SPATIAL CHARACTERISTICS AND DETERMINANTS OF CARBON EMISSION EFFICIENCY IN CHINESE ROAD FREIGHT ENTERPRISES

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Abstract. The highway transportation industry is an important component of the transportation industry and one of the key industries contributing to global climate change. To identify the carbon emission level of highway transportation enterprises, this article uses a set of panel data from China's highway and waterway transportation enterprises to calculate the carbon emissions from the movement of trucks in highway freight transportation enterprises. The research results indicate that: (1) both economic efficiency and carbon emission efficiency exhibit spatial agglomeration characteristics, but in 2021, the degree of spatial agglomeration decreased. (2) From 2020 to 2021, the carbon emission efficiency rankings of various regions remained relatively stable, with the western, eastern, central, and northeastern regions ranking in order of carbon emission efficiency; Due to the impact of COVID-19, the economic efficiency of various regions fluctuated to some extent in 2020-2021, and the fluctuation of unified efficiency was closer to the fluctuation of economic efficiency. (3) The results of the impact analysis on carbon emission efficiency are as follows: the faster the Internet develops and the more stringent the urban environmental requirements are, the higher the carbon emission efficiency of road transport enterprises will be; The more diversified the business model and the longer the transportation distance, the higher the carbon emission efficiency of the enterprises.
Keywords: *carbon emission efficiency, economic efficiency, unified efficiency, spatial distribution, large-scale road freight transportation enterprises, regional differences*

Introduction

With the advancement of the social economy, rising living standards, and improvements in transportation efficiency, the demand for transportation has increased significantly. In parallel, energy consumption and environmental pressures have been on the rise. As a global transportation powerhouse, China leads the world in several key metrics: high-speed railway network length, highway extent, urban rail transit operational mileage, and the number of port berths capable of accommodating vessels of 10,000 tons or more. While the rapid expansion of transportation infrastructure and services has significantly enhanced mobility, it has also led to a marked escalation in energy use and carbon emissions. Since 2000, the growth rate of energy consumption and carbon emissions from the transportation sector has been among the highest across all industries in China. Presently, transportation-related carbon emissions constitute approximately 10% of the nation's total carbon emissions, placing it third among emitting sectors, following electricity, heat generation, and industrial activities. Consequently, achieving peak carbon and carbon neutrality within the transportation sector is pivotal to meeting the country's overall carbon reduction objectives.

Amid the rapid growth of China's national economy and transportation industry, the sector's technical level and energy mix have not seen fundamental transformation,

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resulting in the sustained growth of total carbon emissions. The *Action Plan for Carbon Peaking Before 2030* advocates integrating green low-carbon development concepts into the planning, construction, operation and maintenance of transportation infrastructure, targeting full-lifecycle reductions in energy consumption and carbon emissions from transportation projects. By estimation, the transportation industry's annual greenhouse gas emissions represent roughly 12% of China's total, with road transport accounting for more than 80% of the sector's emissions. As a key part of road transportation, road freight contributes over 60% of total emissions, becoming the core battlefield for transportation carbon abatement. This research intends to clarify the overall level and differentiated characteristics of carbon emission efficiency among Chinese road transport enterprises, identify critical influencing factors, furnish theoretical support for optimizing their carbon reduction routes, and provide practical references for government departments in developing targeted policies and promote road freight's low-carbon transition.

This article uses the DEA-RAM model to evaluate the economic carbon emission reduction win-win performance of large road freight enterprises in China, and analyzes the spatiotemporal characteristics of carbon emission efficiency from an efficiency perspective, filling the gap in existing research. This study comprehensively evaluates the win-win performance in balancing economic development and carbon emissions, and analyzes the influencing factors of corporate carbon emission efficiency from the perspectives of cities and enterprises, providing practical suggestions for improving the carbon emission efficiency and reducing emissions of the road freight sector.

Literature review

Current research on carbon emission efficiency mainly falls into two categories: carbon emission efficiency evaluation methods and analyses of its influencing factors. This paper reviews and comments on the literature in these two areas.

Research on carbon emission efficiency evaluation methods

Kaya and Yokobori (1997) first proposed the concept of carbon productivity, defined as economic output per unit of carbon dioxide emissions, which serves as an indicator of economic efficiency per unit of CO_2. Currently, two primary methods are used to evaluate total factor carbon emission performance: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) (Park et al., 2016; Ignatius et al., 2016). DEA has been extensively used in logistics-related energy consumption and CO_2 emission research. Traditional DEA models, however, tend to ignore the influence of external environmental factors, internal management, and random variations on slack variables, resulting in biased efficiency measurements (overestimation or underestimation). By comparison, the SBM (Slack-based Measurement) optimization model offers superior efficiency evaluation accuracy, particularly for undesirable outputs. Though DEA is widely applied in logistics energy consumption and CO_2 emission research, traditional DEA models often fail to account for the impact of external environment, internal management, and random noise on slack variables, leading to deviations between efficiency measurements and actual levels.

DEA (Data Envelopment Analysis) assesses "relative efficiency" through comparisons of multiple decision-making units (DMUs). Amid growing environmental concerns, researchers have gradually incorporated environmental factors into DEA models to refine efficiency evaluations. Previous DEA research (Haynes et al., 1997; Sueyoshi et al., 2011)

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typically regarded energy consumption as a traditional input. Yet Renshaw (1981) contended that this method fails to fully reflect the energy factor substitution effect on efficiency. Zhou (2008) further emphasized that expanded alternative energy adoption can substantially cut other energy consumption, which may improve efficiency. Therefore, increased consumption of certain energy types does not invariably indicate lower efficiency.

Research on factors influencing carbon emission efficiency

With the intensification of energy issues and growing global attention to climate change, academia has increasingly focused on the carbon dioxide emission efficiency of transportation enterprises. The integration of information technology has significantly improved the carbon emission efficiency of German freight companies. Existing studies mainly adopt regression methods to explore this topic, examining influencing factors such as technology, energy consumption structure, environmental regulations, fleet age, cargo volume, and fuel characteristics. For example, Hadi-Vencheh et al. (2020) analyzed the impact of technology types on airline carbon emission efficiency. Xu et al. (2021) employed the Tobit regression model to explore the impact of fleet age and cargo volume on environmental efficiency. Wu et al. used the bootstrap truncated regression method to analyze how fuel utilization rates affect corporate operational efficiency. Lo et al. (2020) examined the effects of fuel prices and technological progress on air transport carbon emissions. Common methods for analyzing carbon emission drivers in the logistics industry also include Laspeyres decomposition, Paasche decomposition, and arithmetic mean Divisia decomposition (AMDI). Yet these methods have inherent limitations, including the inability to decompose multiple factors concurrently or large residual terms after decomposition. Miyoshi and Merkert (2015) studied 14 major European airlines to analyze the correlation between aviation industry carbon emission performance and economic benefits, identifying a 20% rise in carbon emission efficiency, a 13% drop in unit costs, and a significant negative association between them. Yasmeen (2020) used the LMDI method to evaluate carbon emissions in Pakistan’s logistics sector during 1972–2016. LMDI-based decomposition indicated that economic development positively contributed to per capita carbon emissions, with energy structure and efficiency playing a mitigating role. M’Raihi et al. (2015) employed LMDI to explore drivers of road freight CO_2 emission growth in Tunisia, pinpointing economic growth as the key driver. Additional regression methods in this domain include the STIRPAT model, multiple linear regression, and ordinary least squares (OLS). Existing research has investigated transportation carbon emission drivers from diverse macro dimensions. This study focuses on road transportation enterprises above designated size, seeking to clarify their current carbon emission situation and identify factors influencing carbon emission efficiency through the analysis of micro-level behavioral and operational data.

Research methods

Carbon emissions

The carbon emissions of road transportation enterprises consist of direct emissions from vehicle operations and indirect emissions from production and operational processes. Direct emissions stem from fuel combustion during vehicle operations, while indirect emissions arise from electricity or heat consumption during these processes. Using

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Chinese road transport vehicle data as a case study, this research focuses solely on direct carbon emissions. Following the IPCC's carbon emission coefficient method, it calculates emissions from various energy sources. The IPCC's "top-down" method, being the earliest greenhouse gas accounting approach for industries, is chosen for its data accessibility and ease of calculation, and it is widely accepted internationally. By applying this method to the energy consumption data collected from road transportation enterprises, the total carbon emissions from fuel consumption can be derived. Summarizing the emissions from each fuel type yields the total carbon emissions for each enterprise. The calculation formula is as follows:

$$P_i = \sum_{K} M_{i,k} \times NCV_k \times EF_k \times O_k \times 44/12 \quad \text{(Eq.1)}$$

In the formula, P_i represents the carbon emissions caused by the production of road transportation enterprise i; $M_{i,k}$ represents the input amount of the k-th fuel in the production process of road transportation enterprise i; δ k represents the carbon emission coefficient of the k-th fuel; NCV_k, EF_k, and O_k represent the calorific value, carbon content, and carbon oxidation rate of the k-th fuel, respectively. 44 and 12 represent the molecular weights of CO_2 and C, respectively. This paper use *Eq.1* to calculate the carbon emissions of large-scale road transport enterprises.

Carbon emission efficiency

In the field of transportation, the system encompasses various input factors such as capital, energy, and labor, as well as numerous output indicators such as passenger turnover, cargo turnover, and industry GDP, forming a typical multi-input multi-output complex system. The interactions between inputs and outputs are complex and difficult to quantify accurately, which may lead to incomplete parameter selection when constructing models. In addition, there are significant differences in the dimensions of various variables in the transportation production system. The DEA-RAM model, with its unique advantages, can effectively address these problems. Its additive structural characteristics enable a balance between the economic development of the transportation industry and carbon emissions when evaluating the overall efficiency, thus achieving a more scientific and reasonable evaluation. Drawing on Zhou's research (2008), this paper assumes the existence of J enterprises, each containing N common input factors, M energy factors, P desirable outputs, and I un desirable outputs. Additionally, the energy slack variable s_m^e is defined in the RAM model to represent the difference between the energy input and the optimal energy input.

(1) DEA-RAM Model for carbon emission efficiency of road transport enterprises

Improving transportation carbon emission efficiency aims to reduce emissions through energy structure adjustments, technological improvements, and resource optimization, reflecting performance under energy conservation and emission reduction policies. Tian and Qi (2004) highlighted that a low-carbon economy requires balancing economic benefits with energy conservation and emission reduction, as focusing solely on one aspect is biased. Consequently, this study employs the additive structure of the DEA-RAM model to balance these two dimensions. It measures the unified efficiency (UE) of transportation and assesses the coupling degree between transportation economic growth and energy conservation and emission reduction measures, indicating a win-win scenario

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in balancing economic growth with environmental sustainability. The specific model is formulated as follows:

(2) The carbon emission efficiency (CE) RAM model for transportation is:

$$\begin{cases} max\sum_{n=1}^{N} R_n^x s_n^x + \sum_{m=1}^{M} R_m^e s_m^e + \sum_{i=1}^{I} R_i^b s_i^b \\ s.t.\sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_{nj}, \forall_n; \\ \sum_{j=1}^{J} b_{ij}\lambda_j + s_i^b = b_{ij}, \forall_i \\ \sum_{j=1}^{J} e_{mj}\lambda_j + s_m^e = e_{mj}, \forall_m; \\ \sum_{j=1}^{J} \lambda_j = 1, \lambda_j \geq 0, \forall_j; s_n^x \geq 0, \forall_n; s_m^e \geq 0, \forall_{m_2}; s_i^b \geq 0, \forall_i \end{cases} \tag{Eq.2}$$

If b_{ij} represents the unexpected output factor of the i-th enterprise, then according to the above model (*Eq.2*), the DEA-RAM transportation carbon emission efficiency of enterprise *j* during period *t* can be obtained as follows:

$$0 \leq \theta_E = 1 - (\sum_{n=1}^{N} R_n^x s_n^{x*} + \sum_{m=1}^{M} R_m^e s_m^{e*} + \sum_{i=1}^{I} R_i^b s_i^{b*}) \leq 1 \tag{Eq.3}$$

$$\begin{cases} max(\sum_{n=1}^{N} R_n^x s_n^x + \sum_{m=1}^{M} R_m^e s_m^e + \sum_{p=1}^{P} R_p^y s_p^y + \sum_{i=1}^{I} R_i^b s_i^b) \\ s.t.\sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_{nj}, \forall_n; \\ \sum_{j=1}^{J} e_{mj}\lambda_j + s_m^e = e_{m\,j}, \forall_m; \\ \sum_{j=1}^{J} y_{pj}\lambda_j - s_p^j = y_{pj}, \forall_p \\ \sum_{j=1}^{J} b_{ij}\lambda_j + s_i^b = b_{ij}, \forall_i; \\ s_m^e \geq 0, \forall_m; s_p^j \geq 0, \forall_p; s_i^b \geq 0, \forall_i; \end{cases} \tag{Eq.4}$$

Correspondingly, according to model, the DEA-RAM transportation unified efficiency of enterprise *j* during period *t* can be obtained as follows:

$$0 \leq \theta_U = 1 - (\sum_{n=1}^{N} R_n^x s_n^{x*} + \sum_{m=1}^{M} R_m^e s_m^{e*} + \sum_{p=1}^{P} R_p^y s_p^{y*} + \sum_{i=1}^{I} R_i^b s_i^{b*}) \leq 1 \tag{Eq.5}$$

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Spatial correlation analysis

Moran'I

Spatial correlation, also known as spatial dependence, refers to the phenomenon in which the economic efficiency, carbon emission efficiency, and unified efficiency of road transport enterprises in a given province or region are directly or indirectly affected by the economic efficiency, carbon emission efficiency, and unified efficiency of road transport enterprises in neighboring provinces and cities. In other words, there are diffusion and spillover effects on the efficiency of adjacent provinces or regions. It represents the degree of interaction and spatial clustering characteristics of the economic efficiency, carbon emission efficiency, and unified efficiency of road transport enterprises in adjacent provinces and cities. Spatial autocorrelation is generally measured by the Global Moran's I index, which has defined by the following formula:

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \quad \text{(Eq.6)}$$

Where W_{ij} is the spatial weight matrix; n is the number of provinces or regions included, x_i and x_j represent the efficiency values of provinces or regions i and j, respectively, and $\bar{x}$ is the average value of the corresponding efficiency. Generally speaking, the range of values for the spatial autocorrelation coefficient is [-1, 1]. When its value is -1, it indicates perfect negative spatial correlation; when its value is 1, it indicates perfect positve spatial correlation; when its value is 0, it indicates that there is no spatial correlation between adjacent provinces.

OLS model

This study employs econometric regression models to examine the factors influencing the carbon emission efficiency of large-scale road transportation enterprises, analyzes the reasons for their low efficiency, and focuses on improving it from multiple aspects.

$$y_{i,p} = \alpha_0 + \alpha_1 Inter_p + \alpha_2 ER_p + \alpha_3 Div_{i,p} + \alpha_4 Dis_{i,p} + \varepsilon_i \quad \text{(Eq.7)}$$

Among them, $y_{i,p}$ represents the carbon emission efficiency of enterprise i in city p. The core explanatory variables in this paper mainly include two aspects: (1) the Internet development degree of the city where the enterprise is located and whether it is subject to environmental regulation, denoted by *Inter* and *ER* respectively; and (2) whether the enterprise operates in a diversified manner and the average transportation distance of the enterprise, represented by *Div* and *Dis* respectively. εi is a random error term that follows a standard normal distribution.

Geographically weighted regression

Compared to traditional OLS regression models, Geographically Weighted Regression (GWR) utilizes spatial relationships to reflect the non-stationary characteristics of

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parameters at different spatial units, allowing the relationships between research variables to vary with geographical location. The model structure is:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad \text{(Eq.8)}$$

In the formula, y_i is the dependent variable value at the geographic location (u_i, v_i), where (u_i, v_i) is the geographic center coordinate of the sample spatial unit, $\beta_0(u_i, v_i)$ is the intercept at the geographic location (u_i, v_i), $\beta_k(u_i, v_i)$ is the value of the function $\beta_k(u, v)$ at the sample space location i, and ε_i represents the spatial random residual. The framework for using the GWR model to study the level of urbanization coordination is as follows: first, examine the spatial structural characteristics of carbon emission efficiency in each region, then select the kernel function, use the AIC (Akaike information criterion) to determine the optimal bandwidth, and finally construct a GWR model for carbon emission efficiency in each region. Based on the model results, analyze and discuss the driving factors.

Research subjects and data

Research subjects

This study focuses on 5,296 large-scale road transport enterprises across 31 Chinese provinces during 2020–2021. Large-scale transport enterprises are defined as road freight legal entities with an annual operating revenue ≥10 million yuan and ownership of ≥50 freight vehicles. These provinces are classified by region (see *Table 1*) to support subsequent heterogeneity analysis. In line with China's 2020 "Dual Carbon Goals," the study compares the carbon emission efficiency of these enterprises between 2020 and 2021, providing valuable insights into the future implementation of the "Dual Carbon" strategy.

Table 1. *Regional distribution of different provinces in China*

Region	Province	Region	Province
Eastern region	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan	Western Region	Inner Mongolia, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
Central region	Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan	Northeast region	Jilin, Heilongjiang, Liaoning

Data

The data are primarily derived from the 2020 and 2021 China Statistical Yearbooks and the Transportation Comprehensive Statistical Survey System. Employing the OLS model, this study comprehensively analyzes the factors influencing carbon emission efficiency from different perspectives, taking into account relevant research results. The variables involved are shown in *Table 2*.

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Table 2. *Main variables in the regressions*

Variable type	Variable name	Variable Explanation
Dependent variable	Carbon emission efficiency	Carbon emission efficiency of enterprise
Explanatory variable	ER	Environmental Regulation
	Inter	the Internet development degree of the city where the enterprise is located
	Dis	The average transportation distance of the trucks owned by the enterprise
	Div	Whether the enterprise operates in a diversified manner

Results and analysis

Characteristic analysis of carbon emission efficiency

This study explores the spatial distribution of economic efficiency, carbon emission efficiency, and unified efficiency of Chinese road transport enterprises. China's 30 provinces and municipalities are divided into four regions: Eastern, Central, Western, and Northeastern. *Table 3* presents the regional efficiency metrics for 2020–2021. In 2020, the economic efficiency of road transport enterprises in the Eastern and Western regions exceeded the national average, while the Central and Northeastern regions were close to it. By 2021, Northeastern regional economic efficiency surged notably, narrowing the regional efficiency gap, and the Eastern region emerged as the most economically efficient. Carbon emission efficiency varied slightly between 2020 and 2021, but COVID-19 disrupted enterprise operations, causing significant economic efficiency fluctuations. Spatially, road transport enterprises' carbon emission efficiency the ranked of Western > Wastern > Central > Northeastern regions, aligning with Zhang et al. (2018). Unified efficiency's changes and regional rankings closely mirrored those of economic efficiency.

Table 3. *Economic efficiency, carbon emission efficiency, and unified efficiency of road transportation enterprises in different regions*

		ALL	Eastern Region	Central Region	Western Region	Northeast Region
EE	2020	0.9472	0.9488	0.9437	0.9506	0.9354
	2021	0.9678	0.9689	0.9656	0.9687	0.9635
CE	2020	0.9968	0.9968	0.9966	0.9972	0.9964
	2021	0.9971	0.9972	0.9968	0.9974	0.9962
JE	2020	0.9466	0.9481	0.9430	0.9499	0.9346
	2021	0.9670	0.9681	0.9647	0.9677	0.9624

As shown in *Table 4*, China's economic efficiency, carbon emission efficiency, and unified efficiency demonstrated a clear positive spatial correlation in 2020 and 2021. Moran's I for economic and unified efficiency rose, while that for carbon emission efficiency declined slightly. This is likely due to China's strong advancement of energy-saving and emission reduction policies (e.g., new energy vehicle deployment, electrification of transportation hubs, ports, and logistics parks), which promoted carbon

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emission efficiency convergence among road transport enterprises. Nevertheless, regional disparities in policy implementation intensity, capital investment management, and technical support resulted in heterogeneity in regional carbon emission efficiency, intensifying its spatial distribution differentiation and reducing aggregation.

Table 4. *Moran'I index of efficiency of road transport enterprises in China from 2020 to 2021*

	EE			**CE**			**UE**		
	Mean	2020	2021	Mean	2020	2021	Mean	2020	2021
Moran's I	0.5242	0.5227	0.5255	0.5263	0.5263	0.5262	0.5242	0.5226	0.5254
P-value	0.0013	0.0012	0.0007	0.0009	0.0011	0.0011	0.0012	0.0008	0.0010
Z	15.4413	15.3846	15.4887	15.5087	15.5067	15.5105	15.4389	15.3811	15.4872

Note 1: The data in the table was compiled by the author based on the calculation results of GEODA software

The above analysis shows that the economic and carbon emission efficiencies of road transport enterprises remained relatively stable during 2020–2021, with a distinct spatial distribution pattern emerging. To formulate targeted carbon reduction strategies for the transportation sector, this paper uses the 2020–2021 average economic and carbon emission efficiencies of road transport enterprises as a benchmark to explore the combined state characteristics of the two efficiencies across 30 Chinese provinces and municipalities. The specific results are presented in *Table 5*.

Table 5. *Joint distribution of average economic efficiency and carbon emission efficiency of road transportation enterprises in various provinces*

	EE>M_E	**EE<M_E**
CE>M_C	Anhui, Hubei, Yunnan, Beijing, Liaoning, Inner Mongolia, Guangxi, Hunan, Sichuan, Guangdong, Fujian, Chongqing, Qinghai	Shaanxi, Guizhou, Jiangsu, Shanghai, Tianjin, Jiangxi, Hainan, Xinjiang
CE<M_C	Hebei	Heilongjiang, Zhejiang, Shandong, Henan, Jilin, Gansu, Shanxi

Based on the average values, four joint states of economic efficiency (EE) and carbon emission efficiency (CE) were identified across 30 Chinese provinces and municipalities: (a) Double High Efficiency Regions (EE>M_E, CE>M_C), including Anhui, Hubei, Yunnan, Beijing, Liaoning, Inner Mongolia, Guangxi, Hunan, Sichuan, Guangdong, Fujian, Chongqing, Qinghai, etc. Road transport enterprises in these regions exhibit leading national levels of both economic and carbon emission efficiency, with production also at or near the forefront, indicating a win-win scenario for carbon reduction and economic growth. (b) High Economic Efficiency & Low Carbon Emission Efficiency Regions (EE>M_E, CE<M_C), comprising only Hebei, where economic efficiency is high but carbon emission efficiency is low. Moreover, its carbon emission efficiency is significantly lower than the average (CE<M_E), leading to notably lower unified efficiency in these provinces—making them key targets for future road transport enterprise carbon reduction. (c) Low Economic Efficiency & High Carbon Emission Efficiency Regions (EE<M_E, CE>M_E), including 8 provinces: Shaanxi, Guizhou, Jiangsu, Shanghai, Tianjin, Jiangxi, Hainan, and Xinjiang. (d) Double Low Efficiency Regions (EE<M_E, CE<M_E),

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comprising 7 provinces: Heilongjiang, Zhejiang, Shandong, Henan, Jilin, Gansu, and Shanxi. Road transport enterprises in these provinces exhibit low levels of both economic and carbon emission efficiency; therefore, it is urgent to promote carbon reduction alongside economic development and drive dual efficiency improvement.

As shown in the table, based on average scores, the economic efficiency (EE) and carbon emission efficiency (CE) of road transportation enterprises in 30 Chinese provinces/municipalities fall into four distinct categories: (1) Double High Efficiency Regions (EE>M_E, CE>M_C): Anhui, Hubei, Yunnan, Beijing, Liaoning, Inner Mongolia, Guangxi, Hunan, Sichuan, Guangdong, Fujian, Chongqing, and Qinghai. These regions demonstrate nationally leading EE and CE, reflecting a win-win between carbon reduction and economic growth for local road transportation enterprises. (2) High Economic Efficiency but Low Carbon Emission Efficiency Regions (EE>M_E, CE<M_C): Only Hebei Province falls into this category. It exhibits high economic efficiency (EE) but low carbon emission efficiency (CE), with CE significantly below the mean carbon efficiency. This results in notably low overall efficiency, making Hebei a key target for carbon emission reduction in road transportation enterprises. (3) Low Economic Efficiency but High Carbon Emission Efficiency Regions (EE<M_E, CE>M_C): Eight provinces fall into this category: Shaanxi, Guizhou, Jiangsu, Shanghai, Tianjin, Jiangxi, Hainan, and Xinjiang. Their road transportation enterprises exhibit low economic efficiency (EE) but high carbon emission efficiency (CE). (4) Double Low Efficiency Regions (EE<M_E, CE<M_C): Seven provinces are included here: Heilongjiang, Zhejiang, Shandong, Henan, Jilin, Gansu, and Shanxi. Their road transportation enterprises have low levels of both EE and CE. Thus, it is imperative to promote carbon reduction while boosting economic development, to drive the improvement of both efficiencies.

Analysis of factors influencing carbon emission efficiency

Table 6, Column 2 analyzes the factors influencing carbon emission efficiency (CE) of 5,296 large-scale road transport enterprises. The regression results show that environmental regulations have a positive impact on enterprise CE that is statistically at 10% level, increasing it by 0.306. This indicates that urban environmental regulations—such as low-carbon city pilots, which supervise enterprise carbon emissions—can enhance local enterprises' CE. To achieve low-carbon emissions, urban low-carbon transportation systems should adopt low-carbon fuels and actively develop new energy transport options (e.g., trams and hydrogen-powered vehicles). Additionally, in eastern and central China, environmental regulations positively affect CE of large-scale road transport enterprises, effectively promoting its improvement. However, the impact of environmental regulations on CE is less significant in western and northeastern China. This is mainly because these regions have fewer cities implementing environmental regulations, weakening their influence on enterprises' CE. Additionally, environmental regulations exert a stronger impact in the central region than in the eastern region. This may be due to the relatively developed urban economy in the east, where many transportation enterprises have already upgraded their equipment—reducing the marginal effect of environmental regulations on road transport firms.

From the perspective of urban Internet development, the impact coefficient of Internet development on CE of road transport enterprises is 0.388, which is positive and statistically significant at the 1% level. This indicates that the advancement of Internet development can effectively improve enterprise CE. In recent years, the rapid development of the Internet has given rise to online freight platforms. With their high

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permeability and platform-sharing features, these platforms reduce enterprises' information search costs related to cargo sources and transportation. They also effectively alleviate the information asymmetry in the freight market, improve resource allocation efficiency, and prompt enterprises to reduce truck idling rates. This, in turn, cuts carbon emissions from idling vehicles and boosts carbon emission efficiency. Regarding regional differences, Internet development plays a more significant role in promoting the carbon emission efficiency of road transport enterprises in the western region. This indicates that advancements in Internet development in the western region more prominently drive the carbon emission efficiency of road transport enterprises. This is because, compared to other regions, Internet development in the Western is relatively underdeveloped, resulting in a more pronounced marginal impact of Internet development in this area.

Table 6. *Empirical results on the influencing factors of carbon emission efficiency of large-scale road transportation enterprises*

VARIABLES	ALL	Eastern region	Central region	Western Region	Northeast region
ER	0.306*	0.265**	0.697**	-0.0623	-0.988
	(0.170)	(0.215)	(0.467)	(0.340)	(1.064)
Inter	0.388***	0.348***	0.431*	0.544***	0.474
	(0.0995)	(0.133)	(0.232)	(0.159)	(0.725)
Dis	0.422***	0.332***	0.621***	0.353***	0.965***
	(0.0655)	(0.0900)	(0.162)	(0.103)	(0.340)
Div	-0.369**	-0.447**	-0.536*	-0.193	-0.0674
	(0.158)	(0.223)	(0.354)	(0.255)	(0.851)
Constant	-2.259*	-7.671***	9.098***	1.525	9.534
	(1.280)	(1.680)	(3.100)	(2.223)	(7.123)
Observations	5,296	2,977	1,234	814	271
R-squared	0.018	0.028	0.022	0.034	0.035

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

From the perspective of enterprise production and operation, operational diversification exerts a negative impact on CE of road transport enterprises. Specifically, enterprises engaging in diversified operations exhibit lower CE compared to those focusing on specialization in their core business. This is attributable to the fact that specialized transportation enterprises typically maintain more stable cargo sources and possess superior expertise in transportation route, thereby reducing cargo search costs and curbing empty-load carbon emissions, which ultimately enhances CE. Across regions, operational diversification shows a negative impact coefficient on CE, with statistical significance only observed in the eastern and central regions. This may be due to the relatively large number of large-scale road transport enterprises in these two regions, which enhances the reliability of the regression results.

From the perspective of transportation characteristics, transportation distance exerts a positive impact on CE of large-scale road transportation enterprises. Specifically, long-haul transportation contributes to CE improvement. This is attributable to the higher empty-haul costs faced by long-haul operators, which strengthens their incentive to secure cargo sources and reduce truck empty-haul rates. Under a given carbon emission level,

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long-haul enterprises achieve higher freight volumes and operating revenues, thereby enhancing CE.

This study utilizes the ArcGIS spatial autocorrelation analysis module to measure the carbon emission efficiency of urban road transport enterprises for the years 2020 and 2021, generating Moran's I statistics of 0.5263 and 0.5262, respectively. These results indicate significant positive spatial autocorrelation in carbon emission efficiency across prefecture-level cities, rejecting the hypothesis of spatial randomness. Subsequently, a comparative empirical analysis of factors influencing carbon emission efficiency is conducted via ordinary least squares (OLS) and geographically weighted regression (GWR) models to unravel both global and local spatial heterogeneity of impact mechanisms. Using prefecture-level city panel data, this study employs GWR to estimate four categories of factors influencing carbon emission efficiency in road freight enterprises. The results in *Table 7* reveal that environmental regulation, Internet development, and long-haul transportation exhibit positive impact coefficients on enterprise carbon emission efficiency, whereas multi-service operation presents a negative coefficient. These findings are consistent with the OLS regression results, confirming that environmental regulation, advanced Internet infrastructure, and long-haul transportation can enhance the carbon emission efficiency of urban road transport enterprises, while business diversification exerts an inhibitory effect. Such consistency validates the robustness of the empirical results.

Table 7. *Regression results of GWR model*

	Mean	Min	Max	Med
ER	0.297	-0.800	0.924	0.337
Inter	1.003	-0.272	6.871	0.586
Dis	0.228	-0.142	0.382	0.233
Div	-0.721	-1.896	1.163	-0.835

Conclusions and limitations

Conclusions

This study adopts the IPCC (2006) guidelines to quantify transportation-related carbon emissions from road transport enterprises. Leveraging the additive structure of the Range-Adjusted Measure (RAM) model, it integrates economic performance and carbon emission factors into a unified analytical framework. This methodological design enables the measurement of both economic efficiency and carbon emission efficiency of road transport enterprises, while deriving their integrated efficiency that balances economic returns and carbon emission constraints. Key findings are summarized as follows:

(1) The outbreak of COVID-19 in 2020 caused severe disruptions to corporate transportation and production operations, leading to significant volatility in regional economic efficiency values and their rankings during 2020–2021. In contrast, regional carbon emission efficiency rankings remained stable, presenting a spatial pattern characterized by "western regions leading, eastern regions following closely, and central and northeastern regions lagging". This aligns with the strategy of "regionally differentiated emission reduction" embedded in China’s carbon mitigation policies, thereby validating the stability and efficacy of emission reduction policies during extraordinary periods.

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(2) Spatial distribution analysis reveals significant spatial correlation between economic efficiency and carbon emission efficiency, while the decline in Moran's Index in 2021 signifies a weakening of this spatial association. This aligns with China's carbon mitigation policy orientation of "regional coordinated green development", reflecting the gradual convergence of inter-regional emission reduction gaps driven by policy instruments. Practically, it is advisable to enhance inter-regional emission reduction cooperation mechanisms in a targeted manner; regions can reshape agglomeration dividends through industrial relocation, technology spillover, and other pathways to promote spatial equilibrium of carbon emission efficiency.

(3) OLS and GWR models were employed for empirical analysis of road transport enterprises' carbon emission efficiency drivers. Internet development, environmental regulation intensity, and long-distance transportation scale show a statistically significant positive effect on carbon emission efficiency, while business diversification has a significant negative impact. Notably, these factors' marginal effects present obvious spatial heterogeneity, aligning with China's carbon reduction policy direction of "technological empowerment, strict environmental supervision, and transportation structure optimization". In practice, enterprises should prioritize core business and digital technology empowerment to boost emission reduction efficiency, while the government should refine regionally differentiated policies to improve the targeting of environmental regulation and transportation structure optimization.

Limitations

This study has limitations, including the short research time span and the lack of specific national data for small countries without energy consumption records. It relies heavily on data from the National Bureau of Statistics of China and the Ministry of Transport of China—reliable sources, yet lacking comparisons with energy consumption data and research results from other countries. Future research will integrate more data sources to examine the influencing factors of carbon emission efficiency across different industries and time dimensions.

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Data availability. Due to the confidentiality of operational data of road transportation enterprises, the dataset generated and/or analyzed during this study is not publicly available, but can be obtained from the corresponding authors upon reasonable request.

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APPENDIX

(1) DEA-RAM model for economic efficiency of road transport enterprises

Based on the above assumptions and referring to Aida's (1998) research, the Economic Efficiency (EE) of road transportation enterprises is:

$$\begin{cases} \max \sum_{n=1}^{N} R_n^x s_n^x + \sum_{m=1}^{M} R_m^e s_m^e + \sum_{p=1}^{P} R_p^y s_p^y \\ \sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_n^j, \forall_n; \\ \sum_{j=1}^{J} y_{pj} - S_p^y = y_{pj}, \forall_p; \\ \sum_{j=1}^{J} e_{mj}\lambda_j + s_m^e = e_{mj}, \forall_m \\ \sum_{j=1}^{J} \lambda_j = 1, \lambda_j \geq 0, \forall_j; s_p^y \geq 0, \forall_p \end{cases} \tag{A-1}$$

Among them, x_{nj}, e_{mj} and y_{pj} respectively represent the input factors, energy factors and expected output factors of the enterprise; R_n^x, R_m^e and R_p^y are relaxation variables, and s_n^x, s_m^e and s_p^y are adjustment ranges, respectively; λ_j is the weight of enterprise j. Among them, the expressions for R_n^x, R_m^e and R_p^y are:

$$\begin{aligned} &R_n^x = \frac{1}{(N+M+P)\left[Max(x_{nj}) - Min(x_{nj})\right]}; R_n^y = \frac{1}{(N+M+P)\left[Max(y_{pj}) - Min(y_{pj})\right]}; \\ &R_m^e = \frac{1}{(N+M+P)\left[Max(e_{mj}) - Min(e_{mj})\right]}; \end{aligned} \tag{A-2}$$

Assuming that λ^* represents the weight of the cross-sectional observations of the maximum relative efficiency that each province may achieve in the transportation production process when taking the optimal solution of model (A-1); s_n^{x*}, s_m^{e*} and s_p^{y*} are the relaxation variables of input and output in the optimal solution state. At this point, the RAM transportation economic efficiency of enterprise *j* during period *t* can be transformed into:

$$0 \leq \theta_p = 1 - (\sum_{n=1}^{N} R_n^x s_n^{x*} + \sum_{m=1}^{M} R_m^e s_m^{e*} + \sum_{p=1}^{P} R_p^y s_p^{y*}) \leq 1 \tag{A-3}$$

(2) D DEA-RAM model for unified efficiency of road transport enterprises

The Unified Efficiency (UE) RAM model for transportation is:

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$$\begin{cases} max(\sum_{n=1}^{N} R_n^x s_n^x + \sum_{m=1}^{M} R_m^e s_m^e + \sum_{p=1}^{P} R_p^y s_p^y + \sum_{i=1}^{I} R_i^b s_i^b) \\ s.t.\sum_{j=1}^{J} x_{nj}\lambda_j + s_n^x = x_{nj}, \forall_n; \\ \sum_{j=1}^{J} e_{mj}\lambda_j + s_m^e = e_{m\,j}, \forall_m; \\ \sum_{j=1}^{J} y_{pj}\lambda_j - s_p^j = y_{pj}, \forall_p \\ \sum_{j=1}^{J} b_{ij}\lambda_j + s_i^b = b_{ij}, \forall_i; \\ s_m^e \geq 0, \forall_m; s_p^j \geq 0, \forall_p; s_i^b \geq 0, \forall_i; \end{cases} \tag{A-4}$$

Correspondingly, according to model, the DEA-RAM transportation unified efficiency of enterprise j during period t can be obtained as follows:

$$0 \leq \theta_U = 1 - (\sum_{n=1}^{N} R_n^x s_n^{x*} + \sum_{m=1}^{M} R_m^e s_m^{e\,*} + \sum_{p=1}^{P} R_p^y s_p^{y*} + \sum_{i=1}^{I} R_i^b s_i^{b*}) \leq 1 \tag{A-5}$$

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