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Freight transport structure evaluation and optimization toward sustainable development: New evidence from the SBM-DEA model with undesirable outputs

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Abstract

Improving transport efficiency and optimizing freight structure are the core of achieving sustainable transport development. However, few studies have conducted an in-depth analysis of freight structure optimization and transport efficiency at the provincial level in China. Hence, a new economy and carbon dioxide (CO_2) emissions evaluation model based on the slack-based measurement data envelopment analysis (SBM-DEA) with undesirable outputs was proposed to analyze the transport efficiency and optimize freight structure in five provinces of China from 2005 to 2019. And optimization potential of the freight and passenger transport sector was uncovered in the provinces. The results showed that: (1) the regional difference in transport efficiency was significant, which indicated room for improvement in these provinces. (2) Freight structure was estimated and optimized by the slack variables of the evaluation model. The slack variables of railway, road, and waterway freight transport were large among these provinces. (3) The optimization potential of the freight transport sector was greater than that of the passenger transport in the regions. It indicated optimizing freight structure should be prioritized over passenger transport. Finally, some implications were put forward for sustainable transport development in China. The results provide significant insight into freight structure optimization as well as novel perspectives into the formulation of carbon mitigation strategies.

Keywords SBM-DEA model with undesirable outputs · Transport CO_2 emissions · Transport efficiency · Freight structure optimization · Passenger transport

Abbreviations

CO_2	Carbon dioxide
GHG	Greenhouse gas
DEA	Data envelopment analysis
SFA	Stochastic frontier analysis

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SBM	Slack-based measure
SBM-DEA	Slack-based measurement data envelopment analysis
CCR	Charnes, Cooper & Rhodes
DMU	Decision-making unit
IEA	International energy agency
IPCC	Intergovernmental panel on climate change
OECD	Organization for economic co-operation and development
YREB	Yangtze river economic belt
ITS	Intelligent transportation system
ICT	Information communication technology

1 Introduction

According to International Energy Agency (IEA), global carbon dioxide (CO_2) emissions from the transport sector have rebounded in 2021, growing by 8% to nearly 7,700 million tons of CO_2 as pandemic restrictions were lifted. The substantial contribution of this sector to global greenhouse gas (GHG) emissions has become more concerning. Freight transport is regarded as one of the most difficult economic activities to decarbonize in the transport sector, as it is driven by varieties of production, trade, and consumption activities in economic development. Freight carbon emissions have attracted increasingly more attention to transport policy-makers and stakeholders. In this case, sustainable development of freight transport is an effective path to reduce carbon emissions, optimize freight structure and improve high-quality economic development (Shankar et al., 2018, 2019).

In general, freight structure is the proportion of transport volume carried by different transport modes in the total freight transport volume (Chen et al., 2022). And the optimization of freight structure is conducive to achieving sustainable freight transport (Gupta & Garg, 2020; Zhang et al., 2021). However, some challenges remain unaddressed for the freight structure in China. First, the distribution of freight structure is still imbalanced in some regions. Figure 1 shows the change in road and railway freight shares in Liaoning, Zhejiang, Guangdong, Chongqing, and Yunnan. From

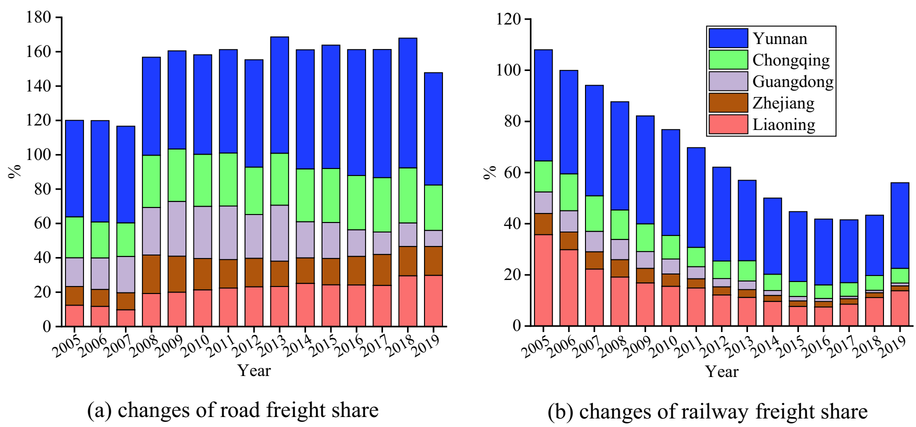


Fig. 1 Comparison of changes in road and rail freight shares in five provinces

Fig. 1, the share of road freight is dominant, while the share of railway freight is yet low in 2005–2019. And shares of road and railway freight are constantly changing in five provinces. Second, the railway infrastructure cannot meet freight transport demand in some regions. These aspects should be given sufficient attention. In 2021, the Ministry of Transport of China issued the "*Green Transportation '14th Five-Year Plan' Development Plan.*" One of the goals of this plan is to optimize freight structure and improve transport efficiency in China. And the significance and urgency of optimizing freight structure are highlighted for green transport development in regions.

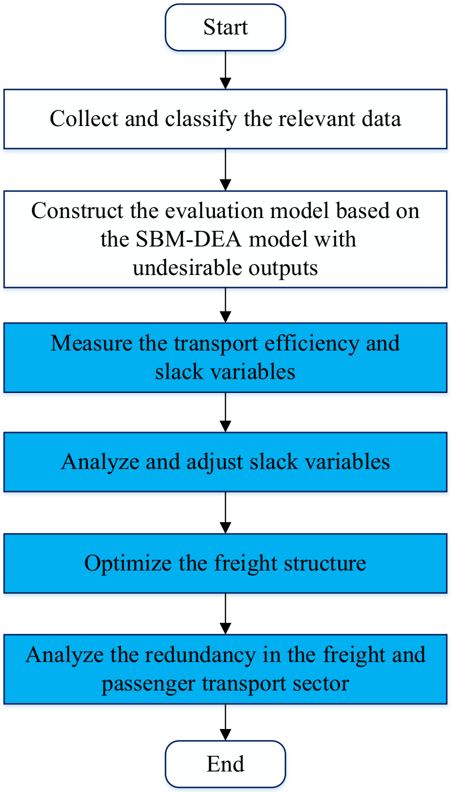
Over recent years, many scholars have focused on transport efficiency (Cui & Li, 2015; Du et al., 2021; Wang & He, 2017; Wei et al., 2021; Zhang et al., 2020). Several research deficiencies can be found in the existing studies. First, most studies tend to measure transport efficiency or focus on a single transport mode (Liu et al., 2019, 2020). Then, the adjustment of input variables is usually ignored when measuring transport efficiency. To the best of our knowledge, only a few studies explore deeply freight structure optimization in various regions. Last, a few studies focus on freight structure optimization in China, especially at the provincial level. Moreover, due to the unbalanced development, and economic characteristics, the regional differences cause the regional disparity in transport carbon emissions. It is of great practical significance to explore transport efficiency and freight structure optimization at the provincial level in China. The study selected Liaoning, Zhejiang, Guangdong, Chongqing, and Yunnan. These provinces in China cover inland and coastal provinces, developed and less developed provinces. As can be seen, the research area is suitable for the in-depth analysis of transport efficiency and freight structure optimization.

To address the above problems, the research objectives were as follows: (1) The evaluation model based on the slack-based measurement data envelopment analysis (SBM-DEA) with undesirable outputs was used to measure transport efficiency in 2005–2019. Railway, road, and waterway freight turnover volume, and total passenger converted turnover volume were input variables. The value added by the transport sector and transport CO_2 emissions was desirable and undesirable output variables, respectively. (2) The slack variables of the model were fully analyzed in different years, and it proposed the adjustment strategy to freight structure in five provinces. (3) The redundancy in the freight and passenger transport sector was uncovered in the study. And some policy implications were proposed for sustainable freight transport in China.

This paper contributes to the existing literature in four aspects. First, a new evaluation model based on the SBM-DEA model with undesirable outputs was proposed to evaluate transport efficiency and optimize freight structure in the paper. Second, the dynamics of transport efficiency are revealed in five provinces, which is conducive to grasping the development trend of transport. Third, the slack variables of the SBM-DEA model with undesirable outputs are analyzed in different years. And freight structure is optimized and adjusted based on the slack variable in these regions. Finally, it conducts a redundant analysis of the freight and passenger transport sector during 2005–2012 and 2013–2019. The differences in optimization potential between freight and passenger transport are confirmed in five provinces during 2005–2012 and 2013–2019. In the long run, the results of this study not only are favorable to optimizing freight structure in some regions but also can generate new understanding in the formulation of carbon reduction strategies for sustainable transport development.

The research structure is shown in Fig. 2. Section 2 introduces a literature review. Section 3 explains the method and data. The results are analyzed in Sect. 4. In Sect. 5,

Fig. 2 Analysis framework for the study



the results of the model are discussed in detail for five provinces. Section 6 provides the conclusions and some policy implications of the study.

2 Literature review

Numerous papers have investigated transport CO_2 emissions and carbon emission efficiency. Different measures have been taken to mitigate transport carbon emissions. Many scholars and managers focus on multimodal transport. The related studies are reviewed based on the research aim.

2.1 Transport efficiency assessment

Many scholars use data envelopment analysis (DEA) to measure transport efficiency. As a nonparametric evaluation model, the DEA has obvious advantages, such as simplifying calculation and reducing errors. Su and Rogers (2012) used the DEA to examine the transport efficiency in Organization for Economic Co-operation and Development (OECD) countries. Using the DEA model with the different return scales, Zhou et al. (2013) evaluated the transport carbon emission performance in 30 provinces of China. And Wei et al. (2021) combined stochastic multicriteria acceptability analysis with DEA to assess the environmental and energy efficiency in the transport sector of China. Moreover, some scholars applied DEA to evaluate the environmental efficiency of a single transport mode, such as the trucking industry (Chen et al., 2019), road transport (Liu et al., 2019, 2020), inland transport (Stefaniec et al., 2020), and ports (Tovar & Wall, 2019).

Despite the many advantages of the DEA, the results of this model are not as accurate in practice. The traditional DEA is a radial model, and the impact of slack variables is not considered, which may cause inaccurate results. To solve the slack problem in the model, Tone proposed a slack-based measurement DEA (SBM-DEA) model (Tone, 2001). Until recently, research on transport environmental-related efficiency using the SBM-DEA model has been increasingly more attention. Table 1 displays some relevant literature. In Table 1, some studies tend to take the transport sector as a whole to evaluate transport efficiency. The other studies focus on major transport modes, such as road transport, and railway transport.

2.2 Multimodal transport analysis

Kaack et al. (2018) focused on decarbonizing intraregional freight systems through the modal shift. Sullivan et al. (2018) explored the effect of mass on multimodal fuel consumption in moving people and freight. Marcucci et al. (2019) discussed modal shifts, emission reductions, and behavioral change in detail. Sun et al. (2020) used the Multi-Agent Transport Simulation to quantify the potential impact of the multimodal transport system on sea level rise. Hu et al. (2020) adopted the system dynamics to simulate integrating logistics activities into the urban passenger rail transit network. Zhang et al. (2021) investigated the impact of the rail-water-port integrated system on air quality. Francisco et al. (2021) assessed the impact of technological investment on a major shift to rail and found positive net impacts from a cost–benefit analysis. Jiao et al. (2021) employed synergistic and cost-effective analysis to identify a sustainable development path for urban transport. Pedinotti-Castelle et al. (2022) adopted a TIMES energy model to examine the impact of modal shifts.

2.3 Other related literature

Some related literature has been reviewed into three strands for simplicity. The first strand examines the effects of different factors on carbon emissions (Sikder et al., 2022). The main determinants cover economic growth (Dai et al., 2023) and transit-oriented development (Ashik et al., 2022). The second group of studies focuses on the impact of technological innovation on transport carbon emissions. Some studies usually use information communication technology (ICT) as an indicator of technological innovation and validate that ICT can decrease transport's negative impacts on the environment (Chatti, 2020, 2021; Chatti & Majeed, 2022a, b). Acheampong et al. (2022) explored the effect of transport infrastructure and technological innovation on carbon emissions. The last strand investigates the effects of different transport policies (Chatti et al., 2019; Peiseler & Cabrera Serrenho, 2022). Studies have shown that different types of policies reduce transport CO_2 emissions, such as environmental regulations (Xu & Xu, 2022) and environmental taxes (Hussain et al., 2022).

In summary, extensive studies have been performed. Nonetheless, some gaps are still highlighted. Most studies tend to the measurement and assessment of transport efficiency. Another part of the study investigates the effect of multimodal transport on carbon

Table 1 Typical literature on transport efficiency research

Literature	Sample	Area	Method	Key finding
Chang et al. (2013)	30 provinces, China	Transport sector	The non-radial DEA model with the SBM model with undesirable outputs	The transport sector in most provinces was not efficient
Li et al. (2016)	29 provinces, China	Transport sector	The super-SBM DEA model with undesirable outputs	The overall average level of total factor transport efficiency was low in China
Liu et al. (2017)	30 provinces, China	Land transport	The parallel SBM-DEA model with undesirable outputs	The performance of railway transport was better than that of road transport
Chu et al. (2018)	30 provinces, China	Transport sector	The SBM-DEA model with parallel computing design	The parallel computing design was conducive to reducing calculation time when completing efficiency evaluation tasks with large data sets
Park et al. (2018)	America	Transport sector	The SBM-DEA model	The transport environmental efficiency was below 0.640 for various states
Wang (2019)	24 OECD countries	Road transport	The SBM-DEA model with undesirable outputs	The joint assessment of environmental and safety factors for road transport could generate distinctive results
Tian et al. (2020)	Shaanxi, China	Transport sector	The super-efficiency SBM-DEA model with weighting preference	Transport sustainability was inefficient for over half the years in Shaanxi
Ma et al. (2021)	30 provinces, China	Transport sector	The SBM-Malmquist model	The social development index could significantly improve comprehensive transport efficiency
Zhao et al. (2022c)	31 provinces, China	Freight transport industry	The super-efficiency SBM-DEA model with undesirable outputs	The overall level of freight carbon emission efficiency was low, with an average of 0.534

emissions. However, the slack analysis of input–output variables is still ignored in the transport efficiency measurement. In addition, detailed and specialized research on the redundancy in different variables remained not been found yet, especially at the provincial level in China, which constrains the exploration of the adjustment and optimization of slack variables (such as freight structure) in the transport efficiency measurement. The paper will fill the above research gaps. This investigation is of great theoretical and practical importance for transport policymakers to formulate policies related to optimizing freight structure and reducing carbon emissions in China.

3 Method and data

3.1 Methods

3.1.1 DEA model

DEA is widely used in efficiency evaluation studies. It is a method that compares the efficiency of nonparametric techniques between decision-making units (DMU), which is suitable to deal with multi-input and multi-output problems. The assumptions related to weights and functional expression are not required in the DEA, and it has strong objectivity (Ali & Lerme, 1997).

A radial model and a non-radial model are more commonly used in DEA models. The Charnes, Cooper & Rhodes (CCR) model, as a radial model, is the most representative while estimating carbon efficiency. The dual programming of the CCR model is shown as follows:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{-} = \theta x_{ik}, i=1, \cdots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{+} = y_{rk}, r=1, \cdots, q \\ \lambda_j \geq 0, j=1, \cdots, n \\ s_i^{-} \geq 0,\ s_r^{+} \geq 0 \end{cases} \tag{1}$$

where DMU_k is the measured DMU. θ indicates the efficiency of DMU_k and its value range is [0,1]. λ_j shows the weight vector. s_i^{-} is the slack variable for m inputs. s_r^{+} is the slack variable for q output. The BCC model is another DEA model, and the only difference between it and the CCR is the addition of the constraints $\sum_{j=1}^{n} \lambda_j = 1$.

3.1.2 SBM model

The DEA model has gradually improved over many years. In 2001, Tone proposed the slack-based measure (SBM) model (Tone, 2001). Inefficiencies are evaluated by this model from the input and output perspectives. The SBM-DEA model is non-oriented and is shown in formula (2).

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1 + \frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{rk}}$$

$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik}, i = 1, \cdots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk}, r = 1, \cdots, s \\ \lambda_j \geq 0, j = 1, \cdots, n \\ s_i^- \geq 0, s_r^+ \geq 0 \end{cases} \tag{2}$$

where ρ shows the efficiency of $\mathrm{DMU_k}$ and its value range is [0,1]. In formula (2), m and q represent the number of slack variables for input and output, respectively. Other variables are the same in formula (1).

3.1.3 SBM model with undesirable outputs

Undesirable outputs are considered in the SBM-DEA model. The SBM-DEA model with undesirable outputs is written as follows:

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

$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik}, i = 1, \cdots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk}, r = 1, \cdots, s \\ \sum_{j=1}^{n} \lambda_j b_{rj} + s_r^{b-} = b_{rk}, r = 1, \cdots, s \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, j = 1, \cdots, s \end{cases} \tag{3}$$

where b_{rk} shows undesirable outputs. The vectors s_i^- s_r^{b-} are the slack variables of inputs and undesirable outputs. s_r^+ represents the slack variables of desirable outputs. Each DMU has m inputs, q_1 desirable outputs, and q_2 undesirable outputs.

For a DMU, it is only effective if the value of the efficiency is 1. At the same time, $s^- = 0, s^+ = 0, s^{b-} = 0$. When the value of the efficiency for DMU is less than 1, it is regarded as ineffective, and input and output variables should be further adjusted. In the case of ineffective DMU, reducing the surplus of inputs and undesirable output, and increasing the shortage of desirable outputs are performed by the following formulas.

$$x_{ij}^* \leftarrow x_{ij} - s_i^- \tag{4}$$

$$y_{rj}^{*} \leftarrow y_{rj} + s_r^{+} \tag{5}$$

$$b_{rj}^{*} \leftarrow b_{rj} - s_r^{b-} \tag{6}$$

where $x_{ij}^{*}, y_{rj}^{*}, b_{rj}^{*}$ represent the optimal solutions obtained by the SBM-DEA model with undesirable outputs based on the adjustment of the slack variables, respectively.

As can be seen from the literature review, the SBM-DEA model with undesirable outputs is widely used in transport efficiency measurement. The SBM-DEA model with undesirable outputs is selected in the paper. Three reasons are considered for this choice. First, this study estimates the transport efficiency by the model for five provinces of China. This model can avoid the error caused by the subjective selection of radial and angle, which can give a clear result. Second, the slack variable for input and output is quantified by this model. Finally, the redundancy of input–output variables would be explored in depth and detail. Freight structure is optimized based on the redundancy of input variables in five provinces. Overall, the SBM-DEA model with undesirable outputs is applicable on a theoretical level. Consequently, the SBM-DEA model with undesirable outputs is adopted in the study.

3.2 Data

The panel data of five provinces (Liaoning, Zhejiang, Guangdong, Chongqing, and Yunnan) were collected from 2005 to 2019 in this paper. Table 2 shows the variable definition and data source in the study. In the table, four are input variables and two are output variables. The data on air passenger and freight turnover cannot be considered due to data unavailability in five provinces. And railway, road, and waterway transport were only considered for passenger transport. The passenger transport should be converted to freight transport for further analysis. The conversion coefficient for each transport mode between freight and passenger transport is from relevant studies (Li et al., 2019; Song et al., 2019). Then, the total passenger converted turnover volume was calculated by the three modes of passenger transport volume converted in the study.

Table 2 Variable definition

Variable	Proxy	Unit	Data source
Railway freight transport	Railway freight turnover volume	100 million ton-km	China Statistical Yearbook (2005–2020)
Road freight transport	Road freight turnover volume	100 million ton-km	
Waterway freight transport	Waterway freight turnover volume	100 million ton-km	
Passenger transport	Total passenger converted turnover volume	100 million ton-km	
Economic growth in transport	The value added by the transport sector (2005 constant price)	100 million RMB	
Carbon emissions	Transport carbon emissions	10^4 tons	China Energy Statistical Yearbook (2005–2020)

Transport CO_2 emissions are calculated based on the top-down model from the Intergovernmental Panel on Climate Change (IPCC). For calculating transport CO_2 emissions, different types of energy consumed in the transport sector were from China Energy Statistical Yearbook (2005–2020). The specific formula is written as follows:

$$C_t = \sum_{j=1} \left(\frac{44}{12} \times E_j^t \times \mathrm{NCV}_j \times \mathrm{CC}_j \times O_j \right) \tag{7}$$

where C_t represents the total emissions from fossil fuel consumption in the year t; E_j^t is the consumption of fuel type j in the year t; NCV_j represents the net calorific value for the jth fuel; CC_j refers to the carbon content for the jth fuel, and O_j shows the carbon oxidation rate for the jth fuel. The parameters in Eq. (7) refer to relevant studies (Chen et al., 2022; Li et al., 2019).

4 Results

4.1 Assessment of transport efficiency

The evaluation model based on the SBM-DEA with undesirable outputs was constructed in the study. The evaluation result of transport efficiency is indicated in Fig. 3. As can be seen, the changes in transport efficiency were distinct in the five provinces. Generally, the evaluation of transport efficiency is the basis to identify whether freight structure is reasonable in a region. The transport efficiency is effective when the efficiency value is 1; otherwise, it is viewed as invalid.

In Liaoning, the minimum value of transport efficiency was 0.263 in 2009. The highest efficiency was 0.450 in 2005. And the average transport efficiency in Liaoning was 0.313

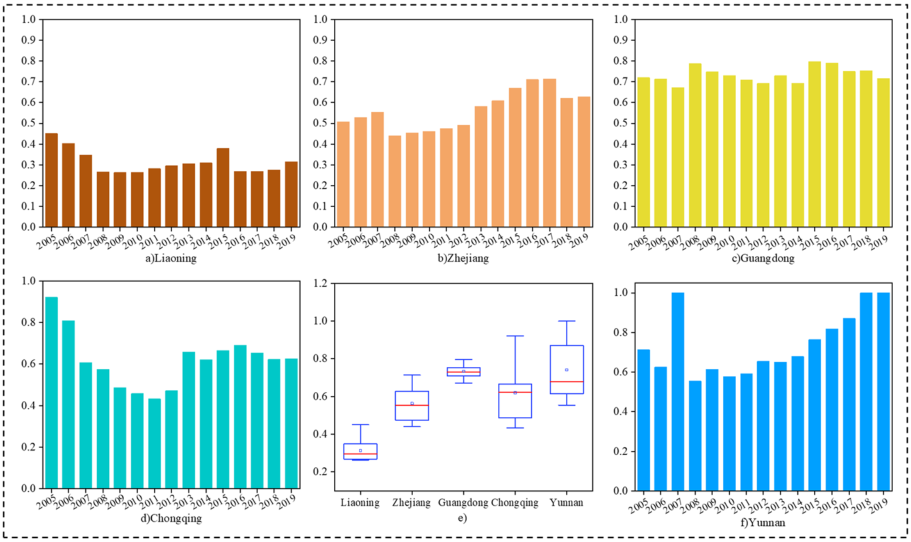


Fig. 3 Evaluation results of transport efficiency in five provinces

during 2005–2019. The transport efficiency ranked last among the five provinces, which meant great room for improvement.

The transport efficiency in Zhejiang was stable during 2008–2012. The lowest efficiency was 0.440 in 2008. And it peaked at 0.714 in 2017. The average efficiency was 0.563 during the study period, greater than that of Liaoning. On the whole, transport efficiency was not yet effective and had great potential for improvement.

In Guangdong, transport efficiency was high. The lowest transport efficiency was 0.672 in 2007, and its highest value is 0.797 in 2015 for Guangdong. From 2005 to 2019, the average transport efficiency was 0.733, the highest in the five provinces.

The smallest transport efficiency in Chongqing was 0.433 in 2011. It peaked at 0.921 in 2005. The average transport efficiency in Chongqing was 0.620, ranking third. Overall, transport efficiency was only at a moderate level; however, the standard deviation of efficiency was large from the box chart (Fig. 3). Thus, the improvement in transport efficiency was significant.

In Yunnan, the lowest transport efficiency was 0.554 in 2008. It reached 1 in 2007, 2018, and 2019, which occurred three times. In addition to the three years, other years were not effective. The average efficiency was 0.741, and it ranked second in the five provinces.

4.2 Analysis and optimization of freight structure

During transport efficiency analysis, the slack variable indicates large reasons for transport efficiency loss and provides a significant reference for freight structure optimization (Sun & Huang, 2021). To further optimize freight structure, slack variables by freight structure for 2015 and 2019 were analyzed in five provinces.

4.2.1 Analysis and optimization of freight structure in 2015

The results of slack variables by freight structure in 2015 are shown in Table 3. Railway, road, and waterway freight transport in Liaoning had a redundancy of 748.43 units (one unit = one hundred million ton-km), 1741.91 units, and 5256.65 units, respectively. The redundancy in carbon emissions was 1613.46 $*10^4$ tons. To make transport effective, Liaoning should decrease railway freight by 83.34%, road freight by 61.11%, waterway freight by 66.01%, and carbon emissions by 43.58%.

Zhejiang needed to reduce 48.01 units of railway freight, 290.21 units of road freight, and 5155.53 units of waterway freight. Meanwhile, carbon emissions were 594.64 $*10^4$

Table 3 Results of slack variables by freight structure in 2015

Provinces	Slack variables			
	Railway (Unit)	Road (Unit)	Waterway (Unit)	CO_2 (10^4 tons)
Liaoning	748.43 (83.34)	1741.91 (61.11)	5256.65 (66.01)	1613.46 (43.58)
Zhejiang	48.01 (22.52)	290.21 (19.17)	5155.53 (63.32)	594.64 (20.51)
Guangdong	0.00 (0.00)	985.61 (31.70)	3890.17 (33.78)	2002.38 (33.46)
Chongqing	90.92 (57.46)	352.57 (41.42)	482.84 (28.40)	852.21 (47.57)
Yunnan	90.41 (22.05)	453.33 (42.06)	1.71 (13.75)	403.19 (19.67)

Note: The percentage in parentheses indicates the proportion for the adjusted value (%)

tons redundant in Zhejiang. The downgrades of the four slack variables were 22.52%, 19.17%, 63.32%, and 20.51%, respectively.

In Guangdong, road and waterway freight had a redundancy of 985.61 units and 3890.17 units, respectively. There was no redundancy in railway freight. Carbon emissions needed to reduce by 2002.38 *10^4 tons. Guangdong should reduce road freight by 31.70%, waterway freight by 33.78%, and carbon emissions by 33.46%, respectively.

Surprisingly, there was no redundancy of railway freight in Guangdong. The possible reason is that road freight is more convenient, and part of railway freight may shift to road transport. In 2015, 604 km of new expressways were built in Guangdong. At the end of 2015, the total mileage of expressways in the province reached 6,884 km and the goal of connecting counties with the expressway had been already achieved. In the same year, the expressway toll system was adjusted and the overall toll level for trucks decreased relative to before. The good development level of the expressway further facilitates road freight transport, which induced a temporary shift of partial railway freight to road transport in Guangdong.

In Chongqing, railway, road, and waterway freight had a redundancy of 90.92 units, 352.57 units, and 482.84 units, respectively. Besides, transport carbon emissions were 852.21 *10^4 tons redundant. It should reduce railway freight by 57.46%, road freight by 41.42%, waterway freight by 28.40%, and carbon emissions by 47.57% in Chongqing.

In Yunnan, freight transport by railway, road, and waterway was redundant at 90.41 units, 453.33 units, and 1.71 units, respectively. Transport carbon emissions were 403.19 *10^4 tons redundant. The downgrades of the four slack variables were 22.05%, 42.06%, 13.75%, and 19.67% to meet the transport efficiency target.

4.2.2 Analysis and optimization of freight structure in 2019

Table 4 showed the results of slack variables by freight structure for the five provinces in 2019. In Liaoning, redundancies were 1117.61 units, 1817.78 units, and 2965.19 units for railway, road, and waterway freight transport, respectively. Transport carbon emissions were 2183.27 *10^4 tons redundant. In other words, Liaoning needed to reduce railway freight by 90.74%, road freight by 68.27%, waterway freight by 58.98%, and CO_2 emissions by 57.84% to make transport effective.

Zhejiang had a redundancy of 42.82 units for railway freight, 649.90 units for road freight, and 6577.65 units for waterway freight. CO_2 emissions were 36.65 *10^4 tons

Table 4 Results of slack variables by freight structure in 2019

Provinces	Slack variables			
	Railway (Unit)	Road (Unit)	Waterway (Unit)	CO_2 (10^4 tons)
Liaoning	1117.61 (90.74)	1817.78 (68.27)	2965.19 (58.98)	2183.27 (57.84)
Zhejiang	42.82 (18.13)	649.90 (31.21)	6577.65 (65.30)	36.65 (1.34)
Guangdong	111.80 (37.09)	706.15 (27.54)	969.14 (3.95)	0.00 (0.00)
Chongqing	124.73 (59.91)	334.23 (35.09)	943.95 (38.48)	687.07 (37.10)
Yunnan	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

Note: The percentage in parentheses indicates the proportion for the slack variables (%)

redundant. The downgrades of four slack variables were 18.13%, 31.21%, 65.30%, and 1.34%, respectively.

The railway, road, and waterway freight transport in Guangdong had a redundancy of 111.80 units, 706.15 units, and 969.14 units, respectively. The redundancy of carbon emissions was 0 tons, which may involve the research data. To accomplish the transport efficiency target, the corresponding slack variables needed to reduce by 37.09%, 27.54%, 3.95%, and 0, respectively.

In Chongqing, freight transport had a redundancy of 124.73 units, 334.23 units, and 943.95 units for railway, road, and waterway freight, respectively. Carbon emissions were 687.07 $*10^4$ tons redundant. Correspondingly, freight transport was reduced by 59.91%, 35.09%, and 38.48% for railway, road, and waterway freight transport. Meanwhile, carbon emissions were reduced by 37.10%.

In Yunnan, transport efficiency is 1 in 2019. In other words, there was no redundancy of railway, road, and waterway freight and carbon emissions. This may be related to the input variable. In 2019, air transport in Yunnan entered a new stage, with steady growth in passenger and freight transport. Air transport belongs to the transport sector, which would inevitably have a certain effect on carbon efficiency. However, air transport is not considered in the SBM-DEA model due to data unavailability. Thus, the carbon efficiency calculated by the SBM-DEA may overestimate the real state of carbon efficiency in Yunnan.

4.3 Redundant analysis of the freight and passenger sector

In the SBM-DEA model, the sum of slack variables in railway, road, and waterway freight is the redundancy in freight transport, which represents the optimized potential in freight transport. During 2005–2012 and 2013–2019, investigating the redundancy in the freight and passenger transport sector is not only favorable to understanding the contribution of two sectors to carbon emissions but also provides a scientific reference for formulating differentiated mitigation policies. A detailed analysis of the redundancy in the freight and passenger sector is performed in this section.

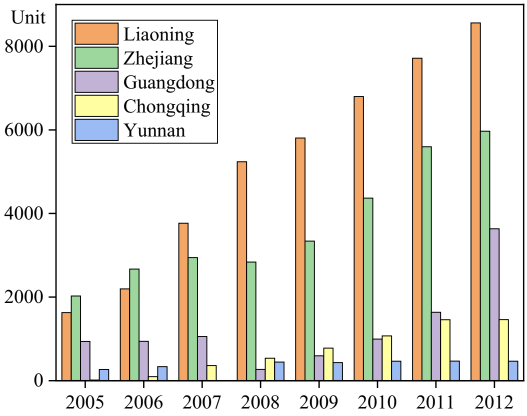
4.3.1 Redundant analysis of the freight and passenger sector during 2005–2012

Figure 4 showed the results of redundancy in freight and passenger transport during 2005–2012. The redundancy in freight transport increased year by year in Liaoning, with a maximum value of 8558.73 units in 2012 (Fig. 4(a)). The redundancy in waterway freight accounted for 63.47% of that in freight transport. And the average redundancy of freight transport was 5213.22 units in Liaoning. The redundancy in passenger transport was relatively stable in 2005–2012. On average, the passenger transport was 315.01 units redundant. It indicated that freight and passenger transport should be averagely reduced the same amount to be effective in Liaoning.

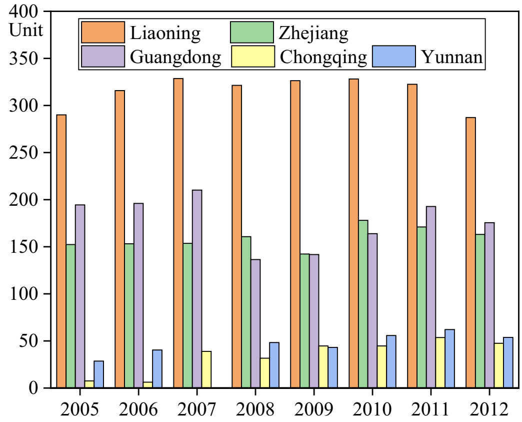
Overall, redundancy in freight transport was considerable in Zhejiang. The average redundancy of freight transport was 3718.32 units in 2005–2012. The highest redundancy of freight transport was 5968.10 units in 2012, of which waterway freight took up 86.65%. And passenger transport had an average redundancy of 159.30 units in 2005–2012. Thus, Zhejiang should reduce by 3718.32 units and 159.30 units on average for freight and passenger transport, respectively.

In Guangdong, the average redundancy of freight transport was 1258.68 units in 2005–2012. Unexpectedly, the change in redundancy of freight transport was relatively

Fig. 4 Redundancy in freight and passenger transport for the five provinces in 2005–2012



(a) Redundancy in freight transport during 2005-2012



(b) Redundancy in passenger transport during 2005-2012

high, especially in 2008. This was most likely due to the negative impact of the 2008 financial crisis on freight transport. Moreover, the redundancy of passenger transport was smaller compared to freight transport (Fig. 4(b)). The average redundancy of passenger transport was 176.37 units in 2005–2012. And on average, Guangdong needed to reduce by 1258.68 units and 176.37 units for freight and passenger transport, respectively.

In Chongqing, the redundancy of freight transport increased year after year, with the highest redundancy 1460.49 units in 2012. The average redundancy of freight transport was 722.63 units. The average redundancy of passenger transport was 34.35 units in 2005–2012. And the smallest redundancy of passenger transport was 6.24 units in 2006. Therefore, Chongqing needed to averagely reduce freight transport by 722.63 units, and passenger transport by 34.35 units in 2005–2012.

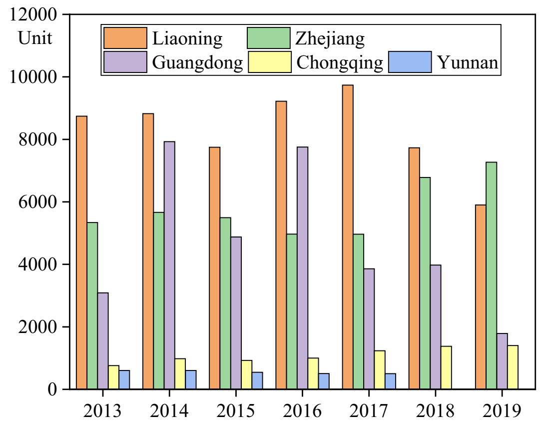
In Yunnan, the largest redundancy of freight transport was 468.76 units in 2011. The freight transport had a redundancy of 360.54 units on average. Notably, transport efficiency was 1 in 2007, which was effective. Thus, all slack variables were 0, and there was no redundancy for freight and passenger transport. This result was kept in line with the study

(Zhang et al., 2015). In Yunnan, the government set strict carbon reduction targets. Some pressure was caused to reduce transport carbon emissions. Nevertheless, strict environmental regulation may stimulate the progress of innovation and the improvement of environment-friendly production processes (Zhao et al., 2022b). Moreover, the average redundancy of passenger transport was only 41.49 units in Yunnan.

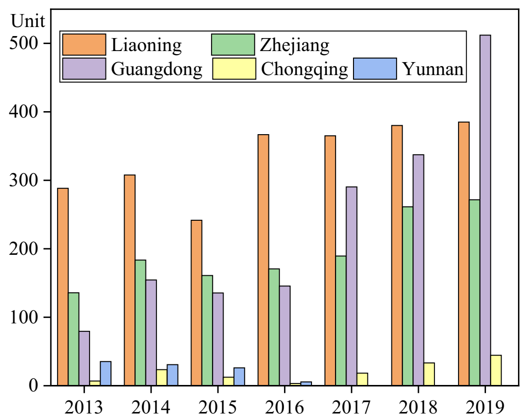
4.3.2 Redundant analysis of the freight and passenger sector during 2013–2019

The results of redundancy in freight and passenger transport during 2013–2019 are shown in Fig. 5. As can be seen, Liaoning's redundancy in freight transport became larger relative to 2005–2012. The highest redundancy of freight transport was 9737.10 units in 2017, with waterway freight transport accounting for 67.24%. On average, the freight transport was 8271.33 units redundant. Moreover, passenger transport had an average redundancy of 333.59 units. Thus, the freight and passenger transport should be reduced by 8271.33 units and 333.59 units on average, respectively.

Fig. 5 Redundancy in freight and passenger transport for the five provinces in 2013–2019



(a) Redundancy in freight transport during 2013-2019



(b) Redundancy in passenger transport during 2013-2019

As can be seen from Fig. 5(a), the redundancy of freight transport was stable in 2013–2019 for Zhejiang. In 2019, freight transport had a redundancy of 7270.37 units and the redundancy of waterway freight took up 90.47%. The freight transport was 5782.53 units redundant on average in 2013–2019. Compared with freight transport, the redundancy in passenger transport was smaller with an average redundancy of 196.21 units in 2013–2019. The freight and passenger transport in Zhejiang needed to be averagely reduced by 5782.53 units and 196.21 units, respectively.

In Guangdong, the redundancy of freight transport varied significantly in 2013–2019. In 2014, the highest redundancy of freight transport was 7926.97 units, of which 84.72% was redundant in waterway freight. This change may be due to the high-quality and large-scale development of waterway transport in Guangdong. According to Guangdong Statistical Yearbook, the freight turnover achieved 29230.88 units in 2019. The redundancy in passenger transport gradually increased in 2013–2019, except in 2015. And the average redundancy was 236.39 units of passenger transport in Guangdong. Some effective policies are proposed by the government to achieve the goal of energy saving and emission reduction in 2015, which may cause a temporary decline in the redundancy of passenger transport.

Compared to 2005–2012, the redundancy of freight transport in Chongqing became greater in 2013–2019. And freight transport had an average redundancy of 1098.26 units. It was 20.29 units redundant in passenger transport on average. And the redundancy of passenger transport declined in 2016 due to national energy conservation and emission reduction policies. Besides, Chongqing should decrease freight transport by 1098.26 units and passenger transport by 20.29 units on average in 2013–2019.

In Yunnan, freight transport had an average redundancy of 394.90 units. From Fig. 5(b), the redundancy of passenger transport gradually decreased in 2013–2019. The average redundancy in passenger transport was 13.98 units. Hence, Yunnan should averagely reduce freight transport by 394.90 units and passenger transport by 13.98 units. The efficiency is 1 in 2018 and 2019, there is no redundancy of freight and passenger transport. The reason may be that it had actively adjusted its industrial structure and improved technological innovation in 2018 and 2019 for Yunnan.

5 Discussion

From the above results, transport efficiency in Liaoning was low, which was in line with the conclusion of previous studies (Chang et al., 2013; Zhou et al., 2013). This may be related to the untransformed economic development in Liaoning. As a typical resource-dependent province, resource overuse and the homogeneity of the industrial structure severely restricted economic development in Liaoning (Li et al., 2020). Inevitably, the transport sector was affected by this economic pattern. Moreover, the redundancy of railway and waterway freight was relatively high in 2015 and 2019. This result may be explained by its special geographical location. Various goods from Jilin and Heilongjiang have to be shipped through Liaoning. Moreover, as a coastal province, most of the waterway freight in the three northeast provinces is largely undertaken in Liaoning. This shows that the pressure of waterway transport is relatively large. In this case, the infrastructure investment in railway, waterway and intermodal connectivity should be further enhanced in Liaoning. And freight structure optimization is further improved by promoting intermodal connectivity among three northeast provinces.

Overall, the transport efficiency in Zhejiang was higher compared to Liaoning. The recent study reported by Ma et al. (2021) also supported this result. An unexpected finding was that the redundancy of waterway freight was highest among railway, road, and waterway freight transport in 2015 and 2019. Several possible explanations accounted for this observation. First, cross-border investment and trade opening activities were flourishing in Zhejiang. The role of waterway freight was utilized fully in various trade activities. Second, in waterway freight transport, marine transport is subdivided into coastal and ocean transport based on distance (Zhou et al., 2021). Shares of coastal and ocean freight transport in Zhejiang were more than 85% in 2019. Several studies have confirmed that pollution emissions from the ship are a significant source of air pollution (Chen et al., 2017; Wan et al., 2020). In this case, pollution emissions from marine freight should be controlled in Zhejiang. For operators and managers of the waterway and port transport, some measures should be conducted to reduce emissions by ships, such as the promotion of clean energy and alternative energy source, and automated scheduling and route planning (Bouman et al., 2017).

In Guangdong, transport efficiency was the highest among the five provinces. This transport development level was supported by the study (Wei et al., 2021). This result could benefit from the successful transformation of economic development and adequate investment in innovation. From the results, the redundancy in waterway freight was considerable among the three transport modes. Two reasons may explain this result. First, Guangdong has flourished in trade exchanges and foreign investment activities. The construction and improvement of the comprehensive transportation system were more favorable to waterway transport. Second, Guangdong has been benefiting from the dividends brought by national policies in recent years. In this case, the advantages and roles of waterway transport have been fully exploited. Moreover, it has been paying more attention to the promotion and application of clean energy and new energy in transport equipment for Guangdong, which is favorable to the green development of the transport sector (Jiao et al., 2021).

Chongqing's transport efficiency ranked in the middle of the five provinces. This result was consistent with previous studies (Zhao et al., 2022a). The redundancy in the road and waterway freight was large in 2015 and 2019. Several reasons could explain this observation. First, Chongqing is an inland region, and the advantages of road freight can be fully utilized. Second, located in the upper reaches of the Yangtze River Economic Belt (YREB), it can facilitate the long-term development of waterway freight for Chongqing. Inland waterway transport accounted for the major part of waterway transport. Besides, the scale of rail freight was not very large. Nevertheless, the redundant proportion for railway freight was 57.46% and 59.91 in 2015 and 2019, respectively. This may be caused by the slow development of railway freight and failed to meet the railway freight demand in Chongqing. In this case, it is necessary to further promote long-term investment in railway infrastructure for Chongqing.

Yunnan's average transport efficiency was second in these provinces. This result contradicted the study (Song et al., 2016). The reason may be due to different objects of study. They took railway transport as the research object. And the transport sector was the object of our study, which resulted in low relative to the previous study. Optimization freight structure was more than passenger transport from the results. Several possible reasons explained this finding. Firstly, the mountainous areas account for more than 85% of the total area in Yunnan. It is more suitable for the development of road freight due to this terrain. Secondly, Yunnan is the radiation center of China facing South and Southeast Asia. With the deepening of the Belt and Road Initiative, trade activities among regions were gradually increasing. Undoubtedly, the role of rail freight is increasingly highlighted in Yunnan. Moreover, the redundancy of waterway freight was low, which was caused by the backward waterway transport infrastructure. Therefore, policymakers should further improve the infrastructure of the waterway transport to make the waterway transport sustainable in Yunnan.

Last but not least, the optimization potential of freight transport was larger than that of passenger transport in the five provinces. Two reasons may account for this result. First, the strong growth of total demand by consumption and investment is the main driving force of freight transport in economic development (Xu et al., 2021). The transport demand for goods and services has maintained strong growth in recent years. Second, international trade activity has seen an unprecedented increase. Economic projects among different countries have further opened up new opportunities for freight transport development, such as the Belt and Road Initiative (Anwar et al., 2020), and the China–Pakistan Economic Corridor (Mohmand et al., 2021). However, the extensive growth of freight transport could cause inevitably carbon emissions. In this case, the urgency of freight structure optimization is highlighted in some provinces. Some measures and policies are encouraged to implement in regions, such as intermodal operations research and planning, and subsidies of low-carbon freight modes.

6 Conclusions and policy implications

The paper presented a novel economy and CO_2 emissions evaluation model based on the SBM-DEA model with undesirable outputs to assess the transport efficiency and optimize the freight structure of five provinces in China from 2005 to 2019. In the model, railway, road, and waterway freight turnover volume and total passenger converted turnover volume were input variables. The value added by the transport sector and transport CO_2 emissions was desirable and undesirable outputs, respectively. The transport efficiency was evaluated, and freight structure was optimized by slack variables in five provinces. The major conclusions are as follows:

(1) The regional difference in transport efficiency was significant in five provinces. The transport efficiency in Guangdong was the highest among these provinces, with an average efficiency of 0.733. The efficiency of Yunnan, Chongqing, and Zhejiang decreased in order. The lowest efficiency was 0.313 in Liaoning.
(2) The slack variable of freight structure was large in these regions. The redundancy in railway, road, and waterway freight was different. For instance, in 2019, Zhejiang needed to reduce railway freight by 42.82 units, road freight by 649.90 units, waterway freight by 6577.65 units, and transport carbon emissions by 36.65 $*10^4$ tons.

In Chongqing, the railway, road, and waterway freight had a redundancy of 124.73 units, 334.23 units, and 943.95 units, respectively. Carbon emissions were 687.07 $*10^4$ tons redundant.

(3) On the whole, the optimization potential of the freight transport sector was greater than that of the passenger transport sector in five provinces. In 2005–2012 and 2013–2019, the redundancy of freight transport was larger than that of passenger transport, which

further suggested that optimizing freight structure should be prioritized over passenger transport in these provinces.

From the above results, some policy implications are proposed to improve sustainable transport development in different regions of China.

(1) Continue to develop an open and efficient transport system. Infrastructure construction is the foundation of sustainable development. The improvement of transport infrastructure is encouraged in some regions, which is conducive to narrowing regional imbalances and optimizing resource allocation among regions. Besides, it is fully supported to application and promotion of advanced transport technologies according to the action situation, especially energy-efficient technologies. Electric vehicle charging and charging infrastructure could generate a very substantial environmental benefit. Of course, renewable fuels, such as natural gas, and green hydrogen, are also promising pathways to decarbonization in the transport sector for some regions.
(2) Deepen to optimize freight structure in some regions. The redundant results of different freight modes provide a valuable reference for the formulation of the carbon mitigation strategy. For example, waterway transport operators and regulators could increase research and development investment in the technological level of ship operating facilities in Zhejiang and Guangdong. In Chongqing and Yunnan, the intelligent transportation system (ITS) and its facilities should be actively promoted in road transport. Last but not least, the development of multimodal transport is an effective way to optimize freight structure. Designing exclusively combined transport modes in the port-hinterland corridor is promising to reduce carbon emissions between inland and coastal cities. Coastal provinces should pay attention to the construction of green port-hinterland corridors to optimize freight structure.
(3) The role of scientific management is indispensable to optimizing freight structure and improving transport efficiency. Two managerial insights are highlighted for the transport sector. On the one hand, optimizing the supply chain structure is supportive to reduce transport carbon for transport enterprises. A disorganized supply chain structure generates extra freight turnover due to the bad freight service, resulting in a waste of transport energy. Selecting suitable suppliers and logistics facilities can reduce transport distance. On the other hand, regional transport management should consider geographical features. The operating strategy of railway, highway, and waterway is different due to the economic characteristics of different regions. Freight transport should be operated in a way that adapts to their economic and social characteristics.
(4) Low-carbon transport policies are customized for the various developmental levels of the transport sector in different regions. For provinces with high carbon emissions, capital investments and technical support for the transport sector should be reinforced in a long run. For example, the policy of new energy vehicle subsidies has been proposed through tax credits and tax deductions. The purpose of this policy is the promotion of the new energy vehicle to further expand its market share. For provinces with low carbon emissions, updating standards for transport systems and vehicle emissions is necessary. The old cars and trucks with high energy consumption and emissions are timely eliminated. For other provinces, it is suggested to adjust carbon emissions through market mechanisms and economic means, which could largely mitigate transport carbon emissions in these provinces.

The study also has some limitations. First, to our knowledge, the evaluation model is only used for theoretical research. The applicability of this model in a real-life engineering setting is very limited. There are two main barriers to the model application. A coupled linkage between freight transport and economic development poses a serious challenge to the application of the model. Moreover, research at the macro-level is difficult to apply to specific engineering practices, especially on a micro-level. Thus, the implementation of the model in the company is uncertain. Even if the model does encounter some difficulties in real-world implementation, its potential benefits in terms of reducing carbon emissions, transport costs, etc., should be considered from the perspective of comprehensive cost–benefit. Second, transport CO2 emissions are only considered in the paper due to data unavailability. The GHG emissions from the transport sector are also considered. Third, the data on the intermodality in transport are not available in five provinces. This type of data is not obtained due to the inconsistency of statistical specification. Thus, a comparative analysis of the slack variable between multimodal transport and different modes is difficult to perform in the study.

There exist four points for the future research direction. First, the model can be attempted to be applied to the actual project. And the benefits of the model for enterprises are further explored. Second, the study was only conducted at the provincial level in China. Optimizing freight structure is very interesting to deeply explore between various countries. Third, based on the evaluation model, it would be valuable to compare the role of intermodality transport with other transport modes if the data on intermodality transport are collected. Last, the research is not only limited to transport efficiency but also extended to transport energy efficiency, which should be further performed.

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Data availability The data in the paper are available from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

Ethical approval.
Ethical approval was not required for the secondary analysis of anonymous data in this study.

Consent to participate Not applicable.

Consent to publish Not applicable.

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