



Research on Green Logistics Efficiency Evaluation and Digital Intelligence Empowerment in Provinces Along "the Belt and Road" from the Perspective of DEA Model

Ruofei Wu^{1,*}, Lianjun Cheng²

¹School of Business Administration, Liaoning Technical University, Huludao, 125105, China

²School of Public Administration and Law, Liaoning Technical University, Fuxin, 123000, China

*1661951606@qq.com

Abstract. Under the background of digitalization and intelligence, the "Belt and Road Initiative" has brought new challenges and opportunities to the logistics industry in the 17 provinces along the route. This study constructed the DEA and Malmquist index model evaluation system, deeply analyzed the green logistics efficiency of these provinces from 2016 to 2020, and used the Tobit regression model to explore the influencing factors. The results show that under the promotion of the initiative, there are significant differences in logistics efficiency among different regions. Technological progress is the core driving force for the growth of total factor productivity. Urbanization has a positive impact on logistics efficiency, while factors such as environmental attention are negatively correlated with it. Based on this, this paper puts forward suggestions such as promoting digital technology, implementing a low-carbon strategy and taking an environmentally friendly growth path to improve the logistics efficiency of the provinces along the route.

Keywords: digital intelligence era; "The Belt and Road"; Green logistics efficiency

1 Introduction

At present, China is accelerating the construction of digitalization, intelligence and ecological civilization, and information technology has a profound impact on the logistics industry. Under the Belt and Road Initiative, improving logistics efficiency is of vital importance to economic cooperation among countries along the routes and the development of key provinces. This study uses the non-parametric DEA model to evaluate the efficiency of green logistics, integrating economic, environmental and social factors to ensure the comprehensive and accurate evaluation. This research innovatively integrates digital, intelligent and green logistics efficiency evaluation, focuses on key provinces along the "Belt and Road Initiative", empirically validates the

effectiveness of the DEA model, builds an evaluation system, and provides theoretical and practical support for the green development of the logistics industry.

This research holds rich theoretical significance. It systematically assesses the green logistics efficiency of 17 key regions along the "Belt and Road Initiative", reveals the current situation and challenges, and provides a basis for decision-makers. Analyze the promoting effect of digital and intelligent technologies on green logistics, facilitate precise policy implementation, and drive the green and efficient development of the logistics industry.

2 Literature Review

In recent years, green logistics has attracted much attention due to its remarkable achievements in addressing environmental and resource issues. Scholars have conducted multi-dimensional research: In the field of low-carbon logistics, Tang^[1] et al. found that reducing the frequency and number of transportation trips can reduce carbon emissions and promote low-carbon guarantees by optimizing transportation. In terms of green logistics efficiency evaluation, Wen Qin^[2] et al. analyzed the logistics efficiency and influencing factors in the northwest region using a three-stage DEA model of super-efficiency, providing strategic references for development and highlighting the role of policies and technologies. Yan Yan^[3] explored the correlation between the dynamic logistics efficiency of the "Belt and Road Initiative" and the dual carbon goals, presenting the evolution trend and potential for low-carbon transformation.

Driven by information technology and artificial intelligence, digital and intelligent logistics have become the core of the logistics industry's transformation. By leveraging technology, the entire process can be made intelligent, automated, and visualized to enhance efficiency and reduce costs. Current research focus: Xiao RQ^[4] et al.'s Research pays attention to the coordinated development of intelligent logistics and the economy in the Yangtze River Delta. It discusses the dual role of smart logistics in the economy and environmental protection from the perspective of carbon footprint and proposes strategies to promote green development. Analyze the application predicament of the Internet of Things in intelligent logistics, propose the success factors, and emphasize technological innovation, data security and talent cultivation; Quantify the improvement of logistics efficiency by digital intelligent technology based on the DEA model and optimize resource allocation. The achievements involve low-carbon logistics, the application of intelligent technologies, regional efficiency assessment and system construction, laying a theoretical and practical foundation for the green development of the logistics industry.

3 Related Theories and Research Methods

3.1 Basic Theory

Digital and intelligent logistics reconstruct traditional logistics by leveraging technologies such as the Internet of Things, big data, and cloud computing, precisely controlling warehousing, transportation, and distribution, optimizing inventory, reducing energy consumption, and enhancing service reliability and security. Under the Belt and Road Initiative, it promotes industrial synergy and economic integration along the routes, marking the global trend of intelligent and efficient transformation of logistics. Logistics efficiency evaluation is based on data, covers core links, and ensures cross-system comparability and operability. In green logistics, the Data Envelopment Analysis (DEA) model takes into account both traditional and environmental factors and has become the mainstream evaluation tool. It is flexible, scalable and customizable, and can be combined with other methods to improve accuracy. In the green logistics practices of the provinces along the "Belt and Road", the DEA model provides scientific support for decision-making, promoting the low-carbon transformation of industries and the sustainable development of regional economies.

3.2 Research Methodology

(1) DEA model construction

The DEA model, as a non-parametric method, is used to evaluate the relative efficiency of multi-input multi-output decision units (DMU) in green logistics under digital intelligence. In this study, the BCC (Variable Return on Scale) model is selected for evaluation, as shown in Equation (1).

$$\left\{ \begin{array}{l} \min [\theta - \varepsilon (e^T S^- + e^T S^+)] \\ \sum_{j=1}^n X_j \lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^n Y_j \lambda_j - S^+ = Y_0 \\ \sum_{j=1}^n \lambda_j = 1 \\ \lambda_j \geq 0, j = 1, \dots, n \\ S^- \geq 0, S^+ \geq 0 \end{array} \right. \quad (1)$$

In Equation (1), X represents input and Y represents output; j stands for Evaluation Unit (DMU); θ represents the green development efficiency value of the logistics industry in each province; S^- and S^+ are relaxation variables. When $\theta=1$ and $S^-=S^+=0$,

DMU is valid. When $\theta=1$ but S^- and S^+ are not all 0, DMU is weakly valid. When $\theta<1$, DMU is not valid.

(2) Malmquist exponential model

To accurately analyze the changes in logistics efficiency in the core provinces of the "Belt and Road Initiative", this study adopts the Malmquist index model to evaluate its dynamic changes. The formula is shown in Equation (2).

$$TFPCH = EFFCH \times TECHCH = PECH \times SECH \times TECHCH$$

$$M = \frac{D_c^{t+1}(x_r^{t+1}, y_r^{t+1})}{D_c^t(x_r^t, y_r^t)} \times \left[\frac{D_c^t(x_r^{t+1}, y_r^{t+1})}{D_c^{t+1}(x_r^{t+1}, y_r^{t+1})} \times \frac{D_c^t(x_r^t, y_r^t)}{D_c^{t+1}(x_r^t, y_r^t)} \right]^{\frac{1}{2}}$$

$$= \frac{D_v^{t+1}(x_r^{t+1}, y_r^{t+1})}{D_v^t(x_r^t, y_r^t)} \times \frac{D_c^{t+1}(x_r^{t+1}, y_r^{t+1}) / D_v^{t+1}(x_r^{t+1}, y_r^{t+1})}{D_c^{t+1}(x_r^t, y_r^t) / D_v^{t+1}(x_r^t, y_r^t)} \times \left[\frac{D_c^t(x_r^{t+1}, y_r^{t+1})}{D_c^{t+1}(x_r^{t+1}, y_r^{t+1})} \times \frac{D_c^t(x_r^t, y_r^t)}{D_c^{t+1}(x_r^t, y_r^t)} \right]^{\frac{1}{2}} \quad (2)$$

In Equation (2), TFPCH represents the total factor productivity from t to $t+1$. It increases when >1 , decreases when <1 , and remains unchanged when $=1$. It can be broken down into Technical efficiency (EFFCH) and Technological progress (TECHCH), and technical efficiency is further subdivided into Pure Technology (PECH) and Scale Efficiency (SECH).

(3) Tobit regression model

The green logistics efficiency value (0-1) obtained by DEA is a restricted variable, and the traditional regression method is not applicable. This study adopts the Tobit model for processing, and its structure is shown in Formula (3).

$$Z = \begin{cases} Z^* = \alpha X + \mu, & Z^* > 0 \\ Z^* = 0, & Z^* \leq 0 \end{cases} \quad (3)$$

In Eq. (3), Z is the vector of the efficiency value; Z^* is a vector of the stage dependent variable; α are parameter vectors; X is the vector of independent variables; μ is the error term, where $\mu \sim (0, \sigma^2)$.

4 Construction of Green Logistics Efficiency Evaluation Index System in the Context of Digital Intelligence

4.1 Selection of Input-Output Indicators

The logistics industry integrates transportation, postal services, warehousing and information management. In China, it is not clearly classified. Scholars often analyze the industry situation by taking transportation, warehousing and postal services as repre-

sentatives. Based on the analysis of core business, this study selects the transportation, warehousing and postal data of 17 provinces (municipalities and autonomous regions) along the "Belt and Road Initiative". The key to evaluating the efficiency of green logistics under the background of digitalization and intelligence lies in the reasonable selection of input-output indicators. This study, drawing on the research of Yao Shanji et al. [5] adopts CO2 emissions, the number of employees, and the investment in fixed assets as input indicators, and the value-added amount of logistics and the volume of goods transportation as output indicators. The price of fixed asset investment is adjusted based on 2015. The total energy consumption is converted into standard coal units as a measurement indicator for material resource input.

$$A_j = \sum_{j=1}^n B_j \times C_j \quad (4)$$

In Eq. (4), A_j the total one-time energy consumption is described; B_j denotes the consumption of the j -th primary energy; C_j Standard coal conversion factor for energy j ; n is the type of energy, and the standard coefficient of energy is derived from the China Energy Statistical Yearbook. The coefficients are shown in Table 1.

Table 1. Conversion coefficient of primary energy consumption (unit: kg of standard coal/kg)

Type of energy	raw coal	diesel	gasoline	crude	kero- sene	natural gas	fuel oil
The coefficient of conversion to stand- ard coal	0.714	1.457	1.471	1.429	1.471	12.143	1.429

The efficiency of the logistics industry is directly influenced by variables of input (such as the number of employed people, carbon emissions, fixed asset investment, etc.) and output (such as freight volume, added value, etc.), and is also restricted by external factors such as macroeconomics, technological innovation, and social environment. When conducting the assessment, uncontrollable environmental factors need to be taken into account, including industrial composition, economic development level, environmental attention, and technological research and development capabilities, etc. These factors together constitute a complex environmental system.

4.2 An Empirical Study on the Evaluation of Green Logistics Efficiency Based on DEA model

Using DEAP Version 2.1 software, this study measures the green logistics efficiency of key provinces and regions under the Belt and Road Initiative from 2016 to 2020, and the relevant analysis results are detailed in Table 2.

Table 2. Efficiency value of green logistics by province from 2016 to 2020

province	2016	2017	2018	2019	2020	mean1	Economies of scale
Heilongjiang	0.371	0.306	0.290	0.410	0.382	0.352	0.955
Jilin	0.458	0.377	0.391	0.570	0.511	0.461	0.943
Liaoning	0.806	1.000	1.000	1.000	1.000	0.961	1.000
chekiang	0.678	0.607	0.751	0.815	0.653	0.701	0.954
Chongqing	0.442	0.403	0.446	0.463	0.406	0.432	0.982
Guangxi	0.557	0.579	0.639	0.661	0.633	0.614	0.783
Hainan	0.370	0.317	0.306	0.798	0.787	0.516	0.675
Shaanxi	0.714	0.715	0.689	0.684	0.713	0.703	0.997
Ningxia	0.777	0.694	0.803	1.000	1.000	0.855	1.000
Yunnan	0.521	0.490	0.545	0.598	0.497	0.530	0.742
Gansu	0.427	0.426	0.494	0.643	0.467	0.491	0.991
Qinghai	0.351	0.306	0.290	0.740	0.280	0.393	0.415
Inner Mongo-lia	0.708	0.766	0.903	1.000	1.000	0.875	1.000
Xinjiang	0.391	0.460	0.372	0.443	0.354	0.404	0.955
Guangdong	0.753	0.784	0.678	1.000	0.637	0.770	0.960
Fujian	0.580	0.514	0.607	0.742	0.685	0.626	1.000
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 2 shows that from 2016 to 2020, the average scale efficiency (0.903) of the logistics industry in key regions of the "Belt and Road Initiative" contributed more to the overall efficiency improvement. More than 70% of the provinces (such as Ningxia) developed well, but the scale efficiency of four places including Hainan failed to meet expectations due to the mismatch between industries and development.

Dynamic logistics efficiency analysis based on the Malmquist exponential model, as shown in Table 3:

Table 3. Analysis based on Malmquist index model

year	Technical efficiency	Technological advancements	Pure technical efficiency	Economies of scale	Total factor productivity
2016-2017	1.013	1.030	0.985	1.028	1.044
2017-2018	0.978	1.092	1.017	0.962	1.069
2018-2019	1.037	1.015	1.024	1.013	1.052
2019-2020	0.975	1.017	0.977	0.988	0.992
average value	1.001	1.038	1.001	1.000	1.039

Table (3) shows that the total factor productivity (TFPCH) of the logistics industry increased by an average of 3.9% annually, mainly due to the significant improvement of the technological progress index, whose growth rate exceeded the 1% increase of the technological efficiency index. The pure technological efficiency also increased slightly by 1%, and the average value of the scale efficiency index remained stable at 1.

4.3 Tobit Regression Results Analysis

The results of Tobit regression analysis are shown in Table 4. The research finds that the regional green logistics efficiency is complex and influenced by multiple factors, and the evaluation of the three-stage DEA model is limited. Therefore, the Tobit model is constructed, with the green logistics efficiency as the dependent variable, and the independent variables include government support, urbanization, etc.

Table 4. Tobit regression analysis results

argument	coefficient	standard error	T	P
Constant terms	1.293	0.179	7.219	0.000***
Level of urbanization	0.012	0.003	4.193	0.000***
The degree of attention paid by the government	-0.005	0.012	-0.417	0.677

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

Tobit regression shows that the logistics efficiency of key provinces along the "Belt and Road Initiative" is affected by multiple factors. The industrial structure, environmental protection focus and urbanization are significant. The environmental protection investment has not been focused on logistics, resulting in insufficient promotion. The industrial structure has not significantly improved efficiency. Urbanization, on the other hand, promotes the improvement of transportation and enhances the efficiency of logistics.

5 Conclusions

The logistics industry in key provinces along the Belt and Road Initiative is faced with both opportunities and challenges. There are three strategies to improve efficiency: Promoting digitalization and intelligence requires the coordination of policies, technologies and talents; Implement a low-carbon strategy to promote green transformation; Deepen regional cooperation to achieve resource sharing. Tobit analysis provides a basis for decision-making, suggesting precise decision-making, strengthened supervision, and promoting international cooperation. In the era of digital intelligence, a green logistics efficiency evaluation system should be established. The assessment of 17 provinces shows that the logistics efficiency in the southeast coastal areas is high, the total factor productivity of logistics has increased, and technological progress has been remarkable. Tobit regression indicates that urbanization promotes efficiency, industrial imbalance and the improvement of environmental protection standards are inhibitory factors, and the effect of government support is not good. It is suggested that the government optimize the layout, enhance technological empowerment and regional coordination, and implement precise policies.

References

1. Tang S, Wang W, Yan H, et al. Low carbon logistics: Reducing shipment frequency to cut carbon emissions[J]. *International Journal of Production Economics*, 2015, 164: 339-350.
2. Qin W, Qi X. Evaluation of green logistics efficiency in Northwest China[J]. *Sustainability*, 2022, 14(11): 6848.
3. Yan Yan. Research on the measurement and influencing factors of regional logistics dynamic efficiency along the "Belt and Road" in China: Based on the dual-carbon perspective[J]. *Business Economics Research*, 2022, 13: 93-97.
4. XIAO R Q, PAN L, XIAO H B, et al. Research of Intelligent Logistics and High-Quality Economy Development for Yangtze River Cold Chain Shipping Based on Carbon Neutrality[J]. *Journal of Marine Science and Engineering*, 2022, 10(8): 1029.
5. Yao Shanji, Ma Lin, Lai Yaojing. Measurement of low-carbon logistics efficiency in key provinces under the Belt and Road Initiative [J]. *Ecological Economy*, 2020, 36(11).

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

