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Data-Driven Resource Efficiency Evaluation and Improvement of the Logistics Industry in 30 Chinese Provinces and Cities

Heping Ding [1,2], Yuxia Guo [1,*], Xue Wu [1], Cui Wang [1,2], Yu Zhang [3], Hongjun Liu [1], Yujia Liu [1], Aiyong Lin [1] and Fagang Hu [1]

1 Business School, Suzhou University, Suzhou 234000, China; dingheping@ahszu.edu.cn (H.D.); snowu@ahszu.edu.cn (X.W.); wangcui@ahszu.edu.cn (C.W.); sxylhj@ahszu.edu.cn (H.L.); lyj@ahszu.edu.cn (Y.L.); linay05@ahszu.edu.cn (A.L.); hufg@ahszu.edu.cn (F.H.)
2 Center for International Education, Philippine Christian University, Manila 1004, Philippines
3 School of Civil Engineering, Central South University, Changsha 410083, China; 204812389@csu.edu.cn
* Correspondence: gyx@ahszu.edu.cn; Tel.: +86-18305571614

Abstract: Improving the logistics industry's resource efficiency (LIRE) is one of the most significant measures for ensuring sustainable development. We offer a data-driven technique for analyzing and optimizing the LIRE to improve it and achieve sustainable development. A LIRE index system is built based on relevant data gathering and a complete examination of the economy, society, and environment. The Super-EBM-Undesirable model was used to calculate the LIRE; the Global Malmquist–Luenberger index model was used to calculate the LIRE's dynamic change characteristics, and ArcGIS and spatial autocorrelation models were used to analyze the LIRE's spatial evolution pattern. The LIRE in 30 Chinese provinces and cities from 2011 to 2019 is used to illustrate the method implementation process. The results indicate the following: (1) The overall LIRE is low, with an average value of 0.717, and there are regional variances with a decreasing gradient pattern of "East–Northeast–Central–West". (2) Changes in pure technical efficiency have a bigger impact in general; increasing technical efficiency is the LIRE's principal motivator. (3) Improving the LIRE should take spatial spillover and inhibitory effects into account. This study provides theoretical and methodological support for the evaluation and optimization of the LIRE and a theoretical foundation for the logistics industry's sustainable development (LISD).

Keywords: sustainable development; resource efficiency of the logistics industry; Super-EBM-Undesirable model; Global Malmquist–Luenberger index model; spatial autocorrelation; data-driven

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1. Introduction

1.1. Research Background

With the increasing severity of energy and environmental concerns in recent years, all countries throughout the world have adopted sustainable development (SD) as a shared development goal. The logistics industry (LI) has become one of the most important measures of a country or region's overall strength as a basic service industry for national economic and social growth [1]. The purpose of the development of the LI is to pursue high efficiency and high profits, and the logistics efficiency is vital to the healthy development of the LI. However, the LI's energy consumption, carbon, and air pollution emissions, as well as its social impact, are all expanding year after year. Excessive pollution of the environment and resource consumption can easily restrict the LI's development and can even affect economic and social progress [2]. The contradiction between the LI's economic expansion, the ecological environment, and social development is becoming increasingly prominent. Improving resource efficiency (RE) is critical for achieving sustainable development goals, as it protects the environment while also promoting economic and social progress [3]. How to improve RE from an integrated perspective of protecting the environment and promoting economic and social development is important for achieving sustainable development goals.

Therefore, under the common goal of global sustainable development, the research topics that need urgent attention include: (1) how to accurately and comprehensively quantify and evaluate the LIRE from the perspective of sustainable development; (2) how to portray the temporal and spatial evolution characteristics of the LIRE; (3) how the logistics industry can achieve resource efficiency improvement from the perspective of temporal and spatial evolution and coordinate with environmental protection and social responsibility; (4) how to provide government and practitioners with targeted recommendations. These topics are necessary to explore in order to achieve sustainable development.

1.2. Research Review

The earliest research on the idea of SD can be traced back to the "Principle of Population" written by Malthus in 1789, who believed that a population exceeding the level that could be sustained with natural resources would inevitably lead to social problems such as hunger and death. The concept of SD was first introduced in the "World Conservation Program" in 1980, and the theory has become a strategic principle for global compliance in subsequent research and practice. The sustainable development idea of LI can be traced back to Bruce (1977) [4], who suggested replacing private transportation with public transportation to reduce the negative impact of transportation on the environment. Since then, more and more scholars have started to pay attention to the LISD and have achieved rich results in the fields of "reverse logistics", "green low-carbon logistics", "green supply chain", etc. The research on the LISD is mainly carried out from the perspectives of customer service, logistics enterprises, efficiency, and industry [5]. The logistics industry efficiency (LIE) is one of the hot spots for scholars to study because improving efficiency means lower costs and increased benefits. With the development and change in social concepts, the connotations and dimensions of the LIE are being enriched continuously. In the early studies, the LIE was more concerned with production efficiency and economic output [6], then scholars began to include ecological environment, low carbon, technological innovation, management level, etc., into the study of the LIE [7]. At present, scholars' studies mostly focus on eco-efficiency, low-carbon efficiency, energy efficiency, etc. [8], and consider the impact of the LI on the environment. However, SD refers to the coordinated development of the economy, society, resources, and the environment, as well as overall human development [9], and studies in this area tend to be less about the impact of the LI on society. Therefore, how the LIE reflects the synergistic development of the economy, society, and the environment has become an important area of academic attention.

The logistics industry resource input–output ratio (LIRE) measures the economic, social, ecological, and environmental benefits created by unit resources [10]. It covers all aspects of the LISD and comprehensively reflects the sustainable development level of the LI. The early research on the LIRE mainly focused on the input–output ratio of logistics industry hardware and less on the impact of the logistics industry on the environment and society; therefore, our literature review focuses on the LIE and divides it into three aspects: the evaluation index system, measurement and evaluation, and improvement countermeasures.

(1) Evaluation index system of the LIE

Scholars have constructed an evaluation index system from different perspectives. For example, scholars have considered environmental factors and constructed an eco-efficiency evaluation index system for the LI using CO_2 and air pollutants as non-expected outputs [11]. Xia et al. (2009) developed a multi-objective decision model for logistics resource integration and proposed recommendations for achieving the LISD [12]. Qi Lu et al. constructed a cold chain logistics efficiency index system from the perspective of green logistics and analyzed the influencing factors of cold chain logistics efficiency by excluding environmental and error elements [13]. Li Xun et al. and Zhang Rui et al. (2021) constructed an index system for energy eco-efficiency in the LI and studied its link with a dynamic causal relationship of influencing factors [8,14]. When studying the LIRE, the existing literature often establishes the evaluation index system from a specific perspective (such as ecology, energy, carbon emissions, etc.), whereas the resource system of the LI includes the economy, society, the environment, and so on. It is critical to create a LIRE assessment index system that considers all system elements.

(2) Measurement and evaluation of the LIE

The current efficiency measurement methods mainly focus on stochastic frontier analysis (SFA) [15,16], the ecological footprint method [17], and data envelopment analysis (DEA) [18,19]. Data envelopment analysis methods can directly use sample data to build corresponding optimization models to evaluate the efficiency of multi-input and multi-output production systems, but CCR and BCC models are not applicable when measuring efficiency that includes non-desired outputs and cannot distinguish efficient decision units with efficiency values greater than one [20]. Thus, drawing on the approach of Andersen and Petersen (1993) [21] to distinguish efficient decision units, Tone proposed the super-efficient SBM model [22], followed by the non-expectation SBM model, which considered non-expectation outputs [23]. Since then, the super-efficient-SBM-bad model [24], which is based on the two models discussed above, has been widely used to measure efficiency. The LIE is mainly evaluated from the perspectives of time and space, and in the study of temporal evolution mechanisms, the GML index avoids the problem of linear programming insolvency of the ML index and can be accumulated cyclically [25], and has thus become the most commonly used measure of full-factor dynamic efficiency. In the study of spatial evolution mechanisms, the existing literature mainly analyzes spatial divergence and agglomeration and usually uses spatial measures such as global and local Moran indices to portray the spatial association of efficiency [2]. The Getis-Ord Gi* index is relatively less applied, but cold hotspot analysis is an effective means to explore the characteristics of local spatial clustering distributions [26].

(3) Measurement and evaluation of the LIE

In terms of LIE improvement countermeasures, scholars have proposed specific countermeasures based on their own research themes, such as establishing an environmental assessment and supervision mechanism for the LI, implementing precise environmental regulation policies [27], and using market-oriented and economic means to achieve carbon emission reductions [7]. The study also focuses on specific measures to improve the LIRE, such as encouraging the integration of the secondary industry and the LI, establishing a joint prevention and control mechanism for environmental management in the LI, improving the efficiency of energy use, formulating differentiated eco-efficiency improvement strategies [2], and forming an "open management" pattern [1]. Most existing studies have proposed countermeasures based on efficiency-influencing factors [14,28], but few have proposed countermeasures based on evaluation and spatiotemporal evolution rules.

1.3. Research Gaps

Scholarly research on the LI's efficiency has given a significant reference for improving the LIRE; however, more intensive research is required.

(1) The LIRE is less studied, but the LIRE can best reflect the connotations of the LISD. Existing studies primarily consider the impact of the LI on the environment to establish the evaluation index system, but it is critical to construct its evaluation index system by considering economic, social, and environmental factors comprehensively. As a result, accurately measuring and evaluating the LIRE is an urgent issue to promote the LI's sustainable development.
(2) The use of DEA models has matured in the measurement and evaluation of the LI's efficiency, but there are various forms of DEA models. Traditional CCR and BBC models are not suitable for dealing with non-desired outputs, and the super-efficiency-SBM-non-desired output model still has some shortcomings [29]. It cannot deal with both radial and non-radial cases, and the measurement results are low and

do not correspond to the actual situation. Furthermore, one of the important aspects of the evaluation is characterizing spatial evolution, and there is still a scarcity of LIRE spatial evolution research. As a result, more realistic models and methods for measuring and evaluating RE must be used to effectively analyze and optimize it.

(3) In terms of suggested responses, the majority of the research findings have been made in terms of factors influencing the LI's efficiency, and further research is needed to provide more precise policy guidance based on spatial and temporal evolution characteristics.

1.4. Research Innovations

To address the above challenges, this paper proposes a data-driven approach to evaluate and improve the LIRE, which integrates economic, social, and environmental considerations, quantitatively evaluates the resource efficiency level of the LI, analyzes the mechanism of the LIRE in time and space evolution, identifies its evolutionary essence, and proposes targeted countermeasures to improve it, thus promoting the LISD. The main innovations of the paper are: (1) Constructing an input–output evaluation index system of LIRE from the perspective of SD that integrates economic, social, and environmental considerations, making it more comprehensive and precise. (2) The Super-EBM-Undesirable and GML models are used to evaluate the LIRE more scientifically and objectively, and the spatial autocorrelation analysis model is used to explore the spatial divergence and agglomeration of the LIRE. (3) A data-driven countermeasure proposal for the improvement of the LIRE is proposed, and policy suggestions are given in terms of technological innovation, regional differences, and linkages, which provide a basis for the government to guide the development of the LI better and provide guidance for relevant practitioners.

1.5. Theoretical Value and Practical Significance

To address the above research challenges, we propose a data-driven method for evaluating and improving the LIRE, drawing on the research ideas of Liu (2021) [30] and Wang (2021) [31], which has certain theoretical and practical value.

The theoretical value lies in the following: (1) This paper adopts a data-driven approach to study the measurement, evaluation, and improvement of the resource efficiency level of the LI, extracts relevant information from the database, constructs an evaluation index system of LIRE by combining the relevant literature, establishes a non-expectation super-efficiency EBM model of the resource efficiency of the logistics industry, and realizes a comprehensive evaluation of the resource efficiency level of the logistics industry that involves economic, social, and environmental aspects. (2) We analyze the evolution mechanism of the LIRE from the perspectives of time and space, provide theoretical support for a "measurable, evaluable and enhanceable" LIRE, and enrich the research basis of the LISD. The practical significance is as follows: the article can help the government and practitioners analyze the RE level of LI from economic, social, and environmental perspectives; tell the government and practitioners how to evaluate the LIRE and how to find countermeasures to improve the LIRE from time evolution, spatial differentiation, and agglomeration; and realize the data-driven improvement of the LISD.

1.6. Manuscript Structure

To improve the LIRE and realize the LISD, we propose a data-driven evaluation and improvement method for the LIRE. On the basis of relevant data collection, we comprehensively consider the economy, society, and the environment and construct resource efficiency evaluation indexes for the LI. We apply the Super-EBM-Undesirable model to measure the LIRE statically and the Global Malmquist–Luenberger index model to measure the dynamic change characteristics of the LIRE. Then, using ArcGIS software and spatial autocorrelation models, we analyze the spatial evolution law of the LIRE, take 30 Chinese provinces and cities as examples to show the process of applying the method and model, and propose countermeasures to improve the LIRE according to the analysis results. The study's framework is as follows: the second part is the methodology, which focuses on the data-driven methodological process, including data collection, data processing, data modeling, and application; the third part is the case study, which measures, evaluates, and improves the LIRE using 30 Chinese provinces and cities as examples; and the fourth part is the conclusion.

2. Materials and Methods

This section is a comprehensive introduction to the methodology for measuring, evaluating, and improving the LIRE, including the methodological process, data collection, data processing, data modeling, and data application.

2.1. Methodology Flow

To improve the LIRE and achieve better sustainable development of the LI, evaluating RE from a system theory perspective and formulating relevant countermeasure suggestions from a global optimization perspective are urgent needs. However, LI's resource system involves diverse data. It is important to study how to use effective and objective models to measure, evaluate, and optimize multiple indicators and to evaluate whether the proposed countermeasures and recommendations can effectively support local government decision-making. These issues present a research challenge in the context of global SD goals.

This paper develops a data-driven strategy for measuring, evaluating, and optimizing the LIRE to meet this challenge and improve the LIRE. Data collection is primarily concerned with gathering the LI's resource input and output data; data processing is concerned with converting raw data into measurement data for use in the evaluation index system; data modeling is concerned with constructing LIRE measurement and evaluation models, including the Super-EBM-Undesirable, Global Malmquist–Luenberger index, and a spatial autocorrelation model; data application is concerned with proposing targeted countermeasures to improve the LIRE. The methodological flow is shown in Figure 1.

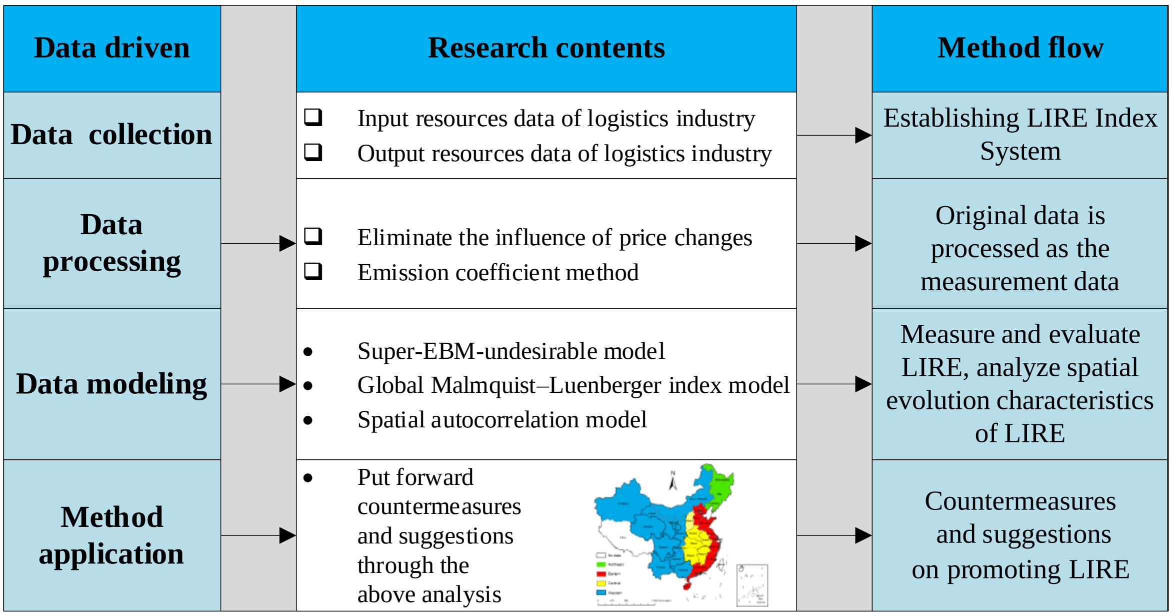

Figure 1. Method flow.

2.2. Data Gathering

Because the goal of this research is to measure, evaluate, and improve the LIRE, a rigorous and scientific evaluation index system is the study's foundation and key. The LI is defined as three sectors based on a review of the relevant literature: transportation, warehousing, and postal services. These three sectors contribute more than 85% of the total LI added value [6], so this definition has a certain degree of reliability. The LIRE evaluation index system is constructed from the input–output perspective according to the principles of conciseness, science, and quantifiability in the construction of indicators, based on the connotation of the LIRE, combined with the use of the EPS database, statistical yearbooks, and other data, and drawing on the results of scholars' existing research on the LIRE. The evaluation index system considers the LI economy–society–environment as a composite system, and its RE reflects the comprehensive input–output ratio of LI economy–society–environment, which is an accurate definition of the LISD.

Human, capital, material, and energy consumption are the most common input indicators [32]. Compared with previous studies, this paper adds "Internet broadband access ports" to the input indicators [33] to reflect the input of information in the LI because information technology input is critical in the Internet era. This section mainly reflects the resource input of the LI in terms of its economic, social, and environmental aspects. The investment in fixed assets, cargo vehicles, logistics network mileage, and Internet broadband access ports reflect the resource input of the LI in economic terms, the number of employees reflects the resource input of the LI in social terms, and the energy consumption reflects the input of energy as an environmental resource.

The expected output indicators mainly include the LI's transport production performance and economic benefits, which have been commonly expressed in the literature in terms of freight turnover and value added [34]. The indicator "vehicle tax revenue" is included in this paper to reflect the social benefits of the LI's resources, i.e., their contribution to society [35]. This part mainly reflects the favorable output of LI to the economy and society after the abovementioned resource input, among which the value added of LI and vehicle tax revenue are important components of the national economy, and the cargo turnover is the contribution of the LI to the cargo transportation of society.

The undesired output indicators mainly include the impact of the LI's resource consumption on the environment and society [36], and scholars have already considered the impact of the LI on the environment when constructing indicators, which can cause climate warming and pollute the environment [37]. This part mainly responds to the adverse output of the LI to society and the environment after the abovementioned resource inputs, among which the adverse impact of CO_2 emissions from the LI on the environment involves causing climate warming, the exhaust emissions from the LI pollute the environment, and the property damage from traffic accidents represents the adverse impact of the LI on society, which is a new indicator added to this paper based on previous studies [35].

This evaluation index system integrates the input–output ratio of the logistics industry in terms of the economy, society, and the environment and measures the LIRE from the perspective of sustainable development, which is very important for the LISD. The details are shown in Table 1.

Table 1. Evaluation index system of the LIRE.

Indicator Category	Indicator Name	Unit	Indicator Description	References
Input indicators of the LI resource	Number of practitioners	10 thousand persons	Human input	[11]
	Investment in fixed assets	100 million CNY	Capital investment	[11]
	Number of vehicles carrying goods	10 thousand units	Infrastructure inputs	[33]
	Logistics network mileage	km	Infrastructure inputs	[11]
	Internet broadband access port	10 thousand units	Information technology input	[33]
	Energy consumption	10^4 tons of standard coal	Energy consumption	[11]
The expected output of the LI resources	Freight turnover	100 million tons/km	Transport results	[11]
	Value added of the LI	100 million CNY	Economic benefits	[11]
	Vehicle tax revenue	100 million CNY	Social contribution	[35]
The undesired output of the LI resources	CO_2 emissions of the LI	10 thousand tons	Carbon emissions	[2]
	Exhaust emissions of the LI	10 thousand tons	Environmental pollution	[2]
	Property damage in traffic accidents	100 million CNY	Negative social impact	[35]

The sample data were mainly obtained from the EPS database, the China Statistical Yearbook 2012–2020, the China Energy Statistical Yearbook, and provincial and municipal development statistical bulletins [38,39]. The Easy Professional Superior (EPS) data platform integrates all kinds of data resources, forming multiple database clusters such as international data, macroeconomic data, financial market data, industrial operations data, regional economy data, trade and foreign economy data, resource and environmental data, county and city data, humanities and social science data, etc. It is a data information service platform that integrates rich numerical data resources and powerful economic measurement systems. The China Statistical Yearbook is an informative annual publication compiled and printed by the National Bureau of Statistics, which comprehensively reflects the economic and social development of China.

2.3. Data Processing

(1) To eliminate the effect of price fluctuations, price-related variables such as LI value added, fixed asset investment amount, and vehicle and vessel tax revenue were converted to actual values with 2011 as the base period.

(2) To calculate the LI's energy consumption, the National Bureau of Statistics' standard coal conversion factor was used, and the LI's terminal energy consumption was used as the base data, multiplied by the standard coal conversion factor, and then summed to get the total energy consumption, as shown in Table 2. For the CO_2 emissions of the LI, referring to the studies of Sun et al. and other scholars [40], combined with the 2006 IPCC Guidelines for National Greenhouse Gas Inventories [41], the carbon emission factors of energy consumption in the LI were obtained, as shown in Table 2, and then their consumption of energy was calculated.

Table 2. Energy consumption discount factors and standard coal and carbon emission factors of the LI.

Energy Type	Raw Coal	Coal Washing	Other Coal Washing	Coal Products	Petrol	Paraffin
Discount factor for standard coal	0.7143	0.9	0.45	0.5286	1.4714	1.4714
Carbon emission factor	0.7669	0.765	0.8079	0.7669	0.5571	0.5723
Energy Type	**Diesel**	**Fuel Oil**	**Liquefied Petroleum Gas**	**Other Petroleum Products**	**Natural Gas**	**Electricity**
Discount factor for standard coal	1.4571	1.4286	1.7143	1.2	12.143	1.229
Carbon emission factor	0.5913	0.6176	0.5042	0.5857	0.4478	0.29

Note: 1. The coefficients are derived from the IPCC Guidelines for National Greenhouse Gas Inventories; 2. The unit for the natural gas to standard coal factor is kg standard coal/10 m^3, the electricity discount factor is kg standard coal/10 kw·h, and the rest are all kg standard coal/kg.

(3) For the exhaust emissions of the LI, drawing on EPA, AP-42, and Beijing emission factors [42], and taking into account the actual situation of China's LI development, the emission factors adopted in this paper are shown in Table 3. The total emissions are calculated using the emission coefficients in Table 3 to estimate SO2, NOX, PM2.5, and PM10 emissions from the LI.

Table 3. SO2, NOX, PM2.5, and PM10 emission factors of the LI.

Indicators	Coal kg/t	Washed Coal kg/t	Other Washed Coal kg/t	Gasoline kg/t	Paraffin kg/t	Diesel kg/t	Fuel Oil kg/t	Natural Gas g/m^3	Liquefied Natural Gas kg/t
SO2	10.0	10	10	1.6	2.75	2.24	2.24	0.18	0.18
NOX	4.0	4	4	16.7	5.09	9.62	5.84	1.76	2.1
PM2.5	0.74	0.74	0.74	0.125	0.06	0.31	0.31	0.17	0.15
PM10	1.61	1.61	1.61	0.25	1.6	0.31	0.31	0.24	0.22

2.4. Data Model

2.4.1. Super-EBM-Undesirable Model

The Epsilon-based Measure (EBM) model makes up for the defects of the traditional DEA model and SBM model and can handle both radial and non-radial situations. It accounts for slack variables in individual factor variability while maintaining the radial ratio between the projected value of the element and the original value [43]. The initial EBM model is improved in this paper by fully combining the characteristics of the resource efficiency index system, data characteristics, decision unit redundancy, efficiency ranking, and other factors in the study of RE in China's LI, finally constructing a RE analysis model applicable to the actual study of this paper. Studying the logistic industry in 30 Chinese provinces and cities is likely to be more representative than studying 1 province or city. Not all logistics industry resource outputs are beneficial to the economy and society; there are some, such as waste gas, carbon, etc., that are harmful to the environment and society—these are non-desired outputs. Thus, the improved model, the Super-EBM -Undesirable model, incorporates super-efficiency and undesirable outputs [44]. It is formulated as follows:

$$\begin{gathered} min\frac{\theta+\varepsilon_x\Sigma_{i=1}^{m}\frac{\omega_i^- s_i^-}{x_{ik}}}{\varphi-\varepsilon_y\Sigma_{r=1}^{q}\frac{\omega_r^+ s_r^+}{y_{rk}}+\varepsilon_z\Sigma_{t=1}^{p}\frac{\omega_t^{b-} s_t^{b-}}{b_{tk}}} \\ s.t.\sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq \theta x_{ik}, i=1,\ldots,m \\ \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \geq \varphi y_{rk}, r=1,\ldots,s \\ \sum_{j=1,j\neq k}^{n} b_{tj}\lambda_j - s_t^{b-} \leq b_{tk}, t=1,\ldots,p \\ \lambda \geq 0, s^- \geq 0, s^+, s^{b-} \geq 0 \end{gathered} \tag{1}$$

where x_{ij} represents the data matrix of input indicator variables—the input indicators are the number of employees, the amount of fixed asset investment, etc. (for details, see the description of the indicator system), y_{ij} represents the data matrix of output indicator variables, φ is the RE under output orientation, and θ is the RE under input orientation (the two representations are separated for ease of understanding). The φ, θ values are the same in non-orientation situations. Slack variables for input and output indicators are represented by s_i^-, s_r^+ respectively. ω_i^- indicates the relative importance of the i-th input indicator and ω_r^+ indicates the relative importance of the r-th output indicator. ε_x indicates the importance of the non-radial component of the efficiency value calculation. The Charles-Cooper transformation is used to transform the output into a linear programming form that can be solved directly.

The weighting coefficients for each indicator within inputs, desired outputs, and non-desired outputs, as well as the parameters characterizing the relevance of the non-radial planning components of inputs, desired outputs, and non-desired outputs, are calculated as follows [45]:

$$\varepsilon_x = \begin{cases} \frac{m-\rho_x}{m-1}\, if\ m>1 \\ 0\, if\ m=1 \end{cases} \quad \omega^- = \frac{\omega_x}{\sum_{i=1}^{m}\omega_{xi}} \tag{2}$$

where ρ_x is the maximum eigenvalues, ω_x is the corresponding non-negative eigenvectors, m is the number of groups of matrix S eigenvalues and eigenvectors, and the parameters of the desired and non-desired output variables can be calculated similarly.

The above formulas are all based on the assumption of constant returns to scale, and the RE obtained is a comprehensive efficiency that includes both pure technical and scale efficiency. Pure technical efficiency is obtained by adding the constraint in Equation (1) "$\sum_{j=1}^{n}\lambda_j = 1$"; scale efficiency can be obtained by the ratio of integrated resource efficiency to pure technical efficiency.

2.4.2. Global Malmquist–Luenberger Index Model (GML)

The Malmquist–Luenberger (ML) index is commonly used for dynamic efficiency studies, but it does not formally satisfy the requirement of transferability, and it has flaws such as no feasible solutions to linear programming when measuring the inter-period directional distance function, making it difficult to conduct comparative efficiency analyses across time series. The GML index has solved these issues [46]. Therefore, this paper adopts the GML index model to conduct a dynamic analysis of the LIRE in 30 provinces and cities in China based on measuring resource efficiency. The GML index is based on the directional distance function (DDF), and the global directional distance function developed by Oh [47] is used in this research.

$$D^{G}(x, y, b) = max\left\{\beta \middle| (y + \beta y, b - \beta b)\epsilon P^{G}(x)\right\} \tag{3}$$

where x represents the input vector, y represents the desired output vector, b is the undesired output vector, β is the value of the directional distance function that maximizes the desired output while minimizing the non-desired output, and $P^{G}(x)$ is the set of global production possibilities.

According to the RD decomposition approach [48], the GML index from period t to period $t + 1$ is defined as follows based on the distance function:

$$\begin{aligned} GML_t^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \\ &= \frac{1+D_v^t(x^t,y^t,b^t)}{1+D_v^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \left[\frac{1+D_c^G(x^t,y^t,b^t)}{1+D_v^G(x^t,y^t,b^t)} \times \frac{1+D_v^G(x^{t+1},y^{t+1},b^{t+1})}{1+D_c^G(x^{t+1},y^{t+1},b^{t+1})}\right] \\ &\times \left[\frac{1+D_v^G(x^t,y^t,b^t)}{1+D_v^t(x^t,y^t,b^t)} \times \frac{1+D_v^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+D_v^G(x^{t+1},y^{t+1},b^{t+1})}\right] = GPEC_t^{t+1} \times GPTC_t^{t+1} \times GSCH_t^{t+1} \end{aligned} \tag{4}$$

where x^t is the t-period input vector, y^t is the t-period desired output vector, and b^t is the t-period undesired output vector. $GPEC_t^{t+1}, GPTC_t^{t+1}$, $GSCH_t^{t+1}$ being greater than (less than) 1 indicates that pure technical efficiency, technical progress, and scale efficiency in period t + 1 increase (decrease) compared to period t. We can observe the trend of the LIRE in China and changes in influencing factors by analyzing the GML index and its decomposition term, allowing us to propose more precise improvement options for the LIRE in each province and city.

2.4.3. Spatial Autocorrelation Model

The Global Moran's I coefficient and the local Getis-Ord G* index were introduced using the following formulae [49] to reflect the LIRE's overall spatial correlation and local clustering, as well as to identify the hot and cold parts of clusters within them.

Global Moran's I factor:

$$I = \frac{n}{\sum_i \sum_j \omega_{ij}} \times \frac{\sum_i \sum_j \omega_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{5}$$

where n is the number of units in the study area. x_i and x_j are the LIRE for study units i and j. $\overline{x}$ denotes the mean value of the LIRE for all study units. w_{ij} denotes the spatial proximity of study units i and j. Here, a binary adjacency matrix with Queen adjacency is used, which means that two areas are considered adjacent as long as there is vertex adjacency. w_{ij} = 1 indicates proximity; w_{ij} = 0 indicates no proximity.

Cold hotspot analysis is a useful tool for exploring the characteristics of local spatial clustering distributions, as it may distinguish the degree of clustering of the variables' spatial distribution via cold hotspots [50]. The distribution of cold hotspots of variables over a local spatial region can be reflected by the local Getis-Ord Gi* index, and the model equation is:

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{ij} x_j - \overline{x} \sum_{j=1}^{n} \omega_{ij}}{s\sqrt{\frac{\left[n\sum_{j=1}^{n} \omega_{ij}^2 - \left(\sum_{j=1}^{n} \omega_{ij}\right)^2\right]}{n-1}}} \ (i \neq j) \tag{6}$$

Of which

$$\overline{x} = \frac{\sum_{j=1}^{n} x_j}{n},\ s = \sqrt{\frac{\sum_{j=1}^{n} {x_j}^2}{n} - (\overline{x})^2}$$

Using ArcGIS 10.2 (It is a geographic software by ESRI, Inc., Redlands, CA, USA) hotspot analysis tools, statistically significant Z-scores and *p*-values were generated in the attribute table of the cold hotspot distribution map. If the *p*-value is significant, the higher the Z-score is above 0, the tighter the clustering of high values of the target attributes (forming hotspots), and the lower the Z-score below 0, the tighter the clustering of low values of the target attributes (forming cold spots).

2.5. Data Application

Given the growing impact of LI's development on the environment and society, improving LIRE and promoting its SD is critical. As the logistics industry resource system involves many factors and a wide range of data sources, a data-driven approach is adopted in this paper. The goal of the research is to apply a data-driven approach to accurately measure, evaluate, and optimize the resource utilization level in the LI, as well as to propose targeted countermeasures based on the quantitative assessment results to provide a decision-making basis for LI practitioners and managers. Figure 2 depicts the data application.

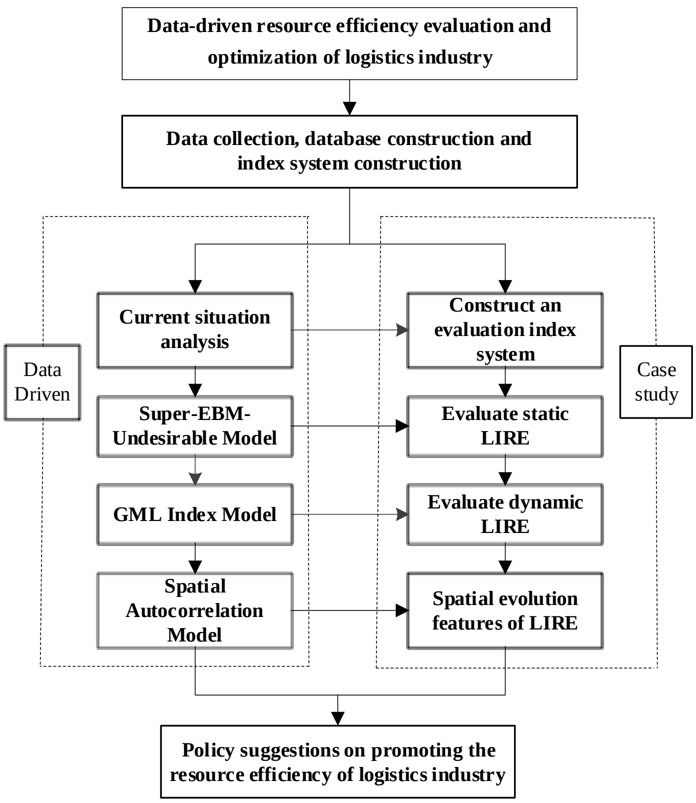

Figure 2. Data application.

The first step involves collecting data related to the development of the LI and establishing a database of the LI's factors list from three aspects: the economy, society, and the environment. According to the principles of data availability and science, the evaluation system of resource efficiency input–output indicators of the LI will be constructed by considering the economy, society, and the environment.

The Super-EBM-Undesirable model of the LIRE is built in the second step to measure the LIRE's level, the GML index model is used to understand the dynamic changes in resource efficiency values better, and a spatial autocorrelation analysis model is built to identify the LIRE's spatial and temporal evolution characteristics.

The research findings are summarized and targeted to fill the shortcomings in the development of the LI and propose countermeasures and recommendations to enhance the LIRE and promote the LI's SD in the third step, which is based on the data-driven quantitative measurement, evaluation, and analysis of the LIRE.

3. Case Study

The LIs in 30 provinces and cities in China were used as examples for the study to verify the feasibility of the above research methodology.

3.1. Case Study Background

China has grown into a great power with worldwide significance as the world's largest developing country and second-largest economy. China's nationwide total social logistics industry was worth 335.2 trillion CNY in 2021, up 9.2% percent from the previous year. The ratio of gross social logistics to GDP was 14.6%, reflecting an improvement in China's LI but still a large gap compared to the level of around 8% in industrialized European and American countries. The improvement of the LIRE in China can contribute to the growth of the domestic and global economies as well as the sustainable development of the global LI. Therefore, through measuring, evaluating, and optimizing the LIRE in China, this paper proposes countermeasures to promote the LIRE in China based on the assessment results, which is of great significance to promoting the sustainable development of the LI in China and the world. The study area is shown in Figure 3 for 30 Chinese provinces and cities (data for Hong Kong, Macau, Taiwan, and Tibet are missing, so they are not considered in this evaluation). Based on their economic status, the regions were divided into four groups: Northeast, Eastern, Central, and Western.

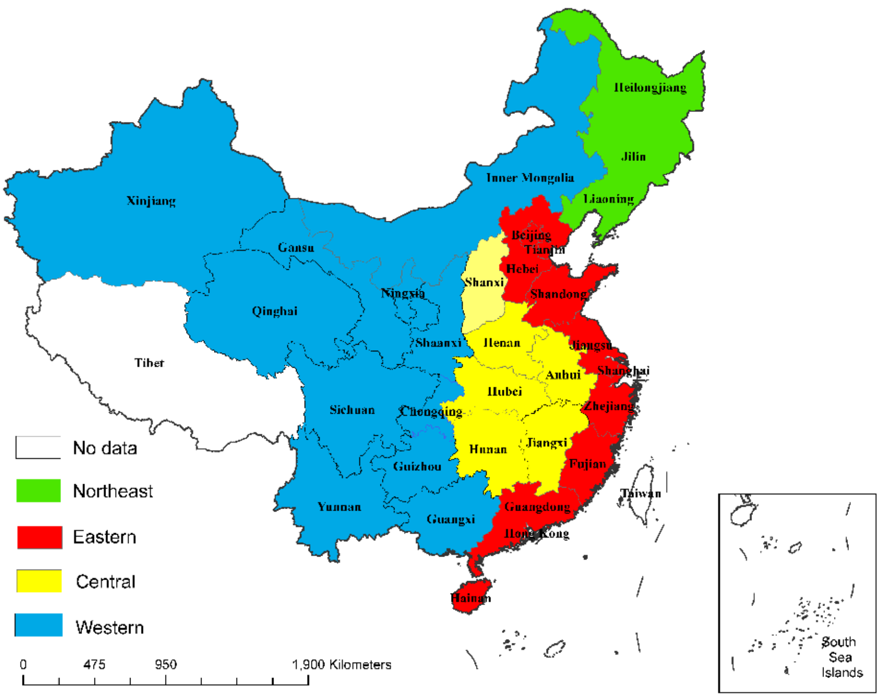

Figure 3. Case study area.

3.2. Results

3.2.1. Static Evaluation of China's LIRE Measurements

RE analysis was conducted on input–output panel data of the LI resource in 30 provinces and cities from 2011 to 2019 using the Super-EBM-Undesirable model, Equation (1), and MaxDEA9 software to obtain the resource efficiency (RE), pure technical efficiency (PTE), and scale efficiency (SE) values of the LI. The mean values of the LIRE in China as a whole and in 30 provinces and cities were drawn on this basis and are shown in Figure 4 to reflect the trends of input–output overall resource efficiency, pure technical efficiency, and scale efficiency of the LI in China from 2011 to 2019, which are also shown in Figure 4.

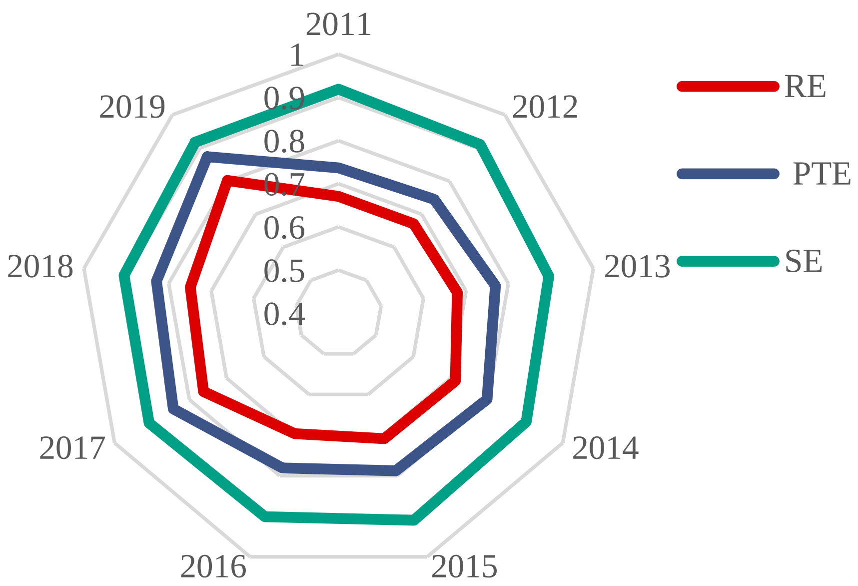

Figure 4. Average LIRE values in China from 2011 to 2019.

According to Figure 4, the average value of the LIRE of China from 2011 to 2019 is less than 1, not reaching DEA significance but showing an overall trend of fluctuating growth. The PTE and SE work synergistically to drive the overall LIRE, and the mean value of PTE is relatively low, playing a large hindering or facilitating role. In China, the value of LIRE fell in 2015 and 2018 due to the drop in PTE. The main reason is that in 2015, China implemented an industry-wide "camp reform" tax system, which increased logistics costs to 204.84 billion USD in that year, which was higher than in previous years, and the decline in transport volume and profit inhibited the development of China's LI, i.e., there was a decrease in cargo turnover in the evaluation index system. In 2017, green development was fully implemented, and China's LI underwent the process of using technology to transform the traditional LI in this context, gradually realizing the transformation from rough development to lean development.

The ranked average LIRE values from 2011 to 2019 in 30 provinces and cities are shown in Figure 5.

According to Figure 5, Inner Mongolia's LI ranks top in terms of average RE, with a score of 0.996. According to the data in the China Statistical Yearbook, compared to other provinces and cities, the LI in Inner Mongolia shows more balanced development. Additionally, Inner Mongolia exhibits higher economic, environmental, and social comprehensive benefits; higher levels of sustainable development; higher LI GDP; less carbon, nitrogen oxide, and particulate matter emissions, which are decreasing year by year; increasing vehicle and boat tax revenue; and decreasing traffic accident property damage, leading to its having the best LIRE. Several top-ranked provinces and cities, such as Shanghai, Jiangsu, Hebei, Shandong, etc., also do better in the logistics industry in terms of economic, environmental, and social comprehensive benefits; in contrast, the bottom-ranked provinces and cities, such as Guangxi, Hainan, Qinghai, etc., are ranked lower due to a lack of balanced development. There is still much room for improvement in these provinces. The improvement of the LIRE, as can be seen, is dependent on the coordinated development of the economy, society, and the environment.

Figure 5. Ranking of 30 provinces and cities based on average LIRE values from 2011 to 2019.

To reflect differences in LIRE between regions, the paper divides the 30 provinces into four regions: Northeastern, Eastern, Central, and Western, and compares the LIRE between these four regions, as shown in Figures 6 and 7.

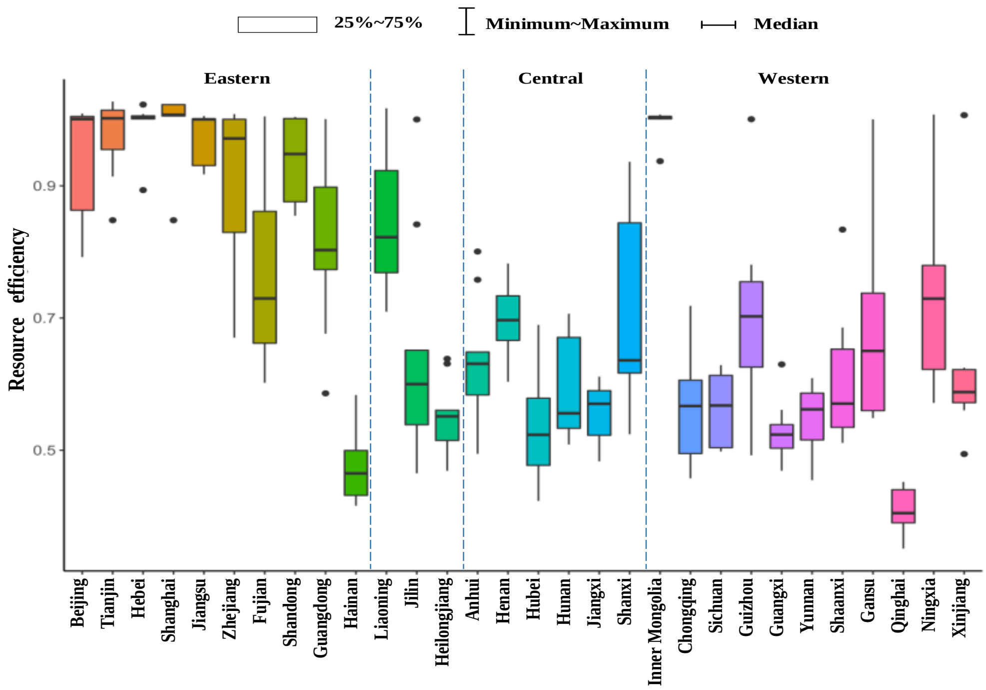

Figure 6. LIRE Boxplot in 30 Chinese provinces, 2011–2019.

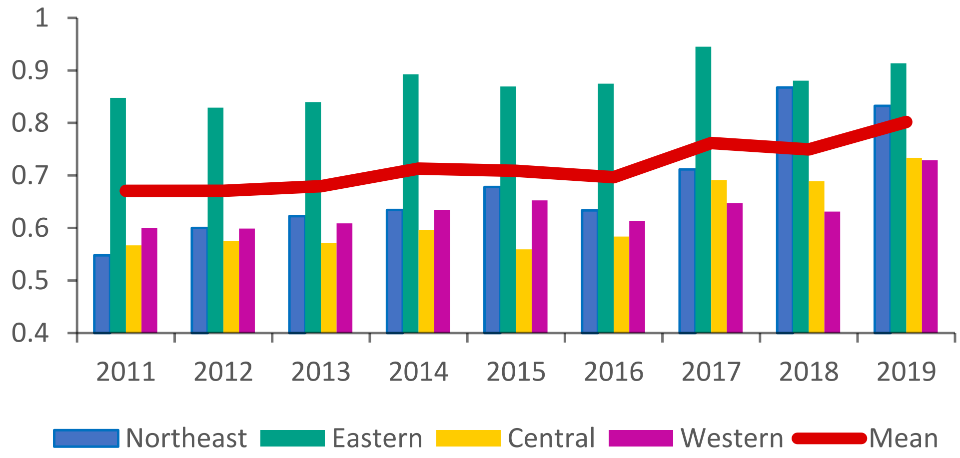

Figure 7. LIRE evolutionary trends in China's Four Regions, 2011–2019.

Figures 6 and 7 show a large disparity in LIRE between regions, with a declining trend from Eastern to Central and Western and a huge efficiency gap in the east when compared to other regions. The causes for this discrepancy are as follows: since the reform and opening up period, China has implemented an unbalanced regional development policy, focusing on financial assistance for the development of the eastern region, which has indirectly promoted a market demand and development space for the LI. Furthermore, the eastern region has achieved a very high economic development level as a result of the rapid development of the manufacturing and logistics industries, with a progressively increasing knowledge of the LIRE and more money invested in environmental protection and social responsibility. In contrast, some polluting firms and industries have relocated to the Central and Western regions, which are relatively economically underdeveloped and are willing to implement relatively lenient environmental regulatory policies. The Central and Western environmental pollution control has remained inadequate as a percentage of GDP over the years, with an average ratio of 1.5 percent, well below the World Bank's recommended 2–3 percent improvement ratio for environmental quality, and the LI has contributed less to society, resulting in a much lower LIRE in the Central and Western areas than in the Eastern area.

3.2.2. LIRE's Dynamic Evaluation Results

This paper uses the GML index model to analyze changes in the total factor resource efficiency of China's LI (GTRECH) and its decomposition terms of pure technical (GPEC), technological progress (GPTC), and scale efficiency change (GSCH) to better understand the dynamic changes and drivers of resource efficiency in China's LI. The results are shown in Table 4 and Figure 8.

Table 4. China GTRECH and its decomposition items (GPEC, GPTC, GSCH), 2011–2019.

Period	GTRECH	GPEC	GPTC	GSCH
2011–2012	0.986545	1.106506	0.874654	1.035832
2012–2013	1.031052	1.010661	1.034	0.993093
2013–2014	1.054622	1.029002	1.018535	1.01033
2014–2015	0.99586	0.966364	1.027188	1.01447
2015–2016	0.989223	1.021952	0.990409	0.984948
2016–2017	1.102431	1.035214	1.059734	1.011826
2017–2018	0.988786	1.005472	1.000209	0.995219
2018–2019	1.098424	1.046088	1.050486	1.008745
Mean	1.030868	1.027657	1.006902	1.006808

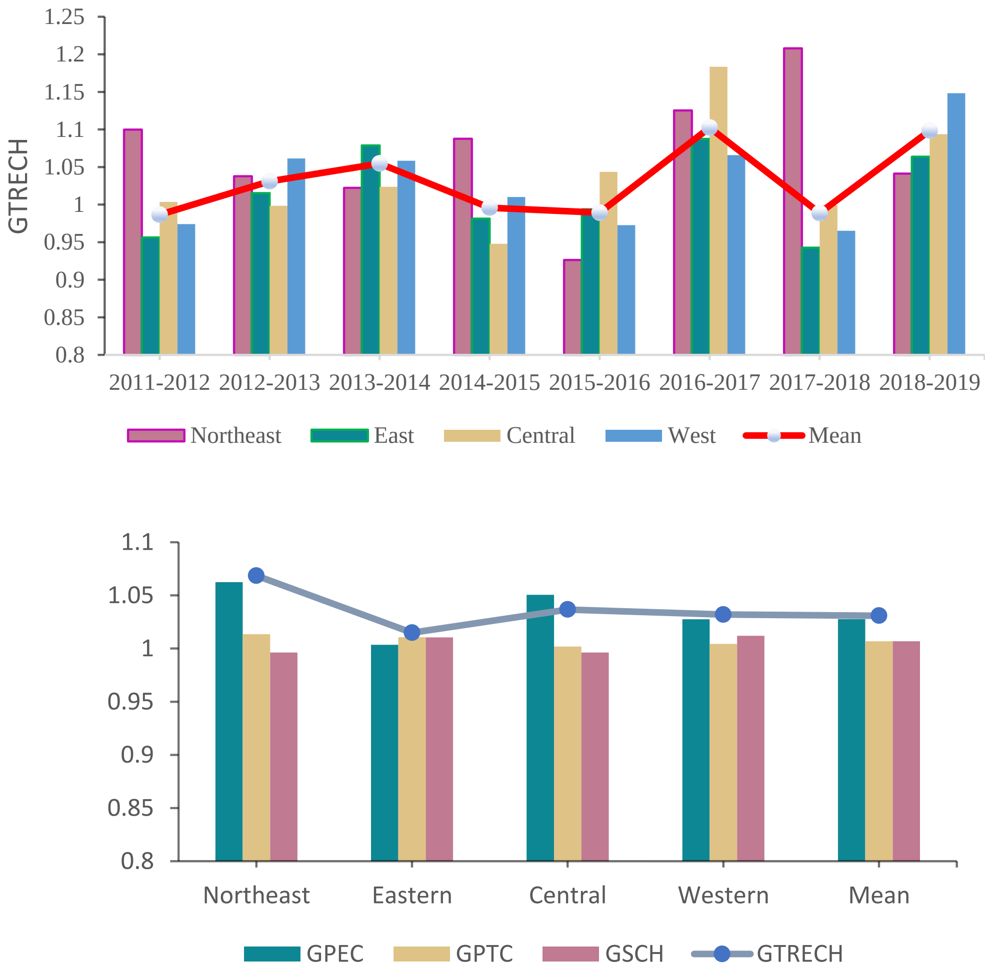

Figure 8. Changes in GTRECH and the decomposition terms GPEC, GPTC, and GSCH in different regions.

Table 4 shows that the average GTRECH from 2011 to 2019 was 1.030868 and that RE is improving overall. In terms of decomposition, the progress stems mainly from improvements in GPEC, while some of the GPTCs and GSCHs are in negative growth. This indicates that although the LI as a whole has adopted some new technologies and improved resource allocation and management, regression in technology and reduced scale efficiency are still pressing issues for the LI. From the results of each period, GTRECH is greater than 1 for 2012–2013, 2013–2014, 2016–2017, and 2018–2019, indicating that China's LIRE has improved in general during these periods, which can be seen from the decomposition results, thanks to the improvement of GPEC and GPTC, while GSCH has lowered RE to varying degrees. GTRECH, on the other hand, was less than 1 during the years 2011–2012, 2014–2015, 2015–2016, and 2017–2018, with 2011–2012 being due to GPTC deterioration, 2014–2015 being due to GPEC retreat, 2015–2016 being due to GSCH and GPTC retreat, and 2017–2018 being due to GSCH and GPTC retreat.

The year 2013 was a "policy year" for the LI when several central and local policies related to the LI were implemented, under the guidance of which the LI's resource allocation capacity and scale were optimized. The LI underwent structural reforms in 2017, accelerating the conversion of old and new dynamics in logistics demand, and the people's consumption behavior became the LI's driving force. The implementation of China's "camp reform" tax system in 2015 resulted in higher logistics costs and lower earnings, inhibiting the expansion of China's LI and resulting in a drop in GTRECH.

As is shown in Figure 8, the GTRECH of the four regions shows a fluctuating upward trend, with the best performance being in the Northeast, where the average growth rate reached 6.86%, followed by the Central region, with an average growth rate of 3.67%. Although the Northeast region's static efficiency is low, it has made significant progress from a dynamic perspective because the three Northeast provinces are China's old industrial bases and main grain-producing areas, providing a solid foundation for developing a modern LI, as well as fostering trade with neighboring countries, strong logistics demand, and strategic location advantages. The Eastern region has high static efficiency, but the dynamic efficiency is on the rise and is fluctuating. The main role of the region with the highest level of economic development is to drive the growth of the LI in the other regions. Despite the central and western regions having more complex topographies, backward related technology, serious brain drain, imperfect infrastructure, and low demand intensity, the GTRECH has been greater than 1 in the last two years, indicating that the government has begun to place a premium on the development of the Central and Western regions, which is inextricably linked to the implementation of national development strategies such as the "One Belt, One Road", "Western Development", and "Revitalization of the Northeast".

While GPEC is a significant constraint on GTRECH in general, the eastern region's GTRECH improvement is strongly reliant on GPTC and GSCH. Technological progress will encourage the LI to reduce the number of employees, decrease the capital required, increase the desired outputs, lower the non-desired outputs, and optimize its industrial structure configuration, all of which contribute to the improvement of GTRECH. This is consistent with the fact that encouraging the eastern region to take the lead in development is an important strategic decision made by the government, with greater investment in technology here than in other regions. The technological progress is faster, the logistics demand is high, the infrastructure is well developed, and the scale efficiency is high. Therefore, different regions should adopt different strategies to enhance LIRE.

3.2.3. LIRE's Spatial Evolution Results

(1) Spatial Heterogeneity Analysis

For the cross-sectional study, we chose the RE values from 2011, 2015, 2019, and the average for 2011–2019, and the RE values were classified into five classes using ArcGIS 10.2 software: low efficiency (<0.6), lower efficiency (0.600001–0.7), medium efficiency (0.700001–0.8), higher efficiency (0.800001–0.9), and high efficiency (0.900001–1.1), generating a spatial distribution of the LIREs, as shown in Figure 9.

It can be seen from Figure 9 that (1) the overall LIRE has a zonal decreasing pattern of "high in the east and low in the west", with an average value of 0.717 nationwide, while the average values are 0.681, 0.877, 0.618, and 0.635 in the Northeastern, Eastern, Central, and Western regions, respectively. LIRE is zonally differentiated, with an East > Northeast > West > Central gradient. The high-efficiency and higher-efficiency provinces and cities are primarily in the Eastern region, including Beijing, Hebei, Shandong, Shanghai, Zhejiang, and Jiangsu, whereas the low-efficiency provinces and cities are generally in the Western and Northeastern regions, including Qinghai, Gansu, Sichuan, Yunnan, and Heilongjiang. (2) The LIRE's extremes distribution is both stable and variable, with a certain degree of spatial inertia and phase variability. The low-efficiency areas are highly concentrated in Qinghai, Sichuan, and Heilongjiang, while the high-efficiency areas are in Hebei, Beijing, Tianjin, Shanghai, and Jiangsu. The range of extremes has changed significantly, and there are still some phase changes. The range of low-efficiency zones is contracting, while the range of high-efficiency zones is expanding, from 5 provinces (Beijing, Hebei, Jiangsu, Shanghai, and Inner Mongolia) at the start of the period to 10 provinces and cities (Beijing, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Inner Mongolia, Liaoning, Xinjiang, and Gansu) at the end of the period. The western and northeastern regions have made a great effort to improve their LIRE, learning from the technological advantages of the eastern region by reducing resource inputs and undesired outputs.

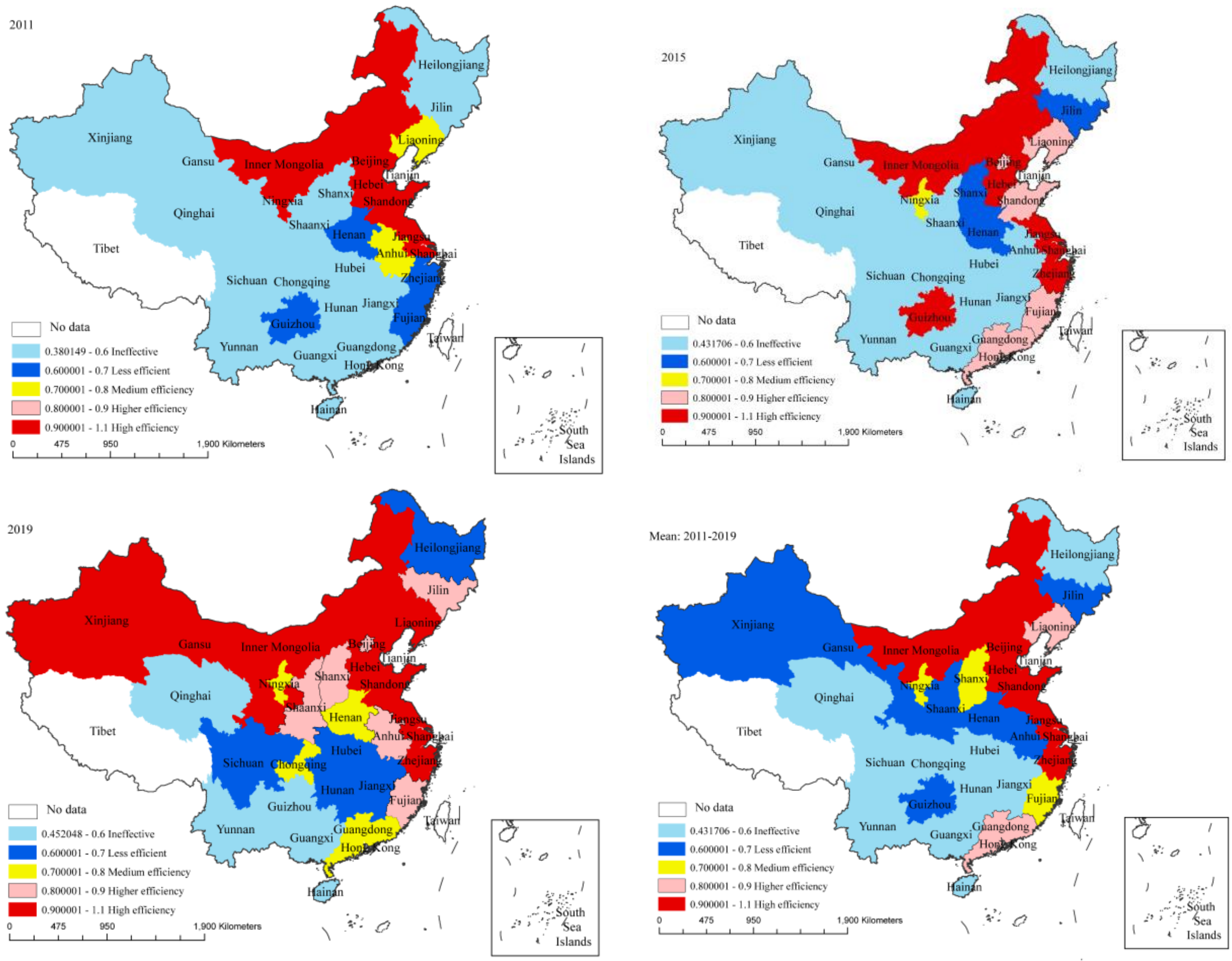

Figure 9. Spatial distribution of the LIRE values in China from 2011 to 2019.

(2) Spatial agglomeration analysis

The overall Global Moran's I index was calculated using the LIRE data above, the spatial autocorrelation analysis model, and the spatial statistics tool in ArcGIS 10.2, as can be seen in Table 5.

Table 5. Global Moran's I index of the LIRE in 30 Chinese provinces and cities.

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Global Moran's *I*	0.5075	0.4535	0.4691	0.4042	0.2536	0.3852	0.3930	0.4647	0.4110
Z	4.3985	3.9701	4.0962	3.5520	2.3231	3.3980	3.4510	4.0365	3.6138
p	0.0000	0.0001	0.0000	0.0004	0.0202	0.0007	0.0006	0.0001	0.0003

From 2011 to 2019, the Global Moran's I index was positive, fluctuating between 0.2536 and 0.5075, and the original hypothesis "there is no spatial correlation between variables" was rejected at the 1% confidence level, indicating that the LIRE in China shows a positive correlation in space and that provinces and cities with similar efficiency values are clustered and distributed in space, with a three-stage development trend. The Global Moran's I index was relatively stable, above 0.4, but showed a declining trend in the first stage (2011–2014). The LI's "policy year" was 2011, when the state attached great importance to the healthy development of the LI, vigorously optimizing the regional layout of the LI and supporting the orderly development of logistics functional clusters, so the LI phenomenon concentration after this year was remarkable. The Global Moran's I index gradually increased in the second phase (2015–2017). Since the new economic normal was initiated, with the introduction of a series of national and local policies to support LI development, it has accelerated. However, due to factors such as the large gap in logistics informatization development within the region and long-standing differences in industrial structure, the gap in LIRE development between regions is still obvious, and the degree of global spatial agglomeration remains weak. The third stage began in 2018, when the Global Moran's I index improved slightly, the LI's development environment improved significantly, and the LI's quality and efficiency improved significantly thanks to the widespread use of big data, cloud computing, and other advanced information technologies, which caused the LIRE's spatial differences to gradually decrease and the agglomeration to slowly increase.

Local spatial autocorrelation analysis, using the ArcGIS 10.2 hotspot analysis tool, was used to observe and analyze the spatial correlation patterns across provinces and cities and neighboring regions more deeply. The LIRE for 2011, 2015, and 2019, as well as the average values from 2011 to 2019, were used for comparative analysis in this paper, as can be seen in Figure 10.

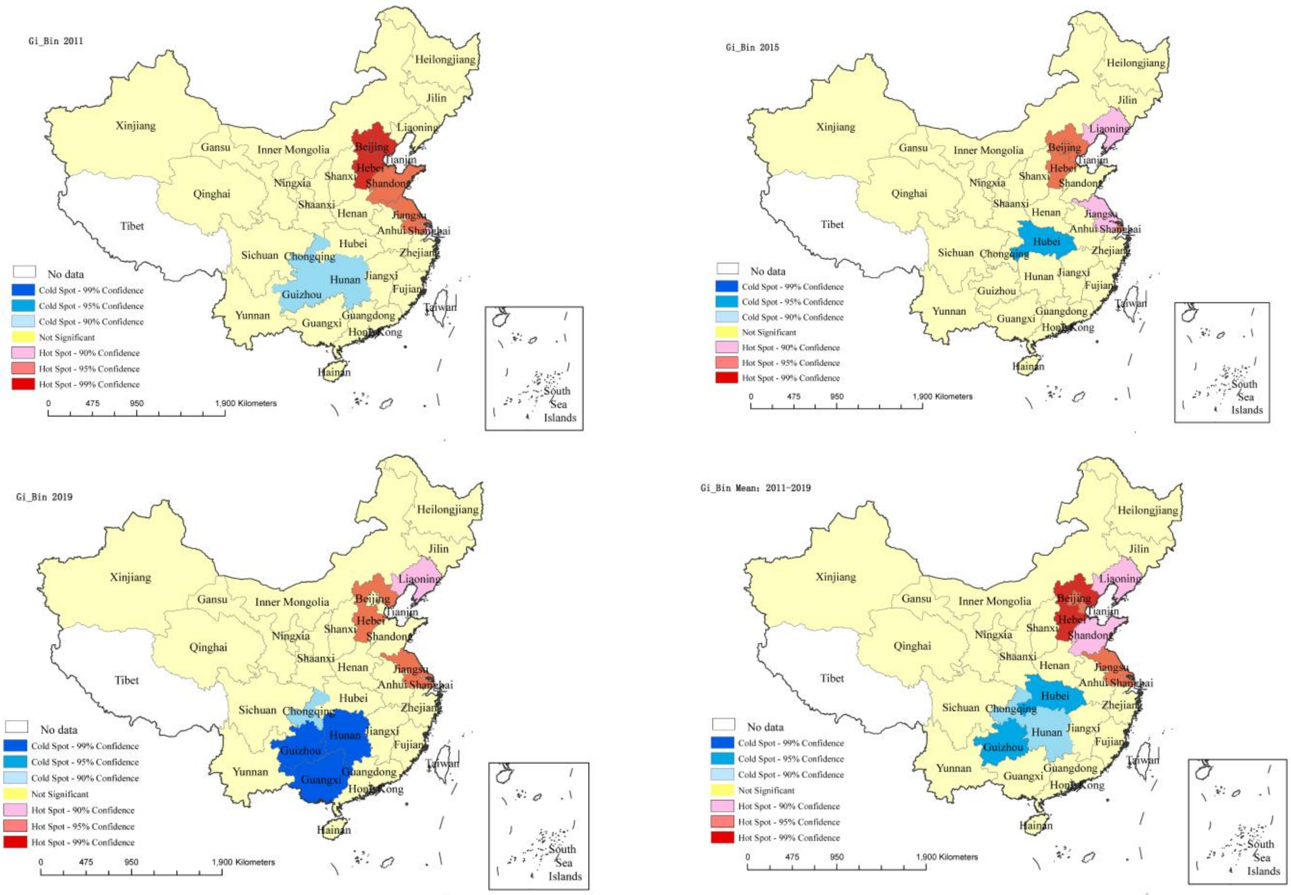

Figure 10. The LIRE's spatial agglomeration evolution in China.

The spatial distribution of the LIRE in China is divided into primary cold spot areas, i.e., 99% confidence interval; secondary cold spot areas, i.e., 95% confidence interval; tertiary cold spot areas, i.e., 90% confidence interval; randomly distributed areas; primary hot spot areas, i.e., 99% confidence interval; secondary hot spot areas, i.e., 95% confidence interval; and tertiary hot spot areas, i.e., 90% confidence interval. According to Figure 10, the cold and hot spot structure of the LIRE is relatively stable, with hot spot areas primarily in the

Eastern region and cold spot areas primarily in the Central and Western regions. The hot spot areas have remained relatively constant, concentrating primarily in five provinces and cities, namely Beijing, Hebei, Shandong, Jiangsu, and Shanghai, whereas the cold spot areas have expanded from the Central to the Western region, indicating that the Western region has become a low-value area for the LIRE due to transportation and location disadvantages, while the more efficient provinces and cities in the Eastern region, such as Zhejiang, Guangdong, and Fujian, have not become hot spot concentration areas. The LI's development scale effect has not yet been formed in these areas. As a result, the key development strategy is to strengthen inter-regional cooperation and increase the LI's geographical spillover effect.

3.3. Policy Recommendations

The mean value of the LIRE in China's 30 provinces and cities is 0.717, which is a low level, but the overall trend is increasing. The LIRE is mostly inhibited by technical efficiency, with regional disparities in the falling gradient pattern of "East–Northeast–Central–West." The GML index of the LIRE is most strongly influenced by changes in pure technical efficiency, with the main driver of LIRE growth being an increase in technical efficiency, but there are also regions where the main drivers are technological change and scale efficiency. There is a significant spatial correlation between regions, with the Eastern region having a higher LIRE and a hotspot province agglomeration with positive spillover effects on neighboring provinces. The Central and Western regions, meanwhile, have a lower LIRE and a cold spot province agglomeration, which is a key area to focus on to improve the LIRE. The following policy recommendations are provided in response to the aforementioned empirical research.

3.3.1. Increase Technology Efficiency and Strengthen Technological Innovation

To improve the LIRE in China, it is vital to strengthen technological innovation, prioritize technical efficiency, and modernize the LI. On the one hand, research and development on and the application of LI-related software and hardware should be increased, and 5G and AICDE (artificial intelligence, internet of things, cloud computing, big data, edge computing) technologies should be deeply integrated with and applied to the LI. On the other hand, we recommend exploring new models suitable for LI development, improving the level of LI resource allocation, and promoting a reduction in inputs and undesired outputs through technology by implementing methods such as adding sensors and other technologies to trucks to reduce the rate of transportation accidents, increase transport safety, and reduce personal injury and property damage in traffic accidents.

3.3.2. Develop Differentiated Improvement Countermeasures and Establish a Linkage Development Mechanism

To improve the LIRE, a combination of regional differences and linkages should be adopted, with a focus on supporting LI development in the Yangtze River Delta region, mainly in Shanghai, Zhejiang, and Jiangsu, as well as in northern China, mainly in Beijing, Tianjin, and Hebei, while increasing construction in provinces with high LIRE potential, such as Hubei, Hunan, Ningxia, Fujian, Liaoning, and Guangdong, gradually forming a LI development pattern of "north–south interaction and east–west connection". The Eastern provinces should emphasize technological development and innovation to reduce carbon and pollutant emissions, as well as social impacts on the LI, and actively provide technical, talent, and financial support to the Central and Western regions. The Central and Western regions should combine the LI resource advantages, actively introduce emission reduction technologies, focus on increasing investment in pollution control, and reduce undesirable social impacts such as traffic accidents.

3.3.3. Promote Coordinated Economic, Social and Environmental Development from a Sustainable Perspective

With a score of 0.996, Inner Mongolia's average LIRE is the highest. It is obvious that the LIRE should be improved from the perspective of sustainable development, focusing on the coordination of relations between the economy, the environment, and society and maximizing the LI's economic, social, and environmental benefits. Specifically, while promoting economic growth, the LI should actively carry out digital information construction, build an intelligent logistics ecosystem, and use technology to increase the LI's contribution to society and reduce its impact on the environment and society. Promoting regional LI synergy, creating regional logistics agglomeration centers, reducing ineffective handling, promoting regional LI industrialization and scale, and realizing the integrated use of LI resources, data, and other elements can improve the LIRE.

With the innovation and progress of technology, differentiated improvement policies, and each province and city giving full play to their respective advantages and helping each other, all Chinese provinces and cities may eventually realize the improvement of the LIRE and promote the LISD.

3.4. Discussion and Management Insights

Compared with previous studies (Zhong et al. 2021, Bai et al. 2021), this paper offers the following advantages. Firstly, guided by the principles of sustainable development strategies, an evaluation index for the LIRE is constructed to provide theoretical support for evaluating the SD capability of the LI. Secondly, based on data-driven methods, an effective tool for evaluating and improving the LIRE is obtained, and the static, dynamic, and spatial autocorrelation analysis of efficiency can clarify the direction of improvement of LIRE and provide a reference for promoting its SD. Lastly, targeted countermeasure suggestions are put forward from the perspective of sustainable development, taking into account the differences between provinces and cities and giving play to their respective advantages to make up for their respective shortcomings and promote the LISD.

The following management insights have emerged in conjunction with the above research and findings.

Firstly, although the government and various enterprises have been attempting to improve the LIRE, it would be worthwhile to improve the LIRE quickly and promote its sustainable development if it can make full use of the relevant data.

Secondly, the major countermeasures to improve the LIRE involve strengthening technological innovation and increasing technical efficiency, based on which the resource advantages of each region may be used for differentiated and linked development between regions. Such optimal decision-making is the key to enhancing the RE and LI's sustainable development level.

Thirdly, the LI's resource system is a complex ecosystem involving economic, social, environmental, and other related subsystems and the interaction between the internal subsystems affects the LIRE's level. Thus, it is necessary to evaluate and improve the RE by identifying and analyzing the LI's subsystems.

4. Conclusions

Sustainable development is a common goal in the world today. Improving the LIRE is a requirement for worldwide sustainable development, given the increasing urgency of global carbon emission reduction, environmental pollution control, and social efficiency enhancement. This paper studies a LIRE evaluation and improvement method based on data-driven research.

The data-driven RE evaluation model and improvement method for the LI can further enhance the logistics system's core competitiveness and sustainability. It can be used for logistics enterprises, supply chains, and industries, and the ability to directly utilize sample data and incorporate super-efficiency while decreasing non-desired outputs are the strengths of the evaluation model. However, the following limitations exist in this paper: (1) The LIRE evaluation index system needs to be further improved; for example, the number of traffic fatalities can be added to the impact of LI on society; (2) The model and method of measuring LIRE in this paper need to be further revised and improved by combining the advantages of various measurement methods, such as energy value, ecological footprint, life cycle, etc.; (3) This paper only analyzes the spatial and temporal evolution characteristics of LIRE but does not consider the external factors, such as the economic environment, industrial environment and policy environment of a region, which provides a research direction for the next step. In future research, we will gradually solve these problems.

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