 2004 to 2016 was analyzed.
In these logistics efficiency concepts, eco-efficiency has a great significance to the sustainable development of the logistics industry. Schaltegger and Sturm (1990) initially proposed the concept of eco-efficiency by emphasizing the unification of the economic and environmental benefits. Presently, more scholars regard eco-efficiency as a suitable measure for the coordinated development of the economy and environment. It has been widely employed in regional development and industries, such as agriculture, steel, tourism, transportation, and energy (Caiado et al. 2017; Guan and Xu 2016; Van Caneghem et al. 2010; Zho ue et al. 2018).

The current measurement methods of eco-efficiency are mainly focused on the stochastic frontier analysis (SFA) (Wang et al. 2018), ecological footprint method (Egilmez and Park 2014), and data envelopment analysis (DEA) (Kounetas et al. 2021; Yang and Zhang 2018). The DEA method can directly use sample data to establish the corresponding optimization model to evaluate the efficiency of the multi-input and multi-output production system. However, traditional DEA models of CCR and BCC are not appropriate when measuring the productivity containing undesired outputs (Zhou et al. 2018). In addition, the traditional DEA models fail in distinguishing effective decision-making units (DMUs) because its maximum efficiency value is 1. As a result, drawing on the Andersen and Petersen (1993) methods for distinguishing the efficient DMUs, Tone proposed the super-SBM model (Tone 2002). Subsequently, taking undesirable outputs in the actual production system and the slack improvement of the weakly efficient DMUs into account (Tone 2001), SBM-undesirable model was proposed (Tone 2004). Since then, the super-SBM-undesirable model based on the above two models was widely used to measure eco-efficiency (Caiado et al. 2017; Long et al. 2020).

**Influencing factors and regression method**

Presently, there are no obvious distinctions between factors that consider sustainable development and those that do not, and the types of factors remain similar. Many scholars have carried out lots of research on the economic factors of industrial structure and economic level; logistics industry factors of port logistics, infrastructure conditions, and logistics human capital; and social factors of information level and urbanization rate; and a wealth of valuable results were accumulated (Hafezalkotob 2017; Long et al. 2020; Rashidi and Cullinane 2019; Tan et al. 2019; Yu and Liu 2010; Zaman and Shamsuddin 2017; Zhang et al. 2015). As an instance, taking the 18 provinces along the “Belt and Road” as study samples, Yu and Liu (2010) discovered that the regional economic level, regional marketization, and port logistics can help to improve the total factor productivity of regional logistics in China. Tan et al. (2019) studied the impact of the economic development level, urbanization level, logistics resource, utilization rate, and other factors on the sustainable efficiency of the logistics industry.

In the conventional research method involving the analyses of factors affecting the efficiency of industries including the logistics industry, econometric regression models such as the linear regression model (Yu and Liu 2010; Zhou et al. 2018), SFA regression model (Zhou et al. 2020), and Tobit regression model (Fujii and Managi 2013; Liang et al. 2019; Tan et al. 2019; Wang et al. 2018) are being used. However, these models ignore the pervasive spatial dependence of economics and fail to effectively explain the influence factor of efficiency. Relatively, due to the consideration of the geographical connection between spatial units, the
spatial econometric model has been widely employed in recent years (Chen et al. 2020; Long et al. 2020; Rios 2016; Guan and Xu 2016; Zhao et al. 2020). Based on the binary adjacency matrix, Guan and Xu (2016) examined the spatial spillover effects and influencing factors of energy eco-efficiency by the spatial econometric model; by constructing the weight matrix of the economic and geographic distance, Long et al. (2020) analyzed the influencing factors of the ecological efficiency of the logistics industry in the Yangtze River Economic Belt using the spatial Dubin model.

General comment

To date, considerable progress and valuable results have been achieved in relevant research of the LEE and its influence factors, but still, the following gaps exist: (1) in considering the environmental impact of the logistics industry, most existing studies only consider CO₂ and ignore the SO₂, NOₓ, and PM produced in the logistics gaps in the following ways: First, the super-SBM-and environmental regulation were largely ignored. (2) These existing studies have resorted to utilizing the spatial econometric model based on geography spatial adjacency or spatial distance and seldom utilized the nested spatial weight matrices based on information, economy, and geography while neglecting the comprehensive influence of information, economy, and geography on the spatial dependence of the logistics industry. (3) In the current analysis of factors affecting the logistics efficiency, more consideration was given to economic and social factors such as economic level, industrial structure, and urbanization rate, while environmental energy factors such as energy use and environmental regulation were largely ignored.

This paper has dealt with the above deficiencies and gaps in the following ways: First, the super-SBM-undesirable model was applied while considering the CO₂, SO₂, NOₓ, PM₂.₅, and PM₁₀ produced during the operation of the logistics industry as undesired outputs, to measure the LEE in China’s 30 provinces from 2005 to 2019. Secondly, based on the four spatial weight matrices of spatial adjacency, spatial distance, economic distance, and information distance, the spatial Dubin model is:

\[
P(\overline{x}, \overline{y}^*, \overline{y}^\prime) = \left\{ (\overline{x}, \overline{y}^*, \overline{y}^\prime) \mid \overline{x} \geq \sum_{i=1}^{n} \beta_{1i} \lambda y_{1i}^*, \overline{y}^* \leq \sum_{i=1}^{n} \beta_{2i} \lambda y_{2i}^*, \overline{y}^\prime \geq \sum_{i=1}^{n} \beta_{3i} \lambda y_{3i}^*, \overline{y}^\prime \geq \overline{y}^* \geq \lambda \geq 0 \right\}
\]

where \( \lambda \) denotes the non-negative intensity vector and \( S_1 (S^*, S^{W+}, S^{b*}) \) indicates the slack in inputs, desirable outputs, and undesirable outputs, respectively. The super-SBM-undesirable is described as follows:

Research methods and indicators

Research regions

The research regions cover 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet). The regions were divided into three based on the geographical location: Eastern, Central, and Western, as detailed in Fig. 2.

The measurement of LEE

Super-SBM-undesirable

According to the previous analysis, the super-SBM-undesirable model has many advantages including considering undesirable outputs and distinguishing the efficient DMUs in measuring the efficiency of the production system. In the real logistics production system, greenhouse gases and air pollutants are unexpected outputs that we have to consider. Under the existing technical conditions, they are inseparable from the expected outputs including the added value and freight turnover of the logistics industry. Additionally, if the maximum LEE is 1 and the LEE of many DMUs is 1 at the same time, this will make it impossible to distinguish these DMUs and will also bother the correctness analysis of factors influencing LEE. To accurately evaluate the efficiency of the logistics industry and its influencing factors, therefore, this paper use super-SBM-undesirable model to measure the LEE.

Drawing on the practices of Fan et al. (2017) and Liu et al. (2019), this paper assumes that the logistics production system has \( n \) DMUs, and each decision-making unit has \( m \) kinds of inputs, \( q_1 \) kinds of expected outputs, and \( q_2 \) kinds of non-expected outputs. For DMUs having an efficiency value of 1 in the SBM-undesirable model, the super efficiency value was further calculated using the super-SBM-undesirable model.

Assuming \( x^* = X_{1\lambda} + S, y^{*\prime} = Y^{*\prime\lambda} - S^{W+}, y^{b*} = Y^{b\prime\lambda} + S^{b*} \), the production possibility set (PPS) of logistics industry is:
The indicators and data of LEE evaluation

In the measurement of the LEE based on the super-SBM-undesirable, the indexes selection deeply impact the overall performance (Zhou et al. 2015). Combined the actual operation of the logistics industry and the existing relevant literature references in Table 1, indicators of inputs, expected outputs, and non-expected outputs are shown in Table 2.

Inputs variables Logistics industry is a capital-intensive and labor-intensive industry, which needs a lot of labor and capital input, and it is also a large energy consumer. In the relevant literature, capital, labor, and energy are also considered to be the three most important and indispensable inputs in measuring the efficiency of logistics production system.

The capital input was measured by the social logistics capital stock and perpetual inventory method (Dong and Wu 2019; Zhou et al. 2015), with the depreciation rate being 9.6%. The social capital stock data were adjusted to the corresponding values based on the year 2004, while the capital stock in 2004 was calculated using the capital-output ratio backward method (Hall and Jones 1999). Employees from the logistics industry were chosen as the labor force, referring to the total number of employees in primary. The energy consumption was obtained from the conversion and summary of the standard coal coefficients for eight types of energy (Fan et al. 2017).

Desired outputs Freight turnover can fully reflect the performance of the logistics transportation production, added value brought by the logistics industry injects vitality into economic development, and they are also considered as the two most commonly used expected outputs in the current literature.

The data of freight turnover were obtained by summing up the highway, railway, and water transport modes. The added value of the logistics industry in all sample provinces of each year was converted into the actual value based on 2004.

Unexpected outputs Fossil energy consumed by the logistics industry brings about the emission of greenhouse gases and air pollutants. Greenhouse gases including CO$_2$ can lead to global warming and have a negative impact on natural ecosystems, while SO$_2$, NO$_x$, PM$_{2.5}$, and PM$_{10}$ brought by the logistics industry are serious air pollutants, posing a threat to air quality and human health. Therefore, this paper takes them as the unexpected outputs of the logistics industry.

According to the energy consumption rate of the eight items in the energy balance sheets of the logistics industry, the emission factor method was used to calculate the emissions of CO$_2$, SO$_2$, NO$_x$, PM$_{2.5}$, and PM$_{10}$ by the logistics...
### Table 1  Indicators for efficiency evaluation in relevant references

| Inputs                                                                 | Expected outputs                  | Non-expected outputs            | Reference                                                                 |
|-----------------------------------------------------------------------|-----------------------------------|---------------------------------|---------------------------------------------------------------------------|
| Capital, labor, and energy                                            | Added value, freight turnover     | CO2 emissions                   | Green logistics total factor productivity (Liang et al. 2019)              |
| Investment, line, energy, employees, land, and trucks ownership       | Freight, added value              | CO2 emissions and logistic accident property loss | Sustainable efficiency of logistics industry (Tan et al. 2019)               |
| Energy, labor, capital, CO2 emissions, and SO2 emissions              | Added value                        | -                               | The eco-efficiency of logistics industry (Zhou et al. 2015)                 |
| Capital stocks, employment, energy, and infrastructure                | Added value, freight turnover     | CO2 emissions                   | Logistics eco-efficiency (Long et al. 2020)                                |
| -                                                                    | GDP                               | CO2, SO2, and NOx emissions     | The eco-efficiency of US states (Kounetas et al. 2021)                     |
| Capital, labor, energy, and land                                      | GDP                               | SO2 emissions, wastewater       | Urban eco-efficiency (Huang 2016)                                          |
| Capital, labor, land, water, and energy                               | Added value                        | Wastewater, exhaust gas, solid waste, and soot-dust | Industrial ecological efficiency (Yu et al. 2018)                           |

### Table 2  The measurement indicator system and variables descriptive statistics of the LEE

| Primary indicators            | Secondary-class indicators            | Unit          | Maximum       | Minimum     | Mean        | Standard deviation |
|------------------------------|--------------------------------------|---------------|---------------|-------------|-------------|-------------------|
| Inputs                       | Capital stocks in logistics industry | 10^6 yuan     | 18328.12      | 183.15      | 3466.36     | 3101.18           |
|                             | Energy consumption in logistics industry | 10^4 tons of standard coal | 5821.16      | 37.44       | 1546.44     | 1036.36           |
|                             | Labor force in logistics industry    | 10^4 person   | 82.06         | 3.22        | 23.56       | 14.07             |
| Desired outputs             | Freight turnover of logistics industry | 10^6 tons kilometers | 30324.90     | 137.20      | 4514.94     | 4866.81           |
|                             | Added-value of logistics industry    | 10^6 yuan     | 5897.46       | 24.09       | 903.91      | 892.42            |
| Undesired outputs           | CO2 emissions of logistics industry | 10^4 tons     | 7417.46       | 54.13       | 2110.46     | 1486.78           |
| Environmental pollution index | SO2 emissions of logistics industry | 10^4 kg       | 7954.14       | 60.03       | 1548.47     | 1222.32           |
|                             | NOX emissions of logistics industry  | 10^4 kg       | 21579.02      | 234.88      | 6111.84     | 4252.78           |
|                             | PM2.5 emissions of logistics industry | 10^4 kg      | 696.21        | 4.64        | 199.07      | 135.22            |
|                             | PM10 emissions of logistics industry | 10^4 kg      | 1376.89       | 9.47        | 277.03      | 211.14            |
industry in 30 provinces from 2005 to 2019. The CO2 emission factors were provided by related literature (Fan et al. 2017; Sun et al. 2019), and the SO2, NOx, PM2.5, and PM10 emission coefficients were based on the EPA, AP-42, Beijing emission coefficients (Li et al. 2018; Sun et al. 2019), and the actual situation of China’s logistics industry. The above emission factors are presented in Table 1 in the Supplementary information.

In addition, in order to avoid the impact of high correlation and singular value, the practice of Huang (2016) was considered, where the entropy weight method was used to measure the environmental pollution index of SO2, NOx, PM2.5, and PM10 emissions.

Basic data corresponding to the above variables were extracted from the China Statistic Yearbook (CSY) (2006–2020) (China Statistical Bureau, 2006–2020), China Energy Statistical Yearbook (CESY) (2006–2020), and Statistical Yearbooks of provinces (2006–2020). Due to the logistics industry statistics is incomplete in China, and referring to the research conducted by Long et al. (2020) and Yu and Liu (2010), this paper takes transportation, warehousing, and postal services as an alternative, which has an 85% proportion rate in the logistics industry.

**Spatial analysis methods**

**Standard deviational ellipse**

To explore the dynamic correlation between the LEE and geographic space from a global perspective, we therefore adopt the standard deviational ellipse method. It is a spatial econometric analysis method to accurately reveal the spatial distribution direction features of economic attribute elements (Wachowicz and Liu 2016). The basic parameters of this method include the mean center, ellipse area, rotation angle, and long and short axes.

The mean center of the large region represents a point at which the weights of small divided regions are balanced. The formulas of the weighted mean center are as follows:

\[
P \left( x, y \right) = \left( \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \right)
\]  

(2)

To show the changes in the spatial distribution of the research regions, the angle between the true north and long axes is defined as the azimuth, and the value of θ can be calculated thus:

\[
tan \theta = \left( \sum_{i=1}^{n} w_i^2 x_i^2 - \sum_{i=1}^{n} w_i x_i \right) + \sqrt{ \left( \sum_{i=1}^{n} w_i^2 x_i^2 - \sum_{i=1}^{n} w_i x_i \right)^2 + 4 \left( \sum_{i=1}^{n} w_i^2 y_i^2 \right) } \]  

\[
2 \sum_{i=1}^{n} w_i x_i y_i
\]  

(3)

In order to present the contraction or expansion of the LEE in a specific spatial direction, the long and short axes can be defined. The standard deviations along the x-axis and y-axis are calculated using Eqs. (4) and (5).

\[
\delta_x = \sqrt{\frac{\sum_{i=1}^{n} \left( w_i x_i \cos \theta - w_i y_i \sin \theta \right)^2}{\sum_{i=1}^{n} w_i^2}}
\]  

(4)

\[
\delta_y = \sqrt{\frac{\sum_{i=1}^{n} \left( w_i y_i \sin \theta - w_i x_i \cos \theta \right)^2}{\sum_{i=1}^{n} w_i^2}}
\]  

(5)

**Spatial autocorrelation analysis**

In order to verify the existence of spatial autocorrelation in the study area, the spatial autocorrelation analysis method was used. It is a method to reveal the spatial relationship of the attributes (Bai et al. 2018; Long et al. 2020; Guan and Xu 2016). The global Moran’s I and local Moran’s I are the two most commonly used indicators.

To judge whether the LEE in China has a statistical agglomeration and dispersion from a global space perspective, the paper employed the global Moran’s I index. The value of Moran’s I ranges from -1 to +1, which indicate a perfect negative and positive autocorrelation, respectively, while 0 represents no autocorrelation. Its formula is expressed as follows:

\[
I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left( x_i - \bar{x} \right) \left( x_j - \bar{x} \right)}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}
\]  

(6)

Although the global Moran’s I index is able to evaluate the overall spatial agglomeration situation of the LEE, it cannot identify the spatial correlation patterns of a specific spatial unit and its adjacent units. As a result, the local Moran’s I index was used to assess the existence of a spatial heterogeneity in the local region of the LEE. The positive spatial autocorrelation is expressed as the HH (high-high) or LL (low-low), while the negative spatial autocorrelation is expressed as the LH (low-high) or HL (high-low). Its formula is as follows:

\[
I_i = \frac{n \sum_{j=1}^{k} w_{ij} \left( x_j - \bar{x} \right)}{\sum_{i=1}^{n} \left( x_i - \bar{x} \right)^2} (i \neq f)
\]  

(7)

where n is the number of research regions; x_i and x_j represent the observed values of LEE in regions i and j, respectively; w_{ij} stands for spatial matrix; and k indicates the number of adjacent regions in a certain region.

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**Spatial econometric model**

**Spatial Dubin model**

Through spatial correlation analysis, if the LEE has significant geographical agglomeration, it is necessary to use spatial econometric model to explore its influencing factors effectively. The spatial correlation and heterogeneity of panel data were considered in the spatial econometric model, making the analysis and conclusions more objective. According to Elhorst (2010), three classical spatial econometric models were included: the spatial lag model (SLM), the spatial error model (SEM), and the spatial Dubin model (SDM). The basic forms of the three models can be expressed as follows:

\[ y_{it} = \alpha_1 + \rho W y_{it} + x_{it} \beta_1 + \varepsilon_{it} \]  
(8)

\[ y_{it} = \alpha_1 + x_{it} \beta_1 + u_{it} \]  
(9)

\[ y_{it} = \alpha_1 + \rho W y_{it} + W x_{it} \gamma_1 + x_{it} \beta_1 + \varepsilon_{it} \]  
(10)

where \( y_{it} \) is the explained variable; \( W \) represents the spatial matrix; \( x_{it} \) stands for the explanatory variable; \( \varepsilon_{it} \) and \( u_{it} \) are the random error term distributed with a mean of 0 and a variance of \( \sigma^2 \); and \( \rho \) and \( \gamma \) are spatial lag parameters. The type of spatial econometric model can be selected by the virtue of these two values being significantly 0. When \( \gamma=0 \) and \( \rho\neq0 \), the SDM would degenerate into SLM, while \( \gamma+\rho\beta=0 \), SDM will be simplified to SEM. Therefore, the SDM is more general than the SLM and SEM.

**Construction of spatial weight matrices**

In the spatial econometric model, different spatial weight matrices directly affect the regression results, and selecting the right matrices for the spatial econometric model is critically important (Elhorst 2010). There are two methods of generating weights in the spatial weight matrix: the contiguity (W1) and generation based on distance (W2). While the aforementioned matrices only reflect the spatial connection in geography, the influence of economic development and information technology on spatial connection is neglected, which is very important in the actual operation of the logistics industry. Therefore, in order to depict a more accurate spatial connection of the logistics industry, the practices of Li et al. (2010), Chen et al. (2020), Chen et al. (2017), and Rios (2016) were considered, with this study constructing two weight matrices based on the geographic economy (W3) and geographic information weight matrix (W4).

The data were obtained from CSY (2006-2020) (China Statistical Bureau, 2006-2020), and the formulas of the four spatial weight matrices are presented as follows:

\[ W_1 = \begin{cases} 
1 & \text{Unit i is adjacent with unit j} \\
0 & \text{Unit i is not adjacent with unit j, and } i = j 
\end{cases} \]  
(11)

\[ W_2 = \left\{ \begin{array}{ll}
1/d_{ij} & i \neq j \\
0 & i = j 
\end{array} \right. \]  
(12)

where \( d_{ij} \) denotes the euclidean distance between unit i and unit j.

\[ W_3 = W_2 * \text{diag} \left( \frac{y_1}{y}, \frac{y_2}{y}, \ldots, \frac{y_n}{y} \right) \]  
(13)

\[ W_4 = W_2 * \text{diag} \left( \frac{\bar{y}_1}{\bar{y}}, \frac{\bar{y}_2}{\bar{y}}, \ldots, \frac{\bar{y}_n}{\bar{y}} \right) \]  
(14)

where \( W_2 \) is the distance weight matrix; \( \bar{y}_i = \frac{1}{1/n \sum_i n_i} \sum_i n_i y_{it} \) denotes the average per capita GDP of the unit i in the research period; \( \bar{y} = \frac{1}{1/n \sum_i n_i} \sum_i n_i y_{it} \) represents the average per capita GDP of all units in the research period; and the per capita GDP was unified to calculate the actual GDP value using the constant prices in 2004.

**Factors influencing LEE**

According to previous research, economic development provides a demand basis for the development of the logistics industry (Yu and Liu 2010), while the industrial structure influences the economic growth. Therefore, the per capita GDP and the ratio of secondary industry to tertiary industry were selected to address the economic aspects of the LEE, representing the economic growth and industrial structure, respectively. The development of the logistics industry was based on the assumption that energy was cheap and sufficient in the past (Halldórsson et al. 2010), precipitating environmental contamination associated with burning fossil fuels. However, the consequences of environment degradation on the public necessitates that ecological environment protection should be included in the scope of government regulation. Thus, the environmental regulation, energy structure, and energy intensity of the logistics industry were selected to analyze the environmental and energy aspects of the LEE. In addition, the level of urbanization, technological innovation, and opening were also considered as social factors to explore their impact on the LEE. Eight factors influencing the LEE from three aspects are reported in Table 3. The data were collected from the CSY (2006-2020) (China Statistical Bureau, 2006-2020), CESY (2006-2020), and Statistical Yearbooks of provinces (2006-2020). Relevant
environmental data were obtained from the China Environmental Statistics Yearbook (2006–2020).

The empirical analysis of LEE

The overall analysis

Based on the super-SBM-undesirable model and selected indexes, the LEE values of 30 provinces in China from 2005 to 2019 were calculated, and the results are presented in the Supplementary information Table 2. The average value of the LEE in China was observed to be equal to 0.657. Only Tianjin, Shanghai, Fujian, and Guangdong exhibited LEE values greater than 1.00; 11 provinces were above average, indicating the poorness of the overall LEE in China.

Figure 3 depicts the changes in the average LEE value of 30 provinces from 2005 to 2019. As a whole, the three-stage trend of the “decreasing first, then rising, and later stable” is presented. It clearly indicates that the LEE attained its lowest value of 0.579 in 2007, depicting a downward trend from 2005 to 2007, a fluctuating upward trend from 2007 to 2013, and a stable fluctuation between 0.681 and 0.716 after 2013. Since 2013, large-scale haze pollution has been recorded in many cities and regions in China, prompting the implementation of a policy by the Chinese government to combine the total amount of pollutants with the concentration control and prohibit the discharge of pollutants from exceeding the prescribed limit. Meanwhile, the environmental protection awareness of logistics enterprises was enhanced to acquire more living space, resulting in the improvement of the LEE after 2013.

Figures 4, 5, and 6 show the significant differences in the LEE among the provinces, which indicates a gradual decline from Eastern to Western China, presenting a decreasing gradient pattern of “Eastern-Central-Western,” and the possible reasons for this include the following:

Since reform and opening up, China had implemented an unbalanced regional development strategy, which is focused on the provision of financial policy support for the eastern region and the indirect promotion of the logistics industry’s market demand and development space. On the other hand, with the rapid development of the manufacturing and logistics industry, the eastern region has attained a very high economic level, and following the enhancement in awareness of ecological and environmental protection, more funds were invested in environmental protection. In contrast, industries and enterprises having serious environmental pollution in the eastern region migrated to the central and western regions, and due to the relatively backward economic development, the central and western regions were more willing to accept these enterprises and set relatively loose environmental regulation policies. The proportion of investment in environmental pollution

Table 3  Factors influencing LEE

| Variable type                  | Variable                  | Definition                                                                 | Main references                                      |
|--------------------------------|---------------------------|---------------------------------------------------------------------------|------------------------------------------------------|
| Economic aspect                | Economic level (EL)       | Per capita GDP (yuan)                                                     | Yu and Liu (2010); Zhao et al. (2020)                |
|                                | Industrial structure (IS) | Ratio of secondary industry to tertiary industry (ratio)                   | Guan and Xu (2016); Long et al. (2020)              |
|                                | Environmental and energy aspect | Investment in industrial pollution as a proportion of GDP (%)            | Wang et al. (2018)                                  |
|                                | Energy intensity (EI)     | Proportion of energy consumption to the added value of logistics industry  | Liang et al. (2019); Long et al. (2020)             |
|                                | Energy structure (ES)     | Proportion of electricity consumption to total energy consumption (%)      | Zhou et al. (2015); Long et al. (2020)              |
|                                | Urbanization level (UL)   | Proportion of urban population to the regional total population (%)        | Haldorsen et al. (2010)                              |
|                                | Technological innovation level (TIL) | Number of patent claims (item)                                           | Long et al. (2018); Zhao et al. (2018)              |
|                                | Opening level (OL)        | Foreign direct investment at current exchange rate (yuan)                 | Fujii and Managi (2013); Zhou et al. (2020)         |
control to GDP was still insufficient in the central and western regions, which remained at an average of 1.5% over the years and is lower than the 2–3% environmental quality improvement ratio recommended by the World Bank (1997).

The spatial distribution analysis

The ArcGIS10.2 software was used to calculate the LEE relative parameters of the standard deviational ellipse in 2005, 2010, 2015, and 2019, and the results are presented in Fig. 7 and Table 4.

The spatial directionality of the LEE exhibited a trend of “northeast to southwest.” The center of gravity was in and near the Henan province and in a consistent movement to the southeast. Standard deviations along the x-axis and y-axis basically hold steady, and the rotation angle increased and then decreased. On the overall, the direction of the LEE in China was obvious, and the “northeast to southwest” trend remained relatively stable.

Spatial autocorrelation analysis

Global autocorrelation analysis

The global Moran’s I was adopted to measure its spatial correlation as shown in Table 5 and Fig. 8. From 2005 to 2019, the global Moran’s I of the LEE was all positive and statistically significant ($p < 0.01$), indicating a significant positive correlation between the 30 provinces in China. As observed in Fig. 8, the global Moran’s I exhibited an overall fluctuating trend during the study period. Moran’s I attained its highest value of 0.618 in 2015, and although declining slightly, its value maintained above 0.32 after 2015. These results indicate that the LEE of China had a significant spatial agglomeration effect.

Fig. 3 The time trend of the average LEE value in China from 2005 to 2019

Fig. 4 The average LEE value in 30 provinces of China from 2005 to 2019
Local autocorrelation analysis

The local Moran’s I index was mapped to display the spatial autocorrelation between a province and its neighboring provinces in 2005, 2010, 2015, and 2019, as presented in Fig. 9. The results indicate that almost all provinces were either in the HH and LL clusters or had no obvious agglomeration, but were not in the LH and HL clusters, indicating a positive spatial autocorrelation of regions. The HH cluster area was always concentrated in the eastern coastal area of China, while the LL cluster area appeared in the western inland area. The above results indicate that the LEE in China exhibits the characteristics of local spatial agglomeration.
The possible reasons for this were speculated as follows: The economy and logistics industry in the eastern region was relatively developed, and the environmental protection system was more complete, which contributed to the positive spillover effect on the surrounding provinces, resulting in a high LEE cluster. However, the western region, which is short of resources and located inland, had lagged behind the eastern region for a long time, and its readiness to develop the economy was stronger than the desire to protect the ecological environment, resulting in a low LEE cluster.

**Spatial effect analysis of factors on LEE**

**Selection of spatial econometric model**

According to the previous analysis, the LEE in China was characterized by a spatial autocorrelation, indicating the necessity of the spatial econometric model. The tests to determine the tendency of the SDM to degenerate into the SLM or SEM are verified under four different spatial matrices, and the details are presented in Table 6. The results supported the selection of the SDM method with double fixed effects in time and space.

**Analysis of SDM regression results**

Based on the SDM, the factors influencing the LEE were analyzed, and results are presented in Table 7, with the prefix “Ln” denoting the natural logarithm. It is noteworthy that the average amount of variance ($R^2$) is a pseudo value in the spatial econometric model, which is unsuitable for the evaluation of the model fit degree. Therefore, the log likelihood (Log-L) ratio test is adopted (Bai et al. 2018). Given the value of Log-L from Table 7, the SDM model with double fixed effects in time and space was selected as the best-fit model. The regression coefficients of the spatial lag term (Spatial-rho) under four unique spatial matrices were positively significant.

| Year | X-axis | Y-axis | X-axis standard deviation (km) | Y-axis standard deviation (km) | Rotation angle (degree) |
|------|--------|--------|--------------------------------|--------------------------------|------------------------|
| 2005 | 115.016| 33.351 | 8.438                          | 11.015                         | 38.018                 |
| 2010 | 114.631| 33.479 | 8.973                          | 11.156                         | 60.813                 |
| 2015 | 115.128| 33.495 | 8.837                          | 11.093                         | 60.107                 |
| 2019 | 115.649| 33.199 | 8.842                          | 11.542                         | 49.461                 |
indicating the presence of a significant spatial spillover effect on the LEE in the Chinese provinces. The improvement of the LEE in the surrounding provinces would promote the progress of the local LEE, and the local LEE could also increase with the enhancement of the LEE in the surrounding provinces.

However, special attention was directed to the fact that the SDM model contains dependent variables of the spatial lag term. Consequently, a change in the independent variable for a local province may affect it, and the surrounding provinces, in turn, have other effects on the original province. Therefore, the regression coefficients in Table 7 cannot accurately depict the real marginal effect of the independent variables. To this end, the best practices in existing literature were referred to Chen et al. (2017) and Rios (2016), and using partial differential decomposition methods, the estimates of direct, indirect, and total effects were obtained to analyze the impact of the independent variables on the LEE of local and surrounding provinces. Detailed results are presented in Table 8.

Under the four different spatial matrices, the direct effect of the economic level (EL) on the LEE was negative with an average coefficient of $-0.3483$, which satisfies the significance level test of 5%, with the indirect and total effects being insignificant. This conclusion disagrees with Tang et al. (2018) and Long et al. (2020) but agrees with Zhou et al. (2018). This indicates that the high economic level of a certain region will promote the development of its logistics industry, but will not necessarily improve the region’s LEE. A possible reason for this is due to China’s economy being in a period of unbalanced and extensive development. The extensive economic growth had enlarged the development scale of the logistics industry but failed to bring about the green ecological development of the logistics industry, while the high economic level had resulted in a reduced LEE.

The direct effect of the industrial structure (IS) on LEE under the four different spatial matrices was positive, given an average coefficient of 0.2765, which is significant at the 1% level, while the indirect and total effects were insignificant. The yielded results accorded with the findings of Zhu et al. (2011) and Zhu et al. (2020), indicating the significant improvement of the local LEE on the secondary industry, with no significant impact on the LEE of surrounding areas. The possible reason could be due to the dependency of the development of the logistics industry on the circulation of industrial products in China. However, following the upgrade of the industrial structure and the development of the tertiary industry, the effect of the logistics industry’s scale will be adversely affected in the short term, resulting in a decrease in LEE. This result enforces that the industrial restructuring of China should not overemphasize the rapid scale expansion of the tertiary industry, but should pay more attention to the integration and linkage development of the tertiary and logistics industries.

Based on the four different spatial matrices, the direct and total effects of environmental regulation (ER) on the LEE were positive, with average coefficients of 0.0895 and 0.1882, respectively, which were significant at the 1% level. These results were consistent with the conclusion of Tang et al. (2017).
Table 6  Test results of the spatial econometric model

| Inspection items | Adjacency matrix W1 | Distance matrix W2 | Economic matrix W3 | Information matrix W4 |
|------------------|----------------------|--------------------|--------------------|-----------------------|
| Moran's I        | 6.132*** (0.000)     | 5.949*** (0.000)   | 157.371*** (0.000) | 136.712*** (0.000)    |
| LMLAG            | 34.006*** (0.000)    | 31.326*** (0.000)  | 27.094*** (0.000)  | 21.904*** (0.000)     |
| R-LMLAG          | 0.073 (0.787)        | 0.001 (0.975)      | 0.099 (0.753)      | 1.283 (0.257)         |
| LMERR            | 80.102*** (0.000)    | 67.938*** (0.000)  | 55.056*** (0.000)  | 25.939*** (0.000)     |
| R-LMERR          | 50.169*** (0.000)    | 36.613*** (0.000)  | 28.061*** (0.000)  | 5.319** (0.021)       |
| Wald-slm         | 53.58*** (0.000)     | 37.02*** (0.000)   | 34.61*** (0.000)   | 36.12*** (0.000)      |
| Wald-sem         | 49.31*** (0.000)     | 34.78*** (0.000)   | 32.78*** (0.000)   | 34.52*** (0.000)      |
| LR- slm          | 50.34*** (0.000)     | 35.57*** (0.000)   | 33.34*** (0.000)   | 34.63*** (0.000)      |
| LR-sem           | 46.37*** (0.000)     | 33.56*** (0.000)   | 31.70*** (0.000)   | 33.20*** (0.000)      |
| Hausman          | 13.97* (0.083)       | 14.71* (0.065)     | 15.01* (0.059)     | 27.24*** (0.001)      |
| LR-ind           | 57.82*** (0.000)     | 36.58*** (0.000)   | 36.66*** (0.000)   | 36.41*** (0.000)      |
| LR-time          | 331.26*** (0.000)    | 347.33*** (0.000)  | 345.02*** (0.000)  | 349.23*** (0.000)     |

Notes: *** Significant at 1% level; ** significant at 5% level; * significant at 10% level
The energy intensity results in a corresponding increase in the local LEE by 0.3922% but may result in the decrease in the LEE of the surrounding provinces by 0.4609%. This may be due to the fact that the rapid development of China’s logistics industry depends on a large amount of energy consumption. In the case of kerosene, gasoline, and the “black electricity” dominating the energy consumption of China’s logistics industry, energy intensity cannot be used as a lone indicator because it enhances the local LEE while also inhibiting the LEE of surrounding areas. This requires the logistics industry to reduce its energy intensity and focus more on green electricity to control the negative spillover effect.

Under the three different spatial matrices other than W1, only the direct effect of the urbanization level (UL) passed the 10% significance level test, indicating a positive effect and an average coefficient of 0.218. This result indicates that the urbanization level significantly promotes the local LEE, which is consistent with the study by Tan et al. (2019). The possible reasons for this are ascribed as follows: The improvement of urbanization levels had granted free access to a large number of rural inhabitants to migrate to urban areas, consequently providing abundant human resources for the logistics industry. The urbanization level significantly promotes the local LEE, which is consistent with the study by Tan et al. (2019). The possible reasons for this are ascribed as follows: The improvement of urbanization levels had granted free access to a large number of rural inhabitants to migrate to urban areas, consequently providing abundant human resources for the logistics industry.
The Technological Innovation Level (TIL) had a significant positive direct effect on the LEE with an average coefficient of 0.0701, under four different spatial matrices. This indicates a pass of the significance test at the 10% level and verifies previous research conclusions from Zhou et al. (2018). Through an upgrade in the production mode of enterprises and the lifestyle of individuals, technological innovations can improve the resource utilization and industrial production efficiencies and also reduce the environmental pollution caused by economic development.

The average coefficients of the direct and indirect effects of opening level (OL) based on four matrices were −0.1085 and −0.1994, respectively. This is nearly at the 10% significance level, indicating that an increase in the foreign direct investment will inhibit the LEE of a certain area and its surroundings, which supports the “pollution haven hypothesis.” This result suggests the establishment of strict environmental admission standards for open projects in the process of opening up, as opposed to blindly attracting foreign investment.

### Conclusions and policy recommendations

#### Conclusions

By employing the super-SBM-undesirable and spatial Dubin models, this study measures the LEE of 30 provinces in China from 2005 to 2019 and also explores its influencing factors. The conclusions are as follows:

First, the LEE is at a low level on the overall with the average of 0.657. During 2005–2007, 2007–2013, and 2013–2019, there is a three-stage trend of “decreasing first, then rising, and later stable.” The LEE shows significant regional differences among the 30 provinces and a gradual decline from Eastern to Western China. Specifically, the eastern provinces have the highest LEE, followed by the central region, and the lowest is in the west.

Second, the spatial directionality of the LEE depicts a “northeast to southwest” trend. The gravity center is located in Henan province and moves to the southeast. The LEE has a significant positive spatial autocorrelation on the whole. There is significant local spatial agglomeration in the geographical

### Table 8 SDM spatial spillover effect decomposition

| Variables  | Adjacency matrix W1 | Distance matrix W2 | Economic matrix W3 | Information matrix W4 |
|------------|---------------------|--------------------|--------------------|-----------------------|
| Direct     |                     |                    |                    |                       |
| LnEL       | −0.3203** (−2.1270) | −0.4024*** (−2.6076) | −0.3557** (−2.3103) | −0.3146** (−2.0446) |
| LnIS       | 0.3008*** (5.2949)  | 0.2904*** (4.6250)  | 0.2659*** (4.2920)  | 0.2488*** (4.0724)   |
| LnER       | 0.0941*** (5.6022)  | 0.0879*** (4.9842)  | 0.0868*** (4.8901)  | 0.0890*** (5.0283)   |
| LnES       | −0.0848*** (−1.9618) | −0.1488*** (−3.5451) | −0.1500*** (−3.5743) | −0.1400*** (−3.3413) |
| LnEI       | −0.4023*** (−8.1991) | −0.3870*** (−7.7295) | −0.3910*** (−7.8092) | −0.3883*** (−7.7601) |
| LnUL       | 0.1858 (1.4550)     | 0.2570*** (2.1285)  | 0.2285* (1.8940)    | 0.2007* (1.6870)     |
| LnTIL      | 0.0906** (2.4782)   | 0.0673* (1.8598)    | 0.0634* (1.7500)    | 0.0590* (1.6352)     |
| LnOL       | −0.1019*** (−3.3152) | −0.1094*** (−3.5773) | −0.1113*** (−3.6250) | −0.1114*** (−3.6371) |
| Indirect   |                     |                    |                    |                       |
| LnEL       | 0.6194** (2.2752)   | 0.0748 (0.2015)     | −0.0192 (−0.0531)   | 0.0116 (0.0337)      |
| LnIS       | 0.2036 (1.3606)     | 0.1979 (0.9688)     | 0.1293 (0.6078)     | 0.0998 (0.4654)      |
| LnER       | 0.0956** (2.3602)   | 0.0870 (1.6303)     | 0.0998* (1.8556)    | 0.1127** (2.2019)    |
| LnES       | 0.2602** (2.5212)   | −0.0544 (−0.4177)   | −0.0152 (−0.1112)   | 0.0658 (0.4824)      |
| LnEI       | 0.3115*** (2.9224)  | 0.4686*** (3.3270)  | 0.5037*** (3.3781)  | 0.5596*** (3.5862)   |
| LnUL       | 0.3546 (1.2335)     | −0.1956 (−0.5875)   | −0.0047 (−0.0141)   | 0.0217 (0.0651)      |
| LnTIL      | 0.0014 (0.0174)     | 0.1196 (1.0448)     | 0.1311 (1.1095)     | 0.1426 (1.1829)      |
| LnOL       | −0.0722 (−0.7914)   | −0.2221*** (−2.0409) | −0.2500*** (−2.2339) | −0.2531*** (−2.1632) |
| Total      |                     |                    |                    |                       |
| LnEL       | 0.2991 (1.0178)     | −0.3276 (−0.7931)   | −0.3749 (−0.9228)   | −0.3029 (−0.7667)    |
| LnIS       | 0.5044*** (3.0347)  | 0.4883** (2.0732)   | 0.3952 (1.6383)     | 0.3486 (1.4521)      |
| LnER       | 0.1879*** (4.1700)  | 0.1749*** (2.9798)  | 0.1866*** (3.1390)  | 0.2017*** (3.5263)   |
| LnES       | 0.1754 (1.4302)     | −0.2032 (−1.3987)   | −0.1652 (−1.0958)   | −0.0742 (−0.4927)    |
| LnEI       | −0.0908 (−0.7192)   | 0.0816 (0.5007)     | 0.1126 (0.6644)     | 0.1713 (0.9750)      |
| LnUL       | 0.5404* (1.9398)    | 0.0613 (0.1758)     | 0.2238 (0.6311)     | 0.2224 (0.6322)      |
| LnTIL      | 0.0920 (1.0267)     | 0.1869 (1.6244)     | 0.1945* (1.6489)    | 0.2016* (1.6717)     |
| LnOL       | −0.1741* (−1.6608)  | −0.3315*** (−2.7205) | −0.3613*** (−2.8981) | −0.3645*** (−2.8150) |

Notes: *** Significant at 1% level; ** significant at 5% level; * significant at 10% level
distribution. HH cluster is mostly observed in eastern China, while LL cluster is in western China. The above conclusions also support that the spatial effects cannot be ignored in the analysis of factors influencing LEE.

Third, the spatial Dubin model shows that there is a significant positive spillover effect on the LEE; that is, the improvement of the local LEE will contribute to elevate the LEE in surrounding areas. The decomposition results of spatial direct effect demonstrate that industrial structure, urbanization level, environmental regulation, and technological innovation level have a positive impact on the local LEE. More in detail, industrial structure displays the most promoting effects with an average coefficient of 0.2765. Energy intensity, economic level, energy structure, and opening level have a significant effect on the local LEE with varying degree of inhibition. The results of indirect effect show that the local energy intensity and environmental regulation have a significantly positive influence on the LEE in neighboring provinces, and the local opening level has significant inhibiting effects on it. There are no statistically significant indirect effects in remaining variables.

Policy recommendations

First, significant regional differences of the LEE in China exist, necessitating the formulation of differentiated ecological efficiency improvement strategies. Eastern provinces should focus on innovative research and development of environmental pollutant emission reduction technology in the logistics industry and actively provide emission reduction technologies, talents, and financial support to the central and western regions. By combining the resource advantages of their logistics industry, the central and western regions should facilitate the development of a secondary industry, improve the urbanization level, actively introduce an emission reduction technology, and focus on increasing investment in pollution control.

Second, the development of the secondary industry has the greatest promotional effect on the LEE, and the integration and linkage development of the secondary and logistics industries should be vigorously encouraged. The government should thoroughly put “the Implementation Plan for Promoting Deep Integration, Innovation and Development of Logistics Industry and Manufacturing Industry” into effect (National Development and Reform Commission of China 2020), accelerating the pace of green development of intelligent manufacturing, establishing the two-industry linkage information service platform, and building the collaborative green cycle system of industry and supply chains in the manufacturing industry.

Third, there exists a restraining impact of energy intensity and energy structure on the LEE; therefore, the energy utilization efficiency in the logistics industry should be further improved. As an industry having a high energy consumption, the logistics industry should emphasize on the use of black electricity from coal and focus more on the use of green electricity from clean energy such as wind, water, and solar energy. Based on the current policies of optimizing logistics transportation organization including multimodal transport and network freight platform, the vehicles monitoring platform for total energy consumption, types, and exhaust emissions should be established, to speed up the ecological development of the logistics industry.

Fourth, since the LEE has a positive spatial spillover effect among the Chinese provinces, a joint prevention and control mechanism of environmental management in the logistics industry should be established. The government should consider integrated elements such as economic base, openness level, energy characteristics, traffic and location conditions, energy use, and transportation location in neighboring provinces. Pollutant emissions at key positions of logistics channels and hubs should be accurately prevented and controlled, and daily environmental monitoring and supervision should be intensified. Based on the policy of urban green freight distribution demonstration project (Transportation Ministry of China 2017), ecological logistics demonstration projects in cross-regional urban agglomerations should be implemented, and the full potentials of government policies should be maximized.

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Author contribution Bai was responsible for the conception and design of the study and was the main writer of the manuscript; Khan and Chen interpreted the results; Wang and Yang contributed to the discussion and revisions; and Dong reviewed and supervised the manuscript. All authors read and approved the final manuscript.

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Data Availability The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

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