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A Study on Logistics Efficiency in the Yangtze River Economic Belt Based on a Three-Stage DEA Model

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Abstract: This study employs a three-stage Data Envelopment Analysis (DEA) model to measure and evaluate logistics efficiency in the Yangtze River Economic Belt based on data from 11 provinces and municipalities covering the period 2012–2023. Results indicate that logistics efficiency in the Yangtze River Economic Belt exhibits an overall upward trend; however, development imbalances persist among the upstream, midstream, and downstream regions. Shanghai and Jiangsu exhibit the highest comprehensive technical efficiency, while Chongqing and Sichuan demonstrate the lowest. ② SFA regression analysis reveals that managerial inefficiency is the primary factor causing input redundancy in logistics. The two environmental variables selected—R&D expenditure and regional GDP—exert differing levels of influence on input redundancy. ③ After controlling for environmental variables and random factors, the comprehensive technical efficiency of logistics industries across provinces and municipalities exhibited varying degrees of change. To further enhance logistics efficiency in the Yangtze River Economic Belt, it is essential to strengthen infrastructure development, introduce advanced technologies, and promote regional cooperation to foster coordinated development across the economic belt.

Keywords: Yangtze River Economic Belt; Logistics Efficiency; Three-stage DEA Model

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1.Introduction and Literature Review

In October 2023, General Secretary Xi Jinping emphasized at the symposium on further promoting high-quality development of the Yangtze River Economic Belt that efforts should be intensified to advance its high-quality development, thereby better supporting and serving China's modernization [1]. To propel the development of the Yangtze River Economic Belt, it is essential to leverage its geographical advantages, build a robust logistics and distribution system, and enhance connectivity between domestic and international markets. In 2020, at the Eighth Meeting of the Central Financial and Economic Affairs Commission, General Secretary Xi Jinping stressed, "The circulation system plays a fundamental role in the national economy. To build a new development paradigm, we must treat the construction of a modern circulation system as a key strategic task." [2]" As an inland river economic belt spanning China's eastern, central, and western regions, the Yangtze River Economic Belt is closely linked to the development of the logistics industry and has played a vital role in advancing the logistics and distribution system. To promote high-quality development in logistics, the state has issued and implemented a series of policy guidelines. In 2017, the 19th CPC National Congress proposed strengthening infrastructure network construction to advance further the development of the logistics industry [3]. In 2021, the Special Action Plan for High-Quality Development of Commerce and Logistics (2021-2025) identified promoting logistics standardization, digitization, and intelligentization as one of its key priorities. The 14th Five-Year Plan for Modern Logistics Development, issued by the State Council in 2022, set the fundamental establishment of a modern logistics system by 2025 as a primary objective. [4] That same year, the report to the 20th CPC National Congress called for accelerating the development of the Internet of Things, building an efficient and smooth circulation system, and reducing logistics costs. The Third Plenary Session of the 20th CPC Central Committee set forth explicit requirements for improving the circulation system and reducing logistics costs across society, charting the course for modern logistics development. Additionally, the 20th China Logistics Entrepreneurs Annual Conference explored new approaches and pathways for the logistics industry within the framework of Chinese modernization. With strong support from both the state and the industry, China's logistics market has grown substantially. By 2024, the national social logistics turnover reached 360.6 trillion yuan, marking a year-on-year increase of 5.8%. However, alongside its rapid development, the logistics industry also faces constraints imposed by environmental factors and other random variables. According to relevant data from the National Bureau of Statistics' Statistical Bulletin on National Economic and Social Development, the average annual growth rate of the transportation, warehousing, and postal services sector over the past five years has been 5.4%, while China's GDP has grown at an average annual rate of 5.5%. This indicates sustained high-speed development in China's logistics industry, which plays a crucial role in the country's national economic growth. Over the same period, the logistics sector in the Yangtze River Economic Belt achieved an average annual GDP growth rate of 8.42%, surpassing the national average. This indicates the sustained recovery and positive trajectory of the regional economy within the Yangtze River Economic Belt. Its development aligns with China's logistics industry policies while simultaneously propelling the advancement of modern logistics. Consequently, researching the efficiency of the logistics sector in the Yangtze River Economic Belt and proposing feasible recommendations for its development is essential.

Current academic research has extensively examined logistics efficiency and its influencing factors across various dimensions. Building upon the work of Kang, Tie Liang et al. [7], Gong Xue [6] employed the DEA-Tobit model to analyze regional logistics efficiency and its determinants in China from 2010 to 2019. The study revealed a pronounced regional disparity in China's logistics sector, characterized by stronger performance in eastern regions and weaker performance in western regions. Liu Huajun et al. [8] employed the EBM model, standard deviation ellipses, and Dagum Gini coefficients to study provincial-level logistics efficiency in China, revealing a trend of efficiency concentration in eastern regions. Yin Yang et al. [9] employed the Super-SBM model and Malmquist index model to investigate factors influencing logistics efficiency across 41 cities in the Yangtze River Delta region, finding sustained positive development in logistics efficiency within this area. Similarly, Pei Donghui [10] employed the DEA model to examine the logistics efficiency of the Guangdong-Hong Kong-Macao Greater Bay Area urban cluster, suggesting that resource utilization in the region's logistics sector remains inadequate and requires further improvement to enhance efficiency. Zhu Taoxing et al. [11] employed the DEA-Malmquist index to examine logistics efficiency in the Beijing-Tianjin-Hebei region, revealing significant disparities in logistics performance. Concurrently, scholars have also measured logistics efficiency along the Yangtze River Economic Belt. Guo Jinyong [12] assessed the ecological efficiency of logistics systems across 11 provinces and municipalities in the Yangtze River Economic Belt from 2008 to 2019. Zhang Zhijian et al. [13] focused on urban logistics efficiency within the Yangtze River Economic Belt, employing a three-stage DEA model to comprehensively evaluate the logistics sector efficiency of 33 cities along the belt from 2008 to 2018. They observed an overall spatial decay pattern characterized by "lower efficiency upstream and higher efficiency downstream." Additionally, other scholars [14][15] conducted separate evaluations of logistics efficiency for individual provinces and municipalities.

In summary, existing relevant research has achieved certain progress at various levels. However, in recent years, scholars' selection of data for studying logistics efficiency in the Yangtze River Economic Belt has lacked timeliness, failing to effectively and accurately reflect the development trends of the logistics industry in recent years. Therefore, this paper will select comprehensive panel data aligned with the latest logistics industry policies. It will construct an evaluation indicator system for the logistics sector in the Yangtze River Economic Belt from 2012 to 2023. Employing a three-stage Data Envelopment Analysis (DEA) model, it aims to more effectively and accurately assess the efficiency of the logistics industry in the Yangtze River Economic Belt. This evaluation will support the goal of achieving high-quality development in the logistics sector within the Yangtze River Economic Belt.

2.Logistics Efficiency Measurement Results for the Yangtze River Economic Belt

2.1 Measurement Methods

2.1.1 DEA Model

Traditional DEA models merely identify the efficiency frontier to calculate the distance between it and DMUs (Decision-Making Units), thereby evaluating the effectiveness of the selected indicator data. However, this model overlooks the impact of environmental factors and random disturbance errors. Based on this limitation, Fried et al. proposed a three-stage DEA model [16]. Incorporating the SFA model in the second stage, it eliminates the effects of environmental factors, random errors, and managerial inefficiency terms. This enables the DEA model to more accurately reflect efficiency values and provide a more robust evaluation of DMUs. The basic steps are as follows [17]:

(1) Phase One: Traditional DEA-BCC Model

The CCR model was developed by Charnes, Copper, and others based on the concept of “relative efficiency.” Subsequently, Banker et al. introduced the BCC model by incorporating the assumption of variable returns to scale [18][19]. The commonly used CCR model can simultaneously evaluate scale efficiency and technical efficiency, but it assumes constant returns to scale—meaning increases or decreases in production inputs occur at the same proportional rate. Considering the variable returns to scale characteristic of the logistics industry, the input-oriented BCC model is more suitable for evaluating logistics efficiency in the Yangtze River Economic Belt. Therefore, the BCC model for evaluating logistics efficiency in the Yangtze River Economic Belt is established as follows:

$$\begin{cases} min[\theta - \varepsilon(\hat{e}^T s^- + e^T s^+)] \\ \sum_{j=1}^{n} X_j \lambda_j + s^- = \theta X_0, \\ \sum_{j=1}^{n} Y_j \lambda_j - s^+ = Y_0, \\ \sum_{j=1}^{n} \lambda_j = 1, \\ \lambda_j \geq 0, j = 1,2,\cdots,n, \\ s^- \geq 0, s^+ \geq 0. \end{cases} \quad (1)$$

Using DEAP 2.1 software for solution and calculation, the technical efficiency, scale efficiency, and overall efficiency of logistics in the Yangtze River Economic Belt were obtained through computation. Based on the evaluation criteria for each efficiency measure in DEA, the logistics efficiency assessment results for the Yangtze River Economic Belt were derived. In the constraints, j=1,2,…,n represents decision units, while X and Y denote input and output quantities, respectively. When $\theta=1$ and $S^+=S^-=0$, the decision unit is considered DEA-efficient, indicating full utilization of production resources without redundancy or waste. When $\theta=1$ but $S^+\neq0$ or $S^-\neq0$, the decision unit is classified as weakly DEA-efficient. If $\theta < 1$, it indicates that the decision-making unit is not DEA-efficient.

2.1.2 Stage Two: Constructing the SFA Model

Stage two utilizes the slack variables from stage one as the explained variables, employing a pseudo-SFA regression model to separate the effects of environmental variables and random disturbance factors. Corresponding to the stage one model, an input-type pseudo-SFA regression function is constructed:

$$\begin{aligned} &S_{ni} = f(z_i; \beta_n) + v_{ni} + u_{ni} \\ &n = 1,2,\cdots,N; i = 1,2,\cdots,I; \\ &v \sim N(0,\sigma_v^2), u \sim N^+(0,\sigma_u^2) \end{aligned} \quad (2)$$

S_{ni} represents the slack variable for the nth input of the i-th decision unit; z_i denotes environmental factors; β_n indicates the estimated coefficient for environmental factors; $v_{ni} + u_{ni}$ represents the mixed error term of the function, with the two components being uncorrelated; v_{ni} denotes random disturbance, i.e., the impact of random disturbance factors on the input slack variable, and follows a $v \sim N(0,\sigma_v^2)$ distribution; u_{ni} represents managerial inefficiency, i.e., the impact of managerial factors on input slack variables, following a $u \sim N^+(0,\sigma_u^2)$ distribution. After SFA regression, other logistics input quantities are adjusted based on the regression results, using the input quantities of the most efficient decision unit as the adjustment benchmark. The expression is as follows:

$$x_{ni}^A = x_{ni} + \left[max\left(f(z_i;\beta_n)\right) - f(z_i;\beta_n)\right] + \left[max(v_{ni} - v_{ni})\right] \qquad (3)$$

Here, x_{ni}^A denotes the input adjusted by slack variables; x_{ni} represents the input before adjustment by slack variables; $max(f(z_i;\beta_n))-f(z_i;\beta_n)$ signifies the adjustment for environmental factors; $max(v_{ni}-v_{ni})$ indicates setting all decision units at the same level [20].

This paper employs the method proposed by Jondrow et al. for estimation, separating it from managerial inefficiency. Drawing on prior research regarding the separation formula for three-stage DEA, it adopts φ as the density function and distribution function of the standard normal distribution. The combined error term is defined as $\varepsilon_i = V_{ni} + U_{ni}$, with $\lambda = \sigma_\mu / \sigma_\upsilon$ and $\sigma_* = \sqrt{\sigma_\mu^2 + \sigma_v^2}$. This yields the formula for separating managerial inefficiency and random disturbance: $= \sqrt{\sigma_\mu^2 + \sigma_v^2}$, $\sigma^* = (\sigma_\mu \sigma_\nu)/\sigma$. This yields the formula for separating managerial inefficiency and random disturbance:

$$E(\mu|\varepsilon) = \sigma_* \cdot \left[\frac{\varphi(\lambda\varepsilon/\sigma)}{\phi(\lambda\varepsilon/\sigma)} + \frac{\lambda\varepsilon}{\sigma}\right] \qquad (4)$$

2.1.3 Stage Three: Adjusted DEA Model

This stage requires reanalyzing the adjusted efficiency. Using the SFA model from Stage II, the adjusted DMU input values are reintroduced into the Stage I DEA-BBC model to calculate efficiency scores. The resulting DMU efficiency values represent technical efficiency, stripped of external environmental factors and random errors. These scores provide a more accurate reflection of the development level of the logistics industry in the Yangtze River Economic Belt and identify key factors influencing its development [21].

2.2 Construction of Indicator System and Data Sources

The selection of logistics industry efficiency evaluation indicators must prioritize scientific rigor and practicality. By referencing existing research [22][23] and considering the actual conditions of the logistics sector, we constructed efficiency evaluation indicators. Fixed asset investment in logistics and the number of logistics industry employees were chosen as input indicators, while logistics value-added and freight turnover serve as output indicators. Environmental variables include urbanization rate, per capita consumption expenditure of residents, R&D expenditure, per capita GDP, and degree of openness. Raw data for these indicators were sourced from the China Statistical Yearbook (2012–2023) and statistical yearbooks of the 11 provinces and municipalities along the Yangtze River Economic Belt. Specific indicators are detailed in Table 1.

Table 1：Logistics Industry Efficiency Evaluation Indicators

Indicator Type	Indicator Name	Unit
Input Indicators	Fixed Asset Investment in the Logistics Industry	¥ billion
	Number of Logistics Industry Employees	10,000 persons
Output Indicators	Value Added of the Logistics Industry	¥ billion
	Freight Ton-Kilometers	100 million ton-kilometers
Environmental Variables	R&D Expenditure	¥ billion
	GDP per Capita	¥10,000/person
	Degree of Opening-up	--

2.3 Analysis of Measurement Results

2.3.1 Phase One Analysis

Using the constructed indicator system and DEA2.1 software, we analyzed input-output data from 2012 to 2023 for 11 provinces and municipalities along the Yangtze River Economic Belt. This yielded logistics efficiency scores and their decompositions for each region, as shown in Table 2 below.

Table 2：Average Logistics Efficiency of the Yangtze River Economic Belt, 2012–2023

Province/City	Efficiency Rank	Overall Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
Shanghai	1	1.000	1.000	1.000
Jiangsu	2	0.978	1.000	0.978
Zhejiang	3	0.962	1.000	0.962
Anhui	4	0.954	1.000	0.954
Jiangxi	5	0.784	0.847	0.926
Hubei	6	0.769	0.932	0.825
Hunan	7	0.750	0.795	0.943
Chongqing	8	0.597	0.647	0.922
Sichuan	9	0.438	0.520	0.843
Yunnan	10	0.391	0.760	0.514
Guizhou	11	0.343	0.371	0.924
Average	—	0.724	0.807	0.890

(1) Comprehensive Technical Efficiency Analysis

Table 2 shows the comprehensive technical efficiency of the 11 provinces and municipalities along the Yangtze River Economic Belt from 2012 to 2023. Anhui Province achieved an average comprehensive technical efficiency of 1.000, indicating that its logistics industry has reached an equilibrium state of input-output balance. This represents DEA effectiveness and a high level of logistics efficiency. Among other provinces, Shanghai, Jiangxi, and Guizhou all achieved comprehensive technical efficiency above 0.9 but below 1.000. This indicates that while these three provinces maintained relatively high logistics efficiency levels from 2012 to 2023, their logistics industries did not achieve balanced input-output ratios. Consequently, they were not DEA-efficient, and output efficiency still requires improvement. Jiangsu, Zhejiang, Hubei, and Hunan exhibit relatively high average comprehensive technical efficiency. However, compared to Anhui, Shanghai, Jiangxi, and Guizhou, they have yet to achieve efficient levels, necessitating further optimization of logistics industry inputs and outputs. In contrast, the southwestern provinces of Chongqing, Sichuan, and Yunnan display very low average comprehensive technical efficiency, indicating extremely low logistics efficiency over the past 11 years. Significant improvements in the logistics industry inputs and outputs are required. Based on the overall data, Anhui's logistics industry demonstrates the highest overall development level, while Chongqing, Sichuan, and Yunnan require further development.

(2) Pure Technical Efficiency Analysis

Among the 11 provinces and municipalities in the Yangtze River Economic Belt, Shanghai, Anhui, Jiangxi, and Guizhou recorded the highest average pure technical efficiency values from 2012 to 2023, all at 1.000. This indicates that these four regions achieved maximum utilization of technical inputs in their logistics industries, fully leveraging logistics resources. The lowest values were recorded in Chongqing and Sichuan, with pure technical efficiency scores of 0.520 and 0.371, respectively. This may be attributed to both regions being located within the Sichuan Basin, which increases the difficulty of logistics infrastructure development and product transportation, leading to higher costs and greater labor input. Although

Jiangsu, Zhejiang, Hubei, Hunan, and Yunnan did not achieve the highest average pure technical efficiency scores, their efficiency levels were significantly higher than those of Chongqing and Sichuan. These provinces demonstrate more effective utilization of logistics resources and a relatively well-developed technical foundation within their logistics industries.

(3) Scale Efficiency Analysis

The average scale efficiency values for the 11 provinces and municipalities along the Yangtze River Economic Belt from 2012 to 2023 were generally high. Anhui's average scale efficiency reached 1.000, indicating that logistics enterprises maximized their input-output ratio during production processes, fully leveraging economies of scale. Except for Yunnan, the average scale efficiency values of other provinces all exceeded 0.8, indicating that the input-output ratio of the logistics industry remained at a relatively high level. However, there is still room for optimization and improvement in resource allocation management. Yunnan's average scale efficiency value significantly diverged from other provinces, likely due to its southern border location constrained by geographical conditions and infrastructure limitations. Predominantly mountainous and plateau terrain, coupled with its remote distance from other regions, resulted in high transportation network construction costs and low coverage density. This led to markedly lower logistics efficiency compared to other provinces, hindering cross-regional transportation and the exchange of Yunnan's products. Furthermore, its industrial structure leans toward traditional sectors like agriculture and tourism, with a weak logistics foundation and a small share of advanced manufacturing and high-value-added industries, resulting in low economies of scale. In contrast, downstream provinces, leveraging the Yangtze River Delta urban cluster, have established highly synergistic industrial chain clusters with significant economies of scale. Consequently, Yunnan's economies of scale level falls below that of the other 10 provinces and municipalities.

2.3.2 Analysis of Second-Stage Regression Results

The SFA regression analysis indicates (as shown in Table 3) that the Gamma value approaches 1, suggesting that management inefficiency is the primary factor causing input redundancy [24]. The regression coefficients for the SFA of the three environmental variables mostly passed the significance level test, indicating that the selected environmental variables—R&D funding, regional GDP, and degree of openness—significantly influence the redundancy of various input factors in the logistics industry. When considering the impact of environmental variables on input slack, examining the sign of regression coefficients reveals the directional relationship between environmental variables and input slack variables. A negative regression coefficient indicates an inverse relationship: an increase in the environmental variable leads to a decrease in input slack and an increase in output value, and vice versa.

Table 3：SFA Regression Model Results

Name	2015		2018	
Indicator	Fixed Asset Investment Lagging Variable	Number of Employees Lagging Variable	Fixed Asset Investment Lagging Variable	Number of Employees Lagging Variable
Constant	-0.01	0.01	0.00	-0.03
R&D Expenditure	-0.02	-0.02	0.00	0.01
GDP per Capita	0.01	0.01	-0.01	0.00
Degree of openness	-0.03	-0.02	0.03	-0.02
σ2	0.01	0.00	0.03	0.00
γ	1.00	1.00	1.00	1.00
LR	8.79	8.32	6.42	6.86

Note: Due to space constraints, only the SFA regression results for 2015 and 2018 are reported.

Based on the above analysis and incorporating regression analysis results, we further examined the impact of environmental factors, yielding the following findings:

(1) R&D Expenditure

Technological advancement appropriately reduces redundant fixed asset investment and workforce in the logistics sector. However, excessive R&D expenditure does not significantly decrease the level of redundancy in the logistics industry investment. Against the backdrop of digital logistics, intelligent logistics, and green logistics, R&D funding has increased significantly across regions. However, the infrastructure required to support these new technologies is massive in scale, with lengthy construction cycles and slow returns on investment. Substantial funding injections will only increase investment redundancy in the logistics sector, hindering its development progress.

(2) Per Capita GDP

Considering both input indicators, per capita GDP influences both logistics fixed asset investment and logistics employment, but its impact on logistics employment is more pronounced. From 2012 to 2023, the regression coefficients between per capita GDP and input slack variables were all positive, indicating that a decline in per capita GDP leads to an increase in the slack values of logistics fixed asset investment and logistics employment inputs, thereby reducing output.

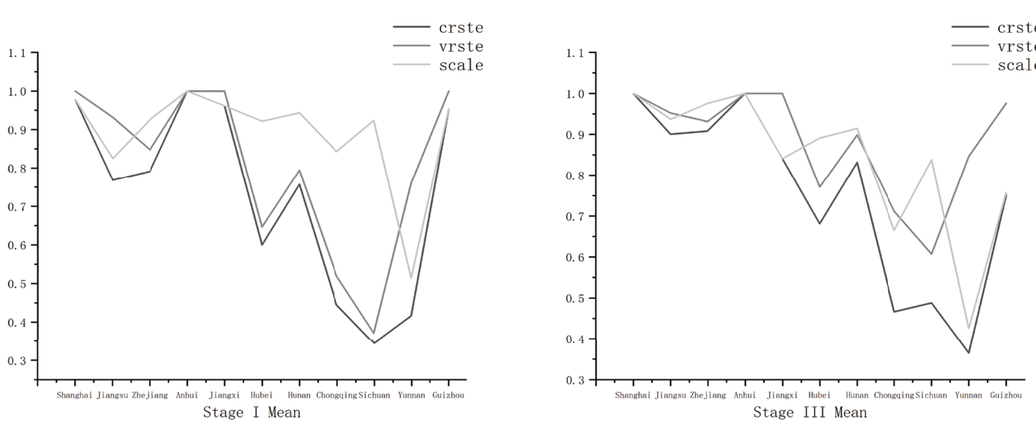
(3) Degree of Openness to the Outside World

Compared to other environmental variables, the degree of openness to the outside world does not significantly impact input redundancy values, but it does exert some influence. Among the 11 provinces and municipalities in the Yangtze River Economic Belt, regions closer to the east—such as Shanghai, Jiangsu, and Zhejiang—exhibit higher levels of openness to the outside world, with input redundancy values approaching zero. However, analysis of the logistics workforce reveals that Shanghai experienced negative input slack in 2014, 2020, and 2021, while Jiangsu has exhibited this pattern for multiple consecutive years. This indicates that even with a relatively complete system of openness, attention must be paid to the rational allocation and utilization of related input resources; otherwise, resources will be wasted.

2.3.3 Third Stage

The input values in the third stage exclude environmental variables and random factors. These adjusted input values replace the original inputs for recalculation, yielding the third-stage results. Comparing the first-stage mean with the third-stage mean produces the findings shown in Figure 1. As illustrated in Figure 1, after eliminating environmental variables and random factors, it becomes evident that environmental variables significantly impact efficiency assessment. After Stage 3 adjustments, upstream provinces demonstrated improvements in overall technical efficiency, pure technical efficiency, and scale efficiency, maintaining their position at the frontier. This indicates that, as economically developed regions, upstream provinces possess relatively mature logistics systems, with R&D funding, per capita GDP, and openness to the outside world effectively supporting efficient resource allocation. Mid-to-downstream provinces showed divergence: Hubei and Hunan saw their adjusted comprehensive technical efficiency rise to 0.681 and 0.832 respectively, indicating efficiency gains after environmental variable correction. Conversely, Jiangxi's comprehensive technical efficiency plummeted from 1.0 to 0.841, revealing that its original efficiency partially relied on environmental advantages (such as higher openness), exposing shortcomings in actual management effectiveness. However, Chongqing, Sichuan, and Yunnan remain at low levels. Notably, Yunnan's comprehensive technical efficiency declined from 0.416 to 0.365, reflecting that its logistics sector is constrained by insufficient R&D investment or low openness, with scale efficiency severely dragging down overall performance.

Figure 1 Comparison of Mean Values Between Phase I and Phase III



3.Conclusions and Recommendations

3.1 Key Findings

(1) Research indicates that logistics industry efficiency in the Yangtze River Economic Belt is generally on an upward trend. However, development remains uneven across upstream, midstream, and downstream regions. Downstream regions exhibit the highest logistics efficiency, followed by midstream regions, with upstream regions ranking lowest. Among provinces, Shanghai and Jiangsu demonstrate the highest overall technical efficiency, influenced by various factors. Zhejiang, Anhui, Jiangxi, and Hunan follow, while Chongqing and Sichuan rank lowest.

(2) SFA regression analysis indicates that managerial inefficiency is the primary factor causing input redundancy. Among environmental variables, R&D expenditure, per capita GDP, and openness to foreign trade significantly influence input redundancy across logistics sectors. Results show that reasonable R&D investment promotes stable logistics development, whereas excessive funding increases input redundancy and hinders progress. Increases in per capita GDP also reduce input redundancy in fixed asset investment and labor input within the logistics sector, thereby boosting output growth. Among environmental factors, the degree of openness has a relatively minor impact on input redundancy.

(3) After controlling for environmental variables and random factors, Upstream provinces exhibit significantly higher comprehensive technical efficiency, indicating that their high R&D investment and openness levels effectively reduce input redundancy through technological upgrading and management optimization; Central provinces exhibit smaller efficiency fluctuations, reflecting an “extensive inertia” stemming from the contradiction between their per capita GDP and technological level. Downstream provinces, however, experience declining adjusted efficiency due to weak economic foundations and insufficient R&D support, exposing structural imbalances between scale investment and output.

3.2 Recommendations

3.2.1 Strengthen Infrastructure Development

Analysis indicates that transportation infrastructure in certain regions remains underdeveloped. The 11 provinces and municipalities along the Yangtze River Economic Belt should optimize navigation channels to enhance waterway capacity; strengthen port facilities to improve cargo throughput efficiency; and expand highway and railway networks to establish a multimodal transport system. Regions with relatively low efficiency, such as Chongqing and Sichuan, should prioritize optimizing resource allocation for the logistics sector and developing logistics warehousing sites to boost overall efficiency.

3.2.2 Introducing Advanced Technologies

Provinces and municipalities such as Shanghai, Jiangsu, and Zhejiang possess objectively high logistics efficiency. They can continue leveraging their geographical and technological advantages by rationally applying modern information technologies like the Internet of Things, big data, and cloud computing to enhance logistics management standards and explore the development of smart logistics. Provinces and cities in the “Two Lakes” region should learn from the practices of logistically efficient areas, adapting measures to local conditions—such as streamlining administrative procedures, lowering barriers and costs for logistics operations, and attracting more leading logistics enterprises from eastern regions. Provinces and cities in the “Two Yangs” region need to optimize the business environment, gradually reducing the interference of environmental variables and random factors on logistics development.

3.2.3 Promoting Regional Cooperation

The 11 provinces and municipalities along the Yangtze River Economic Belt can leverage better-developed regions as a foundation. By facilitating exchanges among logistics professionals and organizing specialized conferences on industrial development, they can promote multidimensional talent mobility, achieving a positive “mentoring and assistance” effect for logistics sector growth. Provincial governments can break down cross-regional policy barriers through favorable incentives, offering tax breaks and financial support to regional logistics enterprises, thereby fostering coordinated development across the Yangtze River Economic Belt.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Xinhua News Agency. (2023, October 12). Xi Jinping presides over symposium on further promoting high-quality development of the Yangtze River Economic Belt, emphasizing: Further promoting high-quality development of the Yangtze River Economic Belt to better support and serve Chinese modernization [Government document]. http://www.qstheory.cn/yaowen/2023-10/12/c_1129913459.htm

[2] China Courts Network. (2020, September 9). Xi Jinping presides over eighth meeting of Central Financial and Economic Affairs Commission, stresses coordinated advancement of modern distribution system to provide strong support for building new development pattern; Li Keqiang, Wang Huning, and Han Zheng attend [Government document]. https://www.chinacourt.org/article/detail/2020/09/id/5449714.shtml

[3] China National Radio Network. (2017, October 27). Xi Jinping: Securing a decisive victory in building a moderately prosperous society in all respects and achieving the great success of socialism with Chinese characteristics for a new era—Report to the 19th National Congress of the Communist Party of China [Government document]. https://news.cnr.cn/native/gd/20171027/t20171027_524003098.shtml

[4] General Office of the State Council of the People's Republic of China. (2022, December 15). Notice on issuing the 14th Five-Year Plan for modern logistics development: State Council General Office Document [2022] No. 17 [Government document]. https://www.gov.cn/zhengce/content/2022-12/15/content_5732092.htm

[5] People's Daily. (2022, October 16). Holding high the great banner of socialism with Chinese characteristics and striving in unity for the comprehensive construction of a modern socialist country—Report to the 20th National Congress of the Communist Party of China [Government document]. http://www.news.cn/politics/cpc20/2022-10/25/c_1129079429.htm

[6] Gong, X. (2022). Measurement of regional logistics efficiency and analysis of influencing factors. Statistics and Decision Making, 38(12), 112–116.

[7] Kang, T. L., & Wang, X. Q. (2020). Analysis of logistics efficiency and influencing factors under the context of supply-side reform. Journal of Harbin University of Commerce (Natural Science Edition), 36(03), 365–371+378.

[8] Liu, H. J., Guo, L. X., Qiao, L. C., et al. (2021). Spatiotemporal patterns and dynamic evolution of China's logistics industry efficiency. Research in Quantitative Economics and Technical Economics, 38(05), 57–74.

[9] Yin, Y., Ye, C., & Jiang, W. T. (2023). Regional logistics efficiency evaluation and influencing factors based on the Super-SBM-DEA model. Journal of University of Electronic Science and Technology of China (Social Sciences Edition), 25(04), 103–112.

[10] Pei, D. H. (2023). Measurement of logistics efficiency and influencing factors in the Guangdong-Hong Kong-Macao Greater Bay Area urban cluster. Research on Business Economics, (18), 180–183.

[11] Zhu, T. X., Han, J. M., & Wang, H. (2022). Evaluation of regional logistics development characteristics in the Beijing-Tianjin-Hebei Region under the "Dual Circulation" Pattern. Ecological Economics, 38(10), 80–87.

[12] Guo, J. Y. (2022). Ecological efficiency driving mechanism and spatial effect decomposition of the logistics industry: A comparative study based on the Yangtze River Economic Belt and interprovincial regions. Research on Commercial Economics, (05), 108–112.

[13] Zhang, Z. J., Zhang, Z., Wan, M. Y., et al. (2023). Comprehensive evaluation of logistics industry efficiency in cities along the Yangtze River Economic Belt from a high-quality development perspective: Based on a 3-Stage DEA model. Journal of Jiangxi Normal University (Natural Science Edition), 47(04), 350–359+367.

[14] Zhang, Y. S. (2022). Evaluation of regional logistics efficiency and analysis of influencing factors: An empirical study based on the Guangxi Region. Research on Business Economics, (12), 111–114.

[15] Qin, W. (2021). Regional logistics efficiency evaluation and influencing factors: A study based on panel data from prefecture-level cities in Guangdong. Research on Business Economics, (09), 97–100.

[16] Fried, H. O., Lovell, C. A. K., Schmidt, S. S., et al. (2002). Accounting for environmental effects and statistical noise in data envelopment analysis. Journal of Productivity Analysis, 17, 157–174.

[17] Liu, L. Y., Li, M., & Chen, J. X. (2024). Research on low-carbon logistics efficiency in western China based on a three-stage DEA-Malmquist model. Frontier Economy and Culture, (02), 40–47.

[18] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 6(2), 429–444.

[19] Banker, R. D. (1984). Estimating the most productive scale size using data envelopment analysis. European Journal of Operational Research, 17, 35–44.

[20] Wang, W. S., & Kao, X. X. (2021). Research on logistics efficiency measurement in the Bohai Rim Region from a high-quality development perspective: Based on a three-stage DEA model. Business Research, (04), 75–84.

[21] Zhao, Y. X. (2022). Evaluation of logistics efficiency in Jiangsu, Zhejiang, and Shanghai based on a three-stage DEA-Malmquist model [Master's thesis or Doctoral dissertation]. Hangzhou Dianzi University.

[22] Zhang, H., & You, J. X. (2021). A two-stage efficiency evaluation model for the logistics industry oriented to production processes. Journal of Tongji University (Natural Science Edition), 49(04), 591–598.

[23] Zhang, Y. S. (2022). Regional logistics efficiency evaluation and analysis of influencing factors: An empirical study based on the Guangxi Region. Research on Business Economics, (12), 111–114.

[24] Wu, M. R. (2021). Measurement of innovation efficiency of provincial R&D resources in China. Statistics and Decision Making, (12).