Traffic & Transportation

Decarbonising Transport – The Spatial Effects of Railway Container Transport on Carbon Emissions

Zhizhen BAI[1], Xiaodong LI[2], Haibo KUANG[3]

Original Scientific Paper
Submitted: 16 Apr 2025
Accepted: 12 Sep 2025
Published: 28 Apr 2026

[1] bzz1118@dlmu.edu.cn, Management Science and Engineering, Maritime Economics and Management, Dalian Maritime University, Dalian, China
[2] Corresponding author, x.li@dlmu.edu.cn, Collaborative Innovation Centre for Transport Studies, Dalian Maritime University, Dalian, China
[3] khb@dlmu.edu.cn, Collaborative Innovation Centre for Transport Studies, Dalian Maritime University, Dalian, China

Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

China is advancing a strategic transport shift to establish railway container transport as a key logistics pillar, supporting its dual carbon goals through sector restructuring. However, empirical research on its low-carbon efficacy remains limited. Based on the spatial Dobbin model, and combining the data from railway container loading and unloading stations, night lighting and socio-economic factors, this study deeply studies the remarkable characteristics of regional changes of railway container transportation and carbon emissions in China, and comprehensively discusses how railway container transportation affects regional carbon emissions at different scales. Key findings: (1) Urban carbon emissions are rising, with eastern cities emitting most intensely and western regions showing widespread high emissions. Railway container flows exhibit spatial disparities, creating "oligarchic cities" with concentrated transport activity. (2) Railway container transportation notably curbs the production of carbon emissions, thereby facilitating the attainment of regional low-carbon objectives. Moreover, when comparing across regions, the suppressive impact of railway container transportation on carbon emissions stands out more prominently in both the eastern and western regions. The railway container transportation conducted in the Yangtze River Delta Economic Zone and the Bohai Rim Economic Zone demonstrates a more pronounced suppressive effect on regional carbon emissions.

KEYWORDS

railway container transportation; regional carbon emission; spatial effect; decarbonisation transport.

1. INTRODUCTION

As a negative consequence of rapid economic development, environmental problems have become an unavoidable problem in the economic and social development of China [1]. In the previous 10 years, China has been among the highest carbon emitters in the world. As the primary and leading industry supporting social and economic development, the transport sector has become an important energy consumer and carbon emitter [2]. Furthermore, according to relevant data, the emissions from the transportation sector are projected to reach 9.6 billion tonnes by 2021, accounting for approximately 10% of the national total emissions [3, 4]. Most previous research on carbon emissions during transportation focused on carbon emissions from public transportation [5], the carbon reduction potential of emissions from industry [6] and the impact of high-speed rail on carbon emissions [7]. However, most of these studies were single analyses, did not consider the carbon effect holistically, and did not comprehensively investigate the carbon emissions from traffic activities. Railway transport is the backbone of the economy of China, a major livelihood project, and the transport system [8]. As strategic enablers of China's dual carbon goals (Carbon peaking by 2030 and Carbon neutrality by 2060) [9], railways accelerate nationwide decarbonisation. Advanced rail infrastructure development is fundamental to transitioning toward a sustainable, low-carbon socioeconomic paradigm. In 2018, the "Three-year Action Plan for Promoting the Adjustment of the Transportation Structure (2018–2020)" issued by the General Office of the State Council proposed the "road-to-rail and bulk-to-container (the transition of bulk commodities from road transportation to railway transportation, and the shift from bulk transportation to containerised transportation for these commodities)" concept as an initiative for restructuring transport infrastructure [10], the urgent need to propel the vibrant development of railway container transportation (RCT) cannot be overstated. Examining the influence of RCT on regional carbon emission (RCE) carries significant theoretical and practical implications for the formulation of carbon reduction strategies and the pursuit of high-quality, green development in both economic and social domains.

This study quantifies RCT impact on regional carbon emissions (RCE) across urban, national, regional and important economic zone scales, considering China's geographical and RCT intensity disparities. Findings reveal scale-dependent effects of RCT on RCE, offering evidence for tailored emission policies to advance low-carbon development in local and neighbouring regions.

The research framework proceeds as follows: (1) Employing nighttime light data and carbon emission inversion modelling to derive city-level carbon emissions across China; (2) Characterising spatiotemporal evolution patterns of RCT and RCE during 2013-2020 using ArcGIS 10.2 and MATLAB platforms; (3) Employing spatial econometric modelling, this study empirically investigates the multiscale impacts of rail container transportation (RCT) on regional carbon emissions (RCE) and their underlying causal mechanisms. (4) Formulating evidence-based policy recommendations derived from empirical findings.

2. LITERATURE REVIEW

Railway transport (RT) development promotes economic growth and increases carbon emissions [11]; however, RT has a lower emission intensity than air and road transport [12]. RCT has immense potential in replacing carbon-intensive and rapidly growing road freight [13] and is a rational substitute for road freight [14]. Furthermore, studies indicate that shifting from traditional road transportation to railway container transport will bring significant transportation and environmental benefits to port cities [15]. The carbon emission of the RT of China RT has increased due to increasing industrial infrastructure, average transportation distance and other factors, whereas vehicle structure and high-speed rail reduce carbon emissions [16]. Reducing carbon emissions through using high-speed rail transport has significant spatial heterogeneity since urban development relies on external investments and secondary industry [17, 18]. High-speed rail improves local carbon efficiency through industrial upgrading and technological advancement. Furthermore, it improves the carbon efficiency of neighbouring cities through industrial agglomeration and factor spillover effect (the unintended consequences whereby regional economic activities, policies or events indirectly influence outcomes in geographically adjacent or economically linked areas) [19]. There are efforts to reduce carbon emissions through using high-speed rail transport [20]; however, there is a need to understand the effects of using high-speed rail transport on carbon emissions [21]. Research on low-carbon RCT primarily focused on multimodal transport methods, including port containers in low-carbon container transportation conditions with path optimisation [22], with carbon emissions as a constraint [23]. However, RCT is rarely studied independently.

Accounting for carbon dioxide emissions involves on-site monitoring and life cycle modelling. The Intergovernmental Panel on Climate Change (IPCC) guidelines for the National Greenhouse Gas Inventory present an important method of accounting for carbon emissions [24]. However, the IPCC cannot measure urban carbon emissions due to limited energy consumption data. Elvideg and Doll [25, 26] provided theoretical support for applying night light data in quantifying microscale energy consumption and carbon emissions, and the related research and application are mature [27, 28]. Using night light data, Hao et al [29] assigned carbon emissions from China's energy consumption to the grid scale. Chen et al [30] revealed that urbanisation and population size were the main drivers of the sustained increase in carbon emissions. Similarly, Qin and Gong [31] obtained carbon emission data from prefecture-level cities in China and used machine learning to identify the factors affecting gross domestic product, financial general budget revenue and foreign investment influencing carbon dioxide emissions. Combining the IPCC method and night lighting data refines the scale at which carbon emissions are quantified.

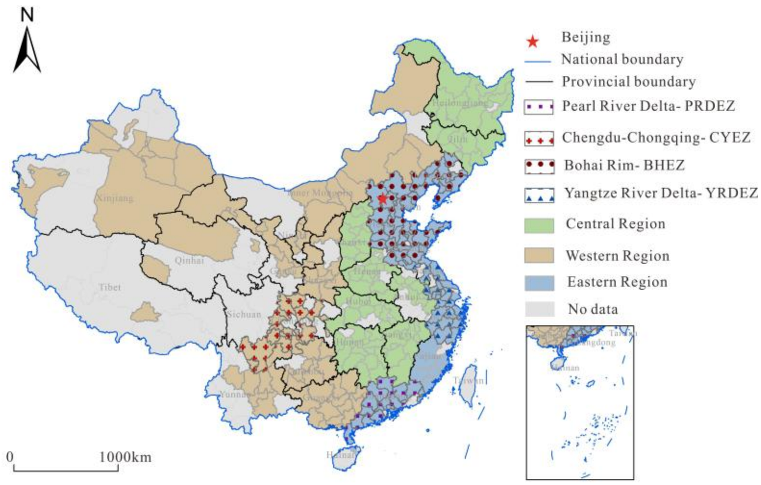
Previous studies have confirmed the carbon reduction effect of high-speed rail, and from a macro perspective, the main research areas concerning carbon emissions from RT include influencing factors, comparisons with other transportation modes and carbon efficiency. However, to date, the academic community has not yet established a definitive understanding of the impact of railway container transport on RCE. Furthermore, there is a notable absence of research that examines this issue at the granular level of individual cities. This study endeavours to clarify the specific effects of RCT on RCE by utilising consolidated freight data from RCT at multiple levels, including the national, regional and key economic zone scales. The study confirms regional variations in railway container transport's carbon impact, providing a basis for tailored emission policies to advance low-carbon growth locally and regionally.

3. MATERIALS AND METHODS

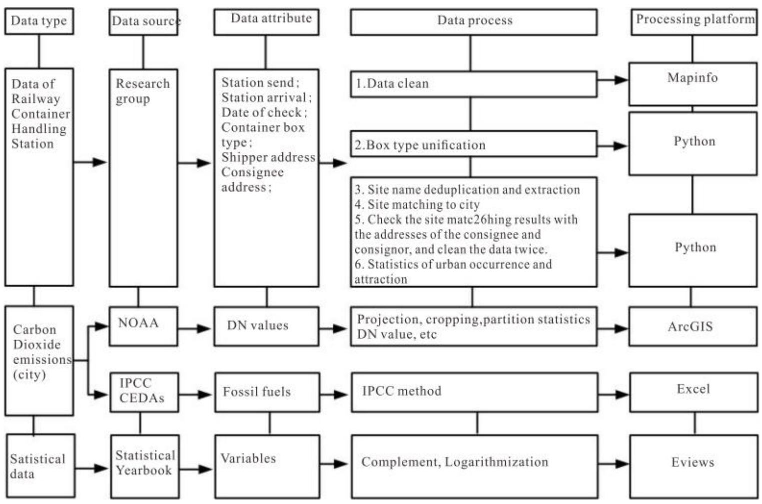
The research area, data processing, variable selection and model construction are outlined.

3.1 Research area overview and data processing methodology

RCT is influenced by road networks and cargo distribution, showing significant regional variations. This necessitates accounting for spatial heterogeneity when analysing RCTs' impact on RCE. Focusing on China's key economic zones (Bohai Rim-BHEZ/Yangtze River Delta-YRDEZ/Pearl River Delta-PRDEZ/ ChengduChongqing-CYEZ) with similar carbon emissions and high energy consumption, this study examines their spatial effects to inform low-carbon transport systems. Building on prior studies [32, 33], China is divided into Eastern/Central/Western regions (*Figure 1a*) and important economic zones. Data sources and processes used in this study are presented in *Figure 1b*. Hong Kong, Macao and Taiwan have not been included in this study at present.



(a)



(b)

Figure 1 – a) Research area division in China (base map sourced from China's Ministry of Natural Resources, approval no. GS[2023]2764, unmodified; b) Data attributes and processing (IPCC, NOAA, DN-Digital Number)

3.2 Variable selection and description

Considering previous research and the particularity of transportation activities, the variables were selected using the following criteria (*Table 1*):

Table 1 – Model variable description

Variable type	Name	Definition/Unit
Explained variable	PC	PC-Carbon emission of prefecture-level cities/Mt
Explanatory variable	RCT	RCT-Railway container transportation/10^5TEU
Control variables	Ln-ps	Population size-Annual average population/10^4
	Ln-ai	Affluence-Per capita GDP/CNY
	Ln-is	Industrial structure-Ratio of the output value of the secondary industry to GDP/%
	Ln-fc	Utilisation of foreign capita-The actual utilisation of foreign capital/10^4CNY
	Ln-el	Educational Level-Education expenditure per capita/CNY
	Ln-ti	Technical input-Proportion of expenditure on science and technology to fiscal expenditure/%

Note: TEU: twenty-foot equivalent unit, CNY: China Yuan. Control variable variables are logarithmic. Abbreviations with 'Ln' mean that variables are in logarithms. The secondary industry: the economic sector that transforms raw materials from the primary industry (e.g. agriculture, mining) into finished goods or products through manufacturing, construction and processing activities.

Explained variable: Carbon emissions from prefecture-level cities (PC) were obtained by combining night light illumination data with the Intergovernmental Panel on Climate Change formula for inversion [31].

Explanatory variable: Railway container transportation (RCT). Given the low-carbon characteristics of RT, combined with the current background of "transition from road to rail and from bulk to containerised transportation", the impact of RCT on RCEs must be described to promote the coordinated development of container transportation and urban environment [34].

Control variables: Population size (ps): population size has been considered to affect RCEs. Affluence (ai): The greater the wealth, the higher the economic value created and the greater the volume of carbon emissions. Industrial structure (is): The higher the proportion of the industrial sector, the greater the volume of carbon emissions [16]. Utilisation of foreign capital (fc): fc may foster technological innovation and enable carbon emission reduction, but it can also give rise to "pollution haven" effects, potentially increasing carbon emissions [35]. Educational level (el): On one hand, education enhances environmental awareness and spurs technological innovation, potentially reducing emissions; on the other hand, it accompanies rising incomes and consumption upgrades, which may result in increased emissions. Technical input (ti): Technological investment negatively impacts carbon emissions by reducing and weakening carbon emissions from the source.

3.3 Model construction

Using night light data and IPCC methods, we inferred city-level carbon emissions, revealing significant spatial variations in RCT and RCE. Spatial econometric models, with their comprehensive and flexible approach to spatial data analysis, are crucial for studying these spatial economic relationships.

1) Measurement of carbon dioxide emissions

China's transport carbon emissions lack direct monitoring, relying on energy consumption models (e.g. vehicle-specific distance/energy use [36]) and provincial-to-urban extrapolation prone to industrial-data bias [37]. Building on night light's correlations with energy use [25] and CO_2 emissions [26], this study integrates Intergovernmental Panel on Climate Change (IPCC) methodologies with night light data to systematically invert city-level emissions (*Figure 2*), complementing CEADs (https://www.ceads.net.cn) partial coverage while ensuring sample completeness.

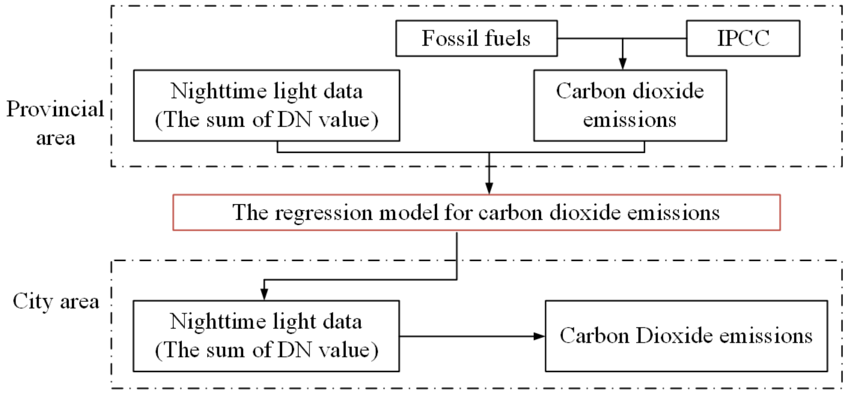


Figure 2 – Steps to calculate carbon dioxide emissions. IPCC- Intergovernmental Panel on Climate Change, DN-digital number

Nightlight data were processed via ArcGIS 10.2 (Esri, USA), involving projection, cropping, partition statistics and DN value (Digital Number: In nighttime light remote sensing, the Digital Number (DN) denotes the original radiometric value per pixel captured by satellite sensors, quantifying relative nocturnal illumination levels on the Earth's surface) extraction. Provincial carbon emissions were calculated using the IPCC method [31], incorporating fossil fuel consumption, fuel-specific parameters (unit heat value, carbon content, oxidation rate) and non-energy carbon storage. The estimation formula is:

$$PC_{it} = \sum_{i=1}^{30} C_{Direct.i}^{t} = \sum_{i=1}^{30}\sum_{j=1}^{27}\left[E_{ij}^{t} \times LCV_{ij}^{t} \times CC_{ij}^{t} \times COR_{ij}^{t} \times \frac{44}{12}\right] \tag{1}$$

where PC_{it} represents carbon dioxide emissions generated by energy use in t years in i province (city). j represents the energy type, and 27 energy types in the Chinese energy balance table were adopted. E^{t}_{ij} is the total energy consumption of class j in year t in province i (city), and LCV^{t}_{ij} is the average low calorific value of class j energy. The product of the E^{t}_{ij} and LCV^{t}_{ij} represents the energy consumption from the calorific value of the fuel unit to the thermal unit. CC^{t}_{ij} is the carbon content per unit calorific value of the j-*th* energy source, and COR^{t}_{ij} is the carbon oxidation rate of the j-*th* energy source.

Nighttime light-based carbon emission models widely employ regression methods (panel, linear, logarithmic, quadratic), with panel regression outperforming linear models in realism. Comparative analysis (*Table 2*) demonstrates that panel regression incorporating individual effects achieves optimal fit for prefecture-level city emission inversion.

$$PC_{it} = \beta * DN_{it} + \alpha + u_i + \varepsilon_{it} \tag{2}$$

where PC_{it} represents the carbon emission of i province in t year, DN_{it} is the total night lighting in i province in t year, β is the coefficient (see *Table 2* for the relationship coefficient between DN value and carbon emission), u_i, and v_t are individual effects and factors that do not change with time, respectively, and ε_{it} are residuals. The number of city night lights was introduced into the fitting formula to obtain the carbon emissions of a city.

Table 2 – Regression results of the panel model

		coef	cons	R^2	ProvinceFE	YearFE	N	F
Ln(PC)/Ln(DN)	(1)	0.27	8.74	0.97	Yes	Yes	240	195.09
	(2)	0.75	-0.92***	0.39	No	Yes	240	18.65
	(3)	0.08	8.05**	0.97	Yes	No	240	237.51
PC/DN	(4)	0.00	6,967.22	0.61	Yes	Yes	240	8.48
	(5)	0.01	5,968.54**	0.17	No	Yes	240	5.90
	(6)	0.00	7,771.19***	0.58	Yes	No	240	9.46

*Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively, same as below; PC-prefecture-level cities, DN-digital number.*

$$\frac{CPC_i}{PC_i} = \frac{CPC_c}{PC_c} \tag{3}$$

where CPC_i represents the provincial carbon emissions calculated using CEADs, PC_i represents the provincial carbon emissions estimated in this study, CPC_c represents the revised municipal carbon emissions, and PC_c represents the municipal carbon emissions estimated in this study.

2) Spatial weights matrix

Spatial weight construction critically determines object correlations. Three schemes were developed to define their spatial interdependencies via weight matrices.

3) Spatial adjacency weight matrix

The spatial adjacency matrix (W1) is typically classified by shared vertices or edges. Given urban units lack shared vertices, we constructed W1 using shared-boundary adjacency (city-based units), calculated as:

$$W_{ij} = \begin{cases} 1 & (City\ i\ and\ j\ have\ a\ common\ boundary) \\ 0 & (Otherwise) \end{cases} \tag{4}$$

4) Spatial distance weight matrix

Three types of spatial distance weight matrices (W2) exist based on the principles of minimum distance, polygons and reciprocal distance [2]. To account for railway-induced connectivity beyond distance constraints, this study employed a distance reciprocal-based spatial weight matrix, calculated as:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{5}$$

where d_{ij} is the distance between the geographic centres of cities *i* and *j*, and the geographic distance is calculated using the longitude and latitude of the city centre.

5) Economic geographical distance weight matrix (W3)

Weight matrices W1 and W2 are symmetrical, and the mutual influence between the evaluation units in the matrix is the same by default. However, the mutual influence between regions differs owing to differences in economic levels and resource endowment between regions, even though the two regions are far apart. Therefore, the spatial weight was asymmetric when calculating the spatial correlation between RCT and RCE. A spatial weight matrix based on the economic distance-inverse distance was constructed using the following formula:

$$W_{ij} = \begin{cases} \left(\frac{G_i}{G_j}\right)^{1/2} \times \frac{1}{d_{ij}} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{6}$$

G_i and G_j represent the per capita GDP of *i* and *j*.

— Testing of spatial econometric models

1) The Lagrange multiplier test (LM test) test assessed spatial correlation in error and lag terms, followed by evaluating whether the spatial autoregressive (SAR) or spatial error model (SEM) better fit the data (*Table 3*). Depending on whether SAR/SEM supported or rejected the ordinary least squares (OLS) results, the spatial Durbin model (SDM) was estimated for robustness
2) The likelihood-ratio test (LR test) test assesses whether the spatial Durbin model (SDM) can be simplified to SAR or SEM via chi-square testing. If all hypotheses are rejected, SDM is retained. If the first hypothesis holds and LM tests favour SAR, SAR is preferred; similarly for SEM. *Table 2* shows significant LR and Wald test results, confirming SDM cannot be simplified to SAR/SEM, thus validating SDM's use [38]. *Table* 2 shows significant LR and Wald test results, confirming SDM cannot be simplified to SAR/SEM, thus validating SDM's use.
3) The Hausman test selected fixed over random effects. A significant statistical value (139.88, *Table 3*) rejected the null hypothesis, validating the fixed effects model.

Table 3 – Test results for the Lagrange multiplier, robust Lagrange multiplier, likelihood ratio tests and Wald and Hausman

Inspection project	Inspection category	Statistic	P-value
LM and robust LM	LM Spatial Lag Test	502.19	0.001
	Robust LM Spatial Lag Test	5.42	0.001
	LM Spatial Error Test	817.71	0.001
	Robust LM Spatial Error Test	320.94	0.001
LR/Wald	LR Test (Both vs Individual)	143.32	0.001
	LR Test (Both vs Time)	5079.39	0.001
	LR Test (SDM vs SAR)	26.36	0.001
	LR Test (SDM vs SEM)	28.6	0.001
	Wald Test	49.72	0.001
Wald/LR	Hausman	139.88	0.001

Notes: LM: Lagrange multiplier test; LR: Likelihood ratio test; SDM: Spatial Durbin model; SAR: Spatial autoregressive model; SEM: Spatial error model.

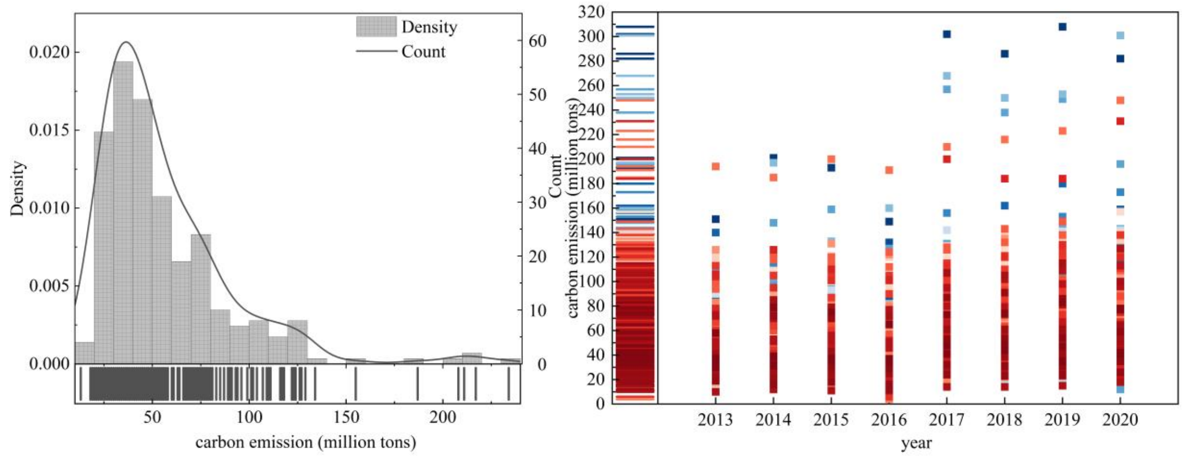
4. RESULTS

This section examines regional disparities in RCE and RCT, quantifying RCT's impact on RCE through a spatial econometric model.

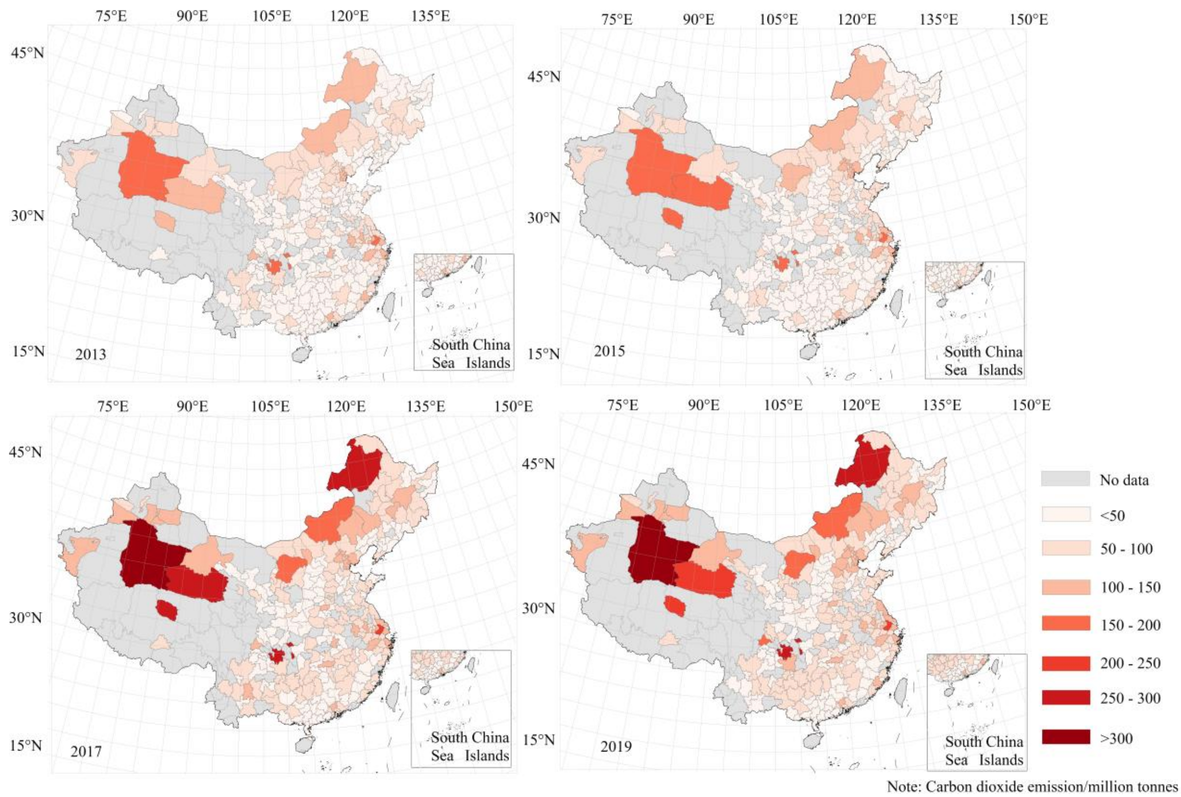
4.1 Carbon emission and RCT differentiation characteristics

1) Urban carbon emission differentiation characteristics

The carbon dioxide emissions of prefecture-level administrative units in China from 2013 to 2020 were calculated using the inversion model described above (*Figure 3a*). *Figure 3a* reveals that carbon dioxide emissions were generally semi-normally distributed and were between 0 and 75 million tons. However, some cities exceeded 75 million tonnes and reached over 200 million tonnes. These areas exceeding 75 million tons may have industries or high population density. *Figure 3a* reveals the changes in emissions during the study period: carbon dioxide increased, some cities continued to produce high emissions, and some cities ignored carbon emission controls while developing their economies.



(a)



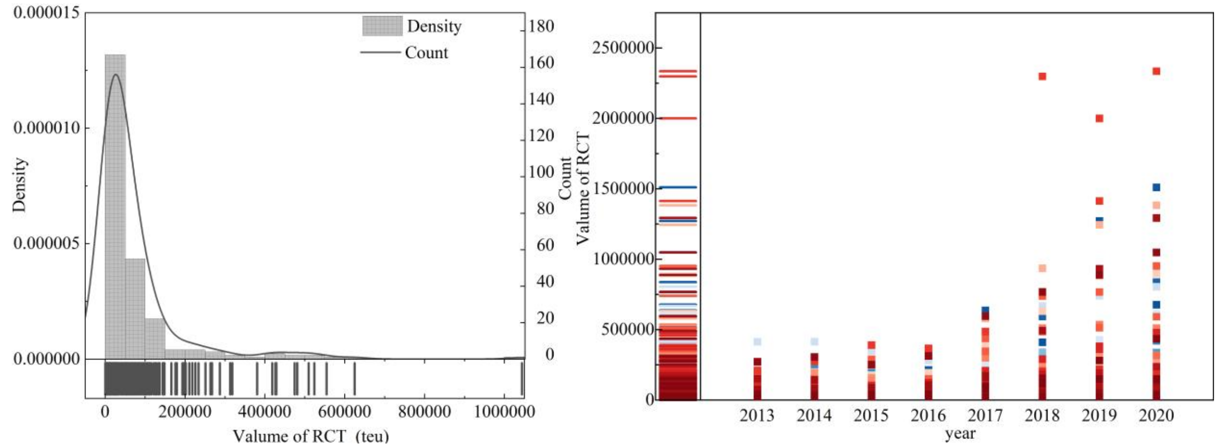
(b)

Figure 3 – Trends of carbon emissions in cities from 2013 to 2020: a) Time trend; b) Space distribution

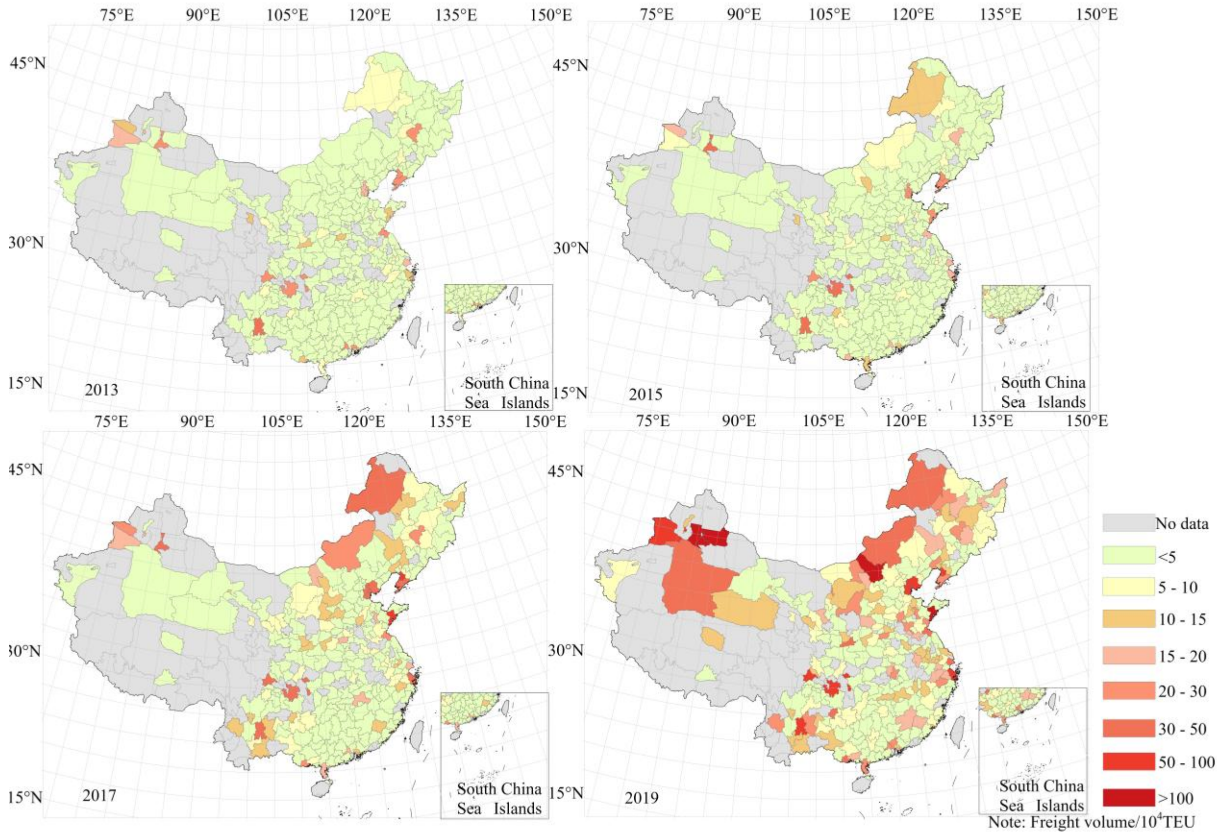
There were significant differences in carbon emissions between cities. The total emissions and cities with high emissions gradually increased (*Figure 3b*). On a regional scale, emissions in the eastern region were higher than those in the central and western regions owing to high population density, economic development and other factors. This is particularly true in the northeastern region, influenced by manufacturing and heavy industries. The Bayinguoleng and Haixi Mongolian Autonomous Prefectures are polarisation centres in the northwestern region, and they were formed primarily because of their extensive energy use. Among the important economic zones, the energy structure, technical level and other factors resulted in the highest emissions in the CYEZ, followed by those of the YRDEZ and BHEZ. Adjusting the industrial structure and environmental protection policies in the PRDEZ promotes low-emission production.

2) RCT differentiation characteristics

The RCT was positively skewed, with a density below 200,000 twenty-foot equivalent units (TEU), and the freight volume in a few cities exceeded 400,000 TEU (*Figure 4a*). During the study period, with 2015 being an important turning point, indicating stability in the early stage, with an increase in the later stage, and a lag during the implementation of the "transition from road to rail and from bulk to containerised transportation" policy. Furthermore, some "oligarchic cities (cities with extremely high traffic volumes)" had a transportation volume over 2 million TEUs, a phenomenon strongly linked to their strategic geographic positioning and level of foreign trade engagement.



(a)



(b)

Figure 4 – Temporal and spatial differentiation of railway container transportation: a) Time trend; b) Space distribution

The spatial difference in the RCT volume increased significantly, and the number of cities with high RCT volume increased significantly (*Figure 4b*). On a regional scale, the traffic volume in the eastern and western regions was higher than that in the central region. The RCT volume in Northeast China, Eastern Inner Mongolia and the Central Xinjiang Autonomous Region was markedly higher than that in other regions. An agglomeration effect was observed in RCT in important economic zones, which was higher than that in the surrounding areas. The BHEZ and CYEZ traffic volumes were higher than those of the YRDEZ and PRDEZ, presumably related to factors such as transportation structures and the development of train routes in China and Europe.

4.2 Regression results of RCE from RCT

1) Spatial weight selection and spatial autocorrelation test

Spatial correlation underpins spatial econometric analysis, requiring selection of an appropriate spatial weight matrix [39]. Moran's I (as a fundamental component of spatial models, Moran's I is commonly used to quantify the degree of correlation with surrounding spatial units), ranging from -1.0 to 1.0 (higher values indicate stronger correlations), was calculated for RCT and RCE across three matrices. W1 demonstrated the best performance ($P < 0.05$, *Table 4*), confirming the necessity of spatial factors in analysing their correlations. Thus, *W1* was used to assess RCT's impact on RCE.

Table 4 – Moran's I test results for carbon emission of prefecture-level cities and railway container transportation in China

Year	W1(PC/RCT)		W2(PC/RCT)		W3(PC/RCT)	
	Moran'I	Z	Moran'I	Z	Moran'I	Z
2013	0.25***/0.04*	6.01/1.29	0.02*/0.01	1.93/0.39	0.12***/0.01	14.75/1.11
2014	0.28***/0.05***	6.55/1.46	0.05***/0.01	4.20/0.97	0.07***/0.01	8.48/0.96
2015	0.29***/0.03*	6.85/0.93	0.05***/0.02	4.19/1.58	0.10***/-0.01	12.01/-0.25
2016	0.27***/0.06***	6.33/1.71	0.04**/0.04	3.31/4.56	0.09***/-0.01	10.98/0.16
2017	0.27***/0.09**	6.78/2.26	0.05***/0.07	4.79/6.71	0.04***/0.01****	5.39/1.47
2018	0.25***/0.07**	6.07/2.34	0.04***/0.07***	3.89/8.16	0.05***/0.01***	6.88/1.43
2019	0.26***/0.14***	6.29/4.09	0.05***/0.12***	4.29/13.48	0.05***/0.02***	6.26/2.69
2020	0.29***/0.16***	7.04/4.18	0.06***/0.14***	4.93/15.18	0.07***/0.02***	8.97/2.83

Note: PC: Carbon emission of prefecture-level cities, RCT: Railway container transportation.

The horizontal axis of *Figure 5* represents the variable, and the vertical axis represents the weighted average of the adjacent areas of the observation values. The scattering points describe the correlation between the variables and spatial lag vectors. RCE and RCT were distributed in the first quadrant, which belongs to high-high agglomeration, considering *Table 4* and *Figure 5* combined. Moran's I index maintained a steady increase during the study period.

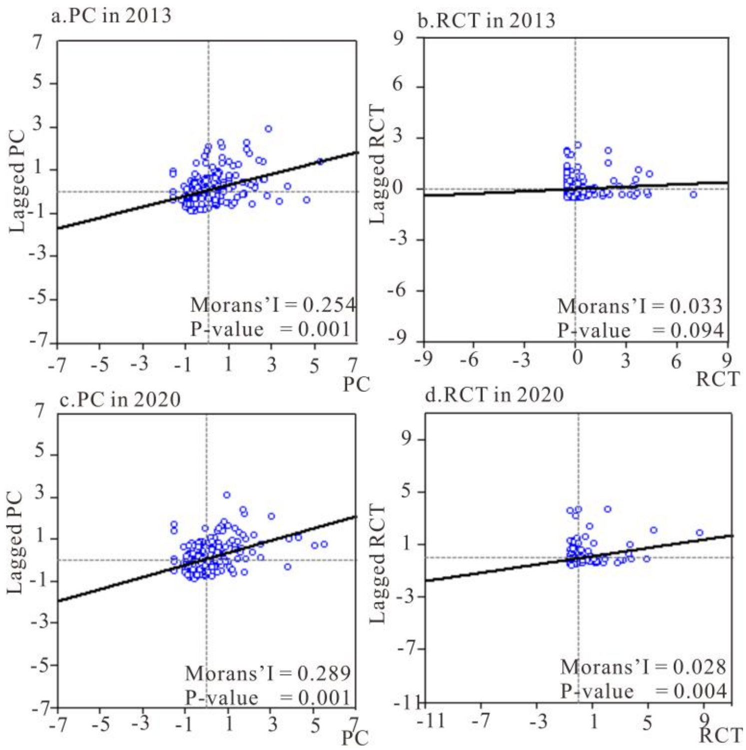


Figure 5 – Comparison of Moran's I between railway container transportation and carbon emission of cities in 2013 and 2020

2) Estimation of model parameters

Table 5 reveals that the coefficient associated with the RCT is -0.0008, which is statistically significant at the 1% level, indicating that RCT has a notable suppressive influence on RCE. The spatial autoregressive coefficient ρ, with a value of 0.6941 and significance at the 1% level, underscores the significant spatial spillover effect in RCE, where emissions in each region are influenced concurrently by both local and neighbouring factors. The direct effect is negative, indicating that RCT contributes to reducing carbon emissions in the local region. Indirect effect and total effect are not significant. This outcome may be attributed to factors such as low transport organisation efficiency, regional disparities in energy utilisation and suboptimal logistics node distribution. Given the significant geographical variations across China, further regionalised analysis is warranted in subsequent studies. As for the control variables, *ps*/*ai* has a significant positive impact on RCE, while other control variables have no significant impact on RCE.

Table 5 – Regression results and decomposition of railway container transport on regional carbon emissions

Variables	Coef.(Z)	Direct effect (Z)	Indirect effect (Z)	Total (Z)
RCT	-0.0008***(-3.36)	-0.0063**(-2.43)	0.0139(1.41)	0.0076(0.68)
ln-ps	0.0339***(2.37)	0.0456***(2.96)	0.1244*(1.87)	0.1701*(2.28)
ln-ai	0.0244***(1.99)	0.0222***(1.84)	-0.0384(-0.78)	-0.0162(-0.30)
ln-is	-0.0009(-0.05)	-0.0124(0.52)	0.1252(1.12)	0.1376(1.07)
ln-fc	0.0009(0.40)	-0.0124(1.39)	0.0306*(2.43)	0.0342*(2.40)
ln-el	0.0040(0.62)	-0.0124(0.11)	-0.0370(-0.92)	-0.0361(-0.78)
ln-ti	-0.0010(0.05)	-0.0006(-0.13)	-0.0086(-0.35)	-0.0092(-0.33)
W_RCT	0.0101***(2.81)			
ρ	0.6941***(40.24)			
θ	0.0088***(31.53)			
Log-likelihood	1884.45			

Note: 'Coef.': coefficient. Direct/ Indirect/Total effect is the direct/ indirect/ total influence of railway container transport (RCT) on regional carbon emissions (RCEs), respectively. t-statistic are in parentheses. W_RCT: weights matrix of the spatial spillover coefficients of nearby areas. See Table 1 for the full names of variables.

3) Robustness test

To account for the control variables' impact on RCE, a one-period lag treatment was applied. Robustness tests (*Table 6*) show RCT's direct effect on local carbon emissions is significantly negative, while indirect and total effects are insignificant, aligning with prior findings. Control variable results remain consistent, confirming validity.

Table 6 – Robustness test results of control variables lag

Variables	Direct effect		Indirect effect		Total	
	Coef.	Z	Coef.	Z	Coef.	Z
RCT	-0.0005**	-1.64	-0.0010	-1.62	-0.0014	-1.63
ln-ps	0.0385**	2.44	0.0686**	2.37	0.1071**	2.41
ln-ai	0.0251**	1.89	0.0448**	1.86	0.0699*	1.88
ln-is	0.0036	0.16	0.0061	0.15	0.0097	0.15
ln-fc	0.0038	1.45	0.0067	1.45	0.0105	1.46
ln-el	-0.0086	-1.1	-0.0153	-1.08	-0.0239	-1.09
ln-ti	0.0080	1.59	0.0142	1.56	0.0222	1.58

Note: Other abbreviations are the same as in Table 5. See Table 1 for the full names of variables.

To further conduct robustness checks, we adopted the approach of adjusting the bandwidth. Specifically, we excluded the data for 2015 (Model 1) and 2016 (Model 2), respectively and performed regression analyses. The results are presented in *Table 7*. It can be observed that after narrowing the time bandwidth, the results of the explanatory variables are basically consistent with those of the benchmark regression model, which verifies the robustness of the findings in this paper.

Table 7 – Robustness test results by adjusting the time bandwidth

Dependent variable		Direct effect	Indirect effect	Total	Control variables	Time fixed	Individual fixed	ρ	θ
Model 1	Coef.	-0.0008^{**}	-0.0018	-0.0026	yes	yes	yes	0.6880^{***}	0.0090^{***}
	z	-2.56	-2.48	-2.52	yes	yes	yes	33.59	27.09
Model 2	Coef.	-0.0009^{**}	-0.0014	-0.0023	yes	yes	yes	0.6720^{***}	0.0100^{***}
	z	-2.39	-2.32	-2.36	yes	yes	yes	28.96	24.78

Note: Other abbreviations are the same as in Table 5. See Table 1 for the full names of variables.

4) Spatial heterogeneity

— Regional level:

Table 8 reveals that RCT had a significantly negative impact on carbon emissions in the eastern (-0.0081) and western regions (-0.0086) but not in the central region. This phenomenon likely stems from regional disparities in economic and industrial development, which result in varying efficiencies in the adoption and utilisation of RCT across regions. Specifically, the transport network in the eastern region had a high density and promotion and utilisation efficiency, significantly reducing carbon emissions. However, the western region was highly dependent on RCT, which has a relatively dominant inhibitory effect. The traditional industries with high energy consumption and emissions in the central region had relatively low demand for RCT, reducing carbon emissions due to RCT.

Table 8 – Regression results of railway container transport on regional carbon emissions (eastern, central and western regions)

	Variables	Coef.(z)	Direct effect (z)	Indirect effect (z)	Total (z)
E	RCT	-0.0081^{**}(-2.57)	-0.0061^{***}(-1.58)	-0.0166^{*}(-1.24)	-0.0228^{***}(0.65)
	ln-ps	0.0899^{***}(3.94)	0.0916^{***}(3.85)	0.0072(0.09)	0.0988(1.04)
	ln-ai	0.0168(1.06)	0.0233(1.63)	0.0433(1.11)	0.0665(1.61)
	ln-is	0.0301(1.28)	0.0551^{*}(1.92)	0.2217^{**}(2.17)	0.2768^{**}(2.25)
	ln-fc	-0.0061(-1.64)	-0.0039(-0.098)	0.0193(1.54)	0.0154(1.05)
	ln-el	0.0189^{*}(1.78)	0.0219^{*}(1.73)	0.0294(0.66)	0.0513(0.96)
	ln-ti	-0.0012(-0.22)	-0.0027(-0.40)	-0.0128(-0.54)	-0.0156(-0.55)
	W_RCT	0.0124^{**}(2.14)			
	ρ	0.6210^{***}(21.69)			
	θ	0.0041^{***}(18.033)			
	Adj.R^2	929.9137			
	Ll	-0.0081^{**}(-2.57)			
C	RCT	-0.0019(-0.36)	-0.0072(-1.03)	-0.0566^{*}(-1.82)	-0.0638^{*}(-1.76)
	ln-ps	0.0749^{***}(2.90)	0.0742^{**}(2.42)	0.0194(0.15)	0.0548(0.37)
	ln-ai	0.0196(1.22)	0.0099(0.59)	-0.1180^{**}(-2.06)	-0.1081(-1.63)
	ln-is	0.0518^{**}(2.44)	0.0582^{**}(-2.32)	0.0624(0.59)	0.1206(0.99)
	ln-fc	-0.0032(-1.06)	0.0004(0.11)	0.0373^{***}(2.83)	0.0376^{**}(2.48)
	ln-el	-0.0094 (-0.77)	-0.0035(-0.22)	0.0583(0.79)	0.0548(0.63)
	ln-ti	0.0126^{*}(1.80)	0.0040(0.48)	-0.0883^{***}(-2.88)	-0.0843^{**}(-2.38)
	W_RCT	-0.0212^{*}(-1.71)			
	ρ	0.6325^{***}(20.68)			

	Variables	Coef.(z)	Direct effect (z)	Indirect effect (z)	Total (z)
	θ	0.0044***(18.29)			
	Adj.R^2	890.2802			
	Ll	-0.0019(-0.36)			
W	RCT	-0.0086**(-2.12)	-0.0071*(-1.65)	-0.0126*(-1.11)	-0.0197**(0.41)
	ln-ps	0.0108 (0.42)	0.0148(0.54)	0.0492(0.55)	0.0640(0.62)
	ln-ai	0.0063(0.22)	-0.0169(-0.59)	-0.2521***(-2.64)	-0.2689**(-2.49)
	ln-is	0.0574(1.07)	0.0751(1.24)	0.1725(0.99)	0.2476(1.15)
	ln-fc	0.0048(1.06)	0.0099*(1.92)	0.04943**(2.58)	0.0593***(2.64)
	ln-el	0.0075(0.66)	0.0069(0.51)	-0.0099(-0.20)	-0.0031(-0.05)
	ln-ti	-0.0029(-0.38)	-0.0030(-0.32)	0.0001(0.00)	-0.0029(-0.07)
	W_RCT	0.0112*(1.85)			
	ρ	0.5857***(16.88)			
	θ	0.0175***(18.15)			
	Adj.R^2	392.3321			
	Ll	-0.0086**(-2.12)			

Note: E, C and W represent the Eastern Region, Central Region and Western Region, respectively. Ll represents Log likelihood. Other abbreviations are the same as in Table 5. See Table 1 for the full names of variables.

The decomposition effects in *Table 8* indicate significantly negative direct and indirect impacts of RCT on RCE in both eastern and western regions. Specifically, the eastern region exhibits direct and indirect effects of -0.0061*** and -0.0166*, respectively, while the western region shows values of -0.0071* and -0.0126*. The central region had a significant negative impact on the surrounding areas (-0.0566*), consistent with the general rule.

— Level of important economic zones:

Table 9 reveals that YRDEZ (-0.0152***) and BHEZ (-0.0158***) have significant inhibitory effects on carbon emissions but not PRDEZ and CYEZ. The high economic development in YRDEZ and BHEZ generated significant transport demand, which is the key area for transport structure adjustment. The "transition from road to rail" policy and the network construction of "sea-rail combined transport" have increased RCT and reduced RCE. The PRDEZ exhibits only a significant indirect effect, indicating that the carbon emission reduction potential of RCT in this region is limited. The high carbon emissions energy structure of the CYEZ and insufficient transport indicate a non-significant inhibitory effect. The PRDEZ transport system, mainly based on road and port transportation, is supplemented by railway and aviation and may offset and reduce the inhibitory effect of RCT on RCE to a certain extent.

Table 9 – Regression results of railway container transport on regional carbon emissions (important economic zone)

	Variables	Coef. (z)	Direct effect(z)	Indirect effect(z)	Total(z)
Y	RCT	-0.0152***(-3.24)	-0.0153***(-2.95)	-0.0027(-0.19)	-0.0180**(-1.06)
	ln-ps	-0.1507***(-2.84)	-0.1736***(-3.48)	-0.2264*(-1.78)	-0.4001***(-2.90)
	ln-ai	0.0337**(2.13)	0.0348**(2.46)	-0.0052(-0.19)	0.0296(1.13)
	ln-is	-0.0460(-1.35)	-0.0488(-1.17)	-0.0346(-0.25)	-0.0835(-0.49)
	ln-fc	0.0124(1.29)	0.0174*(1.70)	0.0537*(1.93)	0.0711**(2.10)
	ln-el	-0.0756(-1.50)	-0.0793(-1.61)	-0.0445(-0.38)	-0.1238(-0.93)
	ln-ti	0.0077(0.41)	0.0099(0.48)	0.0223(0.42)	0.0322(0.49)
	W_RCT	0.0051(0.57)			
	ρ	0.4186***(5.35)			
	θ	0.0013***(8.97)			
	Adj.R^2	312.6461			
	Ll	-0.0152***(-3.24)			

	Variables	Coef. (z)	Direct effect(z)	Indirect effect(z)	Total(z)
P	RCT	-0.0187(-0.93)	-0.0148(-0.72)	0.0796^{*}(1.84)	0.0649(1.30)
	ln-ps	-0.1357^{***}(-3.24)	-0.1343^{***}(-3.40)	0.0928(1.21)	-0.0415(-0.55)
	ln-ai	0.1041^{**}(2.32)	0.1056^{**}(2.54)	-0.0577(-0.79)	0.0479(0.81)
	ln-is	-0.0169(-0.31)	-0.0130(-0.24)	0.0806(0.86)	0.0675(0.62)
	ln-fc	0.0144(1.37)	0.0142(1.37)	-0.0087(-0.39)	0.0055(0.21)
	ln-el	-0.0085(-0.69)	-0.0083(-0.68)	-0.0033(-0.13)	-0.0116(-0.36)
	ln-ti	0.0142(1.53)	0.0142(1.45)	0.0012(0.06)	0.0154(0.73)
	W_RCT	0.0762^{*}(1.83)			
	ρ	0.1271(1.24)			
	θ	0.0036^{***}(8.46)			
	Adj.R^2	199.3820			
	Ll	-0.0187(-0.93)			
B	RCT	-0.0158^{***}(-4.77)	-0.0201^{***}(-4.83)	-0.0399^{***}(-2.83)	-0.0601^{***}(-3.52)
	ln-ps	0.0935^{**}(2.37)	0.1032^{**}(2.49)	0.1047(0.79)	0.2080(1.35)
	ln-ai	-0.0297(-0.75)	-0.0462(-1.23)	-0.1908^{**}(-2.17)	-0.2370^{**}(-2.39)
	ln-is	0.0019(0.07)	0.0063(0.20)	0.0359(0.41)	0.0422(0.39)
	ln-fc	-0.0013(-0.31)	-0.0002(-0.05)	0.0099(0.76)	0.0097(0.61)
	ln-el	0.1063^{***}(3.66)	0.1234^{***}(4.20)	0.1584^{**}(1.98)	0.2818^{***}(3.00)
	ln-ti	0.0121(1.62)	0.0203^{**}(2.25)	0.0756^{**}(2.53)	0.0958^{***}(2.67)
	W_RCT	-0.0125^{*}(-1.84)			
	ρ	0.5217^{***}(11.43)			
	θ	0.0029^{**}(12.58)			
	Adj.R^2	487.0452			
	Ll	-0.0158^{***}(-4.77)			
C	RCT	-0.0153(-1.41)	-0.0138(-1.21)	0.0277(1.28)	0.0139(0.51)
	ln-ps	0.0298(0.69)	0.0224(0.53)	-0.1179(-1.53)	-0.0955(-0.98)
	ln-ai	0.2134^{*}(1.84)	0.2497^{**}(2.35)	0.5488^{**}(2.49)	0.7985^{***}(3.86)
	ln-is	0.1367(1.36)	0.1501(1.54)	0.2976 (1.90)	0.4478^{**}(2.32)
	ln-fc	0.0195(1.33)	0.0195(1.33)	-0.0042(-0.13)	0.0153(0.37)
	ln-el	-0.0267^{**}(-2.08)	-0.0287^{**}(-2.24)	-0.0639^{***}(-2.60)	-0.0926^{***}(-3.07)
	ln-ti	-0.0175^{*}(-1.66)	-0.0184^{*}(-1.70)	-0.0196(-0.81)	-0.0380(-1.35)
	W_RCT	0.0276(1.35)			
	ρ	0.1338(1.31)			
	θ	0.0058^{***}(1.71)			
	Adj.R^2	138.4895			
	Ll	-0.0153(-1.41)			

Note: B: BHEZ-Bohai Rim; Y: YRDEZ-Yangtze River Delta; C: CYEZ-Chengdu-Chongqing Economic Zone; P: PRDEZ-Pearl River Delta. Ll represents Log likelihood. Other abbreviations are the same as in Table 5. See Table 1 for the full names of variables.

As shown in *Table 9*, RCT's direct (-0.0201^{***}) and indirect effects (-0.0399^{***}) on RCE are significantly negative in BHEZ; YRDEZ shows significant direct (-0.0153^{***}) but insignificant indirect effects, while PRDEZ and CYEZ exhibit no notable impacts, aligning with broader trends.

5. DISCUSSION

This section analyses the mechanisms through which rail container transportation (RCT) suppresses carbon emissions and formulates corresponding policy recommendations. It further concludes by addressing the study's limitations and proposing actionable directions for future research.

5.1 Mechanism analysis

RCT is vital for efficient, low-carbon railway systems. Studies have shown that [40] new policies like "Road-to-Railway, Bulk-to-Container" highlight the need to analyse RCT's carbon emissions and their impact on RCE. RCT reduces RCE nationally, with stronger effects in eastern/western regions and key economic zones (e.g. YRDEZ, BHEZ), closely linked to local energy structures and economies.

The negative impact of RCT on RCE is because RCT is gradually being electrified, resulting in low emissions compared with those from other modes of transport [12]. Improving the RCT efficiency, scale and other characteristics reduces carbon emissions. Furthermore, the degree of restraint was closely correlated with the local economy, energy structure and RCT popularity. For areas with high energy consumption and carbon emission industrial structures, such as in Northwest China and CYEZ, RCT has limited inhibitory effects on RCE. RCT significantly inhibits carbon emissions due to policy inclination and high demand. For China, implementing the "Road turns to the railway; bulk turns to container" to adjust the transport infrastructure promotes the intensification, mechanisation, automation and optimisation of the transport system, leading to an efficient transport industry. For regions, developing RCT can reduce carbon emissions and the cost of logistic services, increasing efficiency and strengthening regional development.

5.2 Policies and suggestions

Further advancing the robust development of RCT is instrumental in achieving low-carbon transportation. Consequently, the following measures are recommended: at the national level, considering the persistent positive spillover effects, it is imperative to enhance railway electrification, promote key energy-saving technologies in railways, upgrade container transportation systems, integrate RCT with other transportation modes and bolster its competitive edge. Additionally, it is crucial to reinforce the advantages of railway networking, establish a low-carbon freight network system, optimise the layout of transport stations and improve the organisational efficiency of RCT. These efforts will foster the sustained growth of railway container freight volume and increase the proportion of regional RCT. Given the disparities between regions and their transport infrastructure, the RCT development strategy should be tailored to local conditions. For instance, in regions with high carbon emissions, a balance should be struck between RCT development and industrial structure adjustment. In areas where demand is insufficient, efforts should be directed towards stimulating demand through economic development, while simultaneously making appropriate adjustments to the allocation of transportation resources in these regions.

5.3 Research limitations and future directions

Constrained by data availability limitations, this study's temporal scope is restricted to the 2013–2020 period. Furthermore, given the multifaceted nature of regional carbon emission drivers, our selection of control variables remains incomplete. To address these constraints, future research will expand temporal coverage, incorporate additional control variables, and develop robust mechanistic models to further elucidate RCT carbon suppression mechanisms.

6. CONCLUSION

Building on an analysis of the spatiotemporal evolution patterns of RCT and RCE, this study employs spatial econometrics to investigate the multiscale impacts of RCT on RCE and their underlying mechanisms. The findings provide empirical evidence supporting the theory that developing rail container transportation contributes to regional carbon emission reduction. Methodologically, this work confirms the necessity of incorporating spatial dimensions when examining RCT-RCE relationships.

1) Carbon dioxide emissions in China increased with a semi-normal distribution between 2013 and 2020. Large cities with large industries and high population densities had above-average carbon emissions, indicating that measures to control carbon emissions were ignored during economic development. Concurrently, spatial heterogeneity intensified as aggregate emissions and the number of high-emission cities both increased. Manufacturing and heavy industrial activities have rendered emissions particularly pronounced in eastern China, while extensive energy utilisation practices established northwestern China as a spatial concentration hub for carbon output. Concurrently, the convergence of factors, including energy structure dependencies and technological constraints, collectively positions the CYEZ as the peak emissions region.

2) China's rail container transportation exhibited a positively skewed distribution from 2013 to 2020, with traffic density predominantly below 200,000 TEU. Only a limited number of cities exceeded 400,000 TEU in volume. Distinct phase characteristics emerged: stable fluctuations prevailed before 2015, followed by a pronounced upward trajectory post-2015. The emergence of ultra-high-volume cities correlated strongly with strategic geographic positioning and international connectivity. Spatially, divergence intensified as high-volume urban centres multiplied significantly. Eastern China recorded peak transportation volumes, where major economic zones demonstrated notable agglomeration effects, particularly in the BHEZ and CYEZ, which outperformed the YRDEZ and PRDEZ in container transport.
3) RCT had a restraining effect on RCE, and the dependence of transport modes on RCT was linked to carbon emission levels. The spillover effects varied across different regions or levels of development. Due to significant regional disparities, at the national level, RCT has a significant inhibitory effect on RCE. Further regionalised analysis revealed that the restraining effect of RCT on RCEs was significant in the eastern and western regions, as well as in the YRDEZ and BHEZ, which was associated with regional economic and energy structures.

ACKNOWLEDGEMENTS

We thank Prof. Haibo Kuang and Dr. Xiaodong Li for their contributions. This work was supported by the National Key R&D Program of China (2019YFB1600400), the National Natural Science Foundation of China (72174035), Dalian Talent Planning [No. 2022RG05] and the CPSF Postdoctoral Fellowship Program [No. GZC20230343].

REFERENCES

[1] Jia R, et al. Urbanization and haze-governance performance: Evidence from China's 248 cities. *Journal of Environmental Management*. 2021;288:112436. DOI: 10.1016/j.jenvman.2021.112436.

[2] Ma Q, Jia P, Kuang H. The impact of technological innovation on transport carbon emission efficiency in China: Spillover effect or siphon effect? *Frontiers in Public Health*. 2022;10:1028501. DOI: 10.3389/fpubh.2022.1028501.

[3] Chang D, et al. Temperature shocks and low-carbon performance: Evidence from the transportation sector in China. *Transportation Research Part D: Transport and Environment*. 2024;133:104282. DOI: 10.1016/j.trd.2024.104282.

[4] Gu J, et al. An analysis of the decomposition and driving force of carbon emissions in transport sector in China. *Scientific Reports*. 2024;14:30177. DOI: 10.1038/s41598-024-80486-z.

[5] Jing Q, et al. The Impact of Public Transportation on Carbon Emissions-From the Perspective of Energy Consumption. *Sustainability*. 2022;14:6248. DOI: 10.3390/su14106248.

[6] Lin B, Xie C. Reduction potential of CO2 emissions in China′s transport industry. *Renewable and Sustainable Energy Reviews*. 2014;33:689-700. DOI: 10.1016/j.rser.2014.02.017.

[7] Ou Y, et al. When green transportation backfires: High-speed rail's impact on transport-sector carbon emissions from 315 Chinese cities. *Sustainable Cities and Society*. 2024;114:105770. DOI: HTTPS://DOI.ORG/10.1016/j.scs.2024.105770.

[8] China State Railway Group Co. Outline of Powerful Nation Railway Advance Planning in the new era. http://www.china-railway.com.cn/xwzx/rdzt/ghgy/gyqw/202008/t20200812_107636.html/ [Accessed 12th August 2024].

[9] Wang Z. Research on the Potential of Energy Consumption and Carbon Emission Reduction of China's Railway Transportation under the Goal of "Carbon Peaking and Carbon Neutrality". *Railway Economics Research*. 2022;5-9. DOI: 10.3969/j.issn.1004-9746.2022.02.002.

[10] General Office of the State Council of the People's Republic of China. General ffice of the State Council on Printing and Distributing the three-year action plan for promoting transportation structure adjustment (2018-2020). http://www.gov.cn/zhengce/content/2018-10/09/content_5328817.htm/ [Accessed 9th October 2023].

[11] Wang Y, Guan Z, Zhang Q. Railway opening and carbon emissions in distressed areas: Evidence from China's state-level poverty-stricken counties. *Transport Policy*. 2023;130:55–67. DOI: 10.1016/j.tranpol.2022.11.003.

[12] Tian P, et al. Analysis of carbon emission level and intensity of China's transportation industry and different transportation modes. *Advances in Climate Change Research*. 2023;19:347-356.

[13] Kaack LH, et al. Decarbonizing intraregional freight systems with a focus on modal shift. *Environmental Research Letters.* 2018;13:083001. DOI: 10.1088/1748-9326/aad56c.

[14] Bilgili L, et al. Evaluation of railway versus highway emissions using LCA approach between the two cities of Middle Anatolia. *Sustainable Cities and Society*. 2019;49:101635. DOI: 10.1016/j.scs.2019.101635.

[15] Zhang J, et al. Air quality improvement via modal shift: Assessment of rail-water-port integrated system planning in Shenzhen, China. *Science of the Total Environment*. 2021;791:148158. DOI: 10.1016/j.scitotenv.2021.148158.

[16] Wang Y, et al. Study on Influencing Factors of Carbon Dioxide Emissions from Railway Operations in China. *Journal of the China Railway Society*. 2021;43:189-95.

[17] Zhao L, et al. In fluence and mechanism of hige-speed raliway on urban carbon emission. *Journal of railway engineering society*. 2023;40:100-104+110.

[18] Chen Y, Wang Y, Zhao C. How do high-speed rails influence city carbon emissions? *Energy*. 2023;265:126108. DOI: 10.1016/j.energy.2022.126108.

[19] Zhou T, Huang X, Zhang N. Does the high-speed railway make cities more carbon efficient? Evidence from the perspective of the spatial spillover effect. *Environmental Impact Assessment Review*. 2023;101:107137. DOI: 10.1016/j.eiar.2023.107137.

[20] Nie L, Zhang Z. Is high-speed rail heading towards a low-carbon industry? Evidence from a quasi-natural experiment in China. *Resource and Energy Economics*. 2023;72:101355. DOI: 10.1016/j.reseneeco.2023.101355.

[21] Yan Z, Park SY. Does high-speed rail reduce local CO_2 emissions in China? A counterfactual approach. *Energy Policy*. 2023;173:113371. DOI: 10.1016/j.enpol.2022.113371.

[22] Jiang B, Li J, Mao X. Container Ports Multimodal Transport in China from the View of Low Carbon. The Asian *Journal of Shipping and Logistics*. 2012;28:321-44.

[23] Yang L, Zhang C, Wu X. Multi-objective path optimization of highway-railway multimodal transport considering carbon emissions-all databases. *Applied Sciences*. 2023;13:4731. DOI: 10.3390/app13084731.

[24] Majumdar D, Gajghate DG. Sectoral CO_2, CH_4, N_2O and SO_2 emissions from fossil fuel consumption in Nagpur City of Central India. *Atmospheric Environment*. 2011;45:4170-9. DOI: 10.1016/j.atmosenv.2011.05.019.

[25] Elvidge CD, et al. Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *International Journal of Remote Sensing*. 1997;18:1373-1379. DOI: 10.1080/014311697218485.

[26] Doll CNH, Muller JP, Elvidge CD. Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. *Ambio*. 2000;29:157-162. 10.1579/0044-7447-29.3.157.

[27] Du X, et al. Decoupling economic growth from building embodied carbon emissions in China: A nighttime light data-based innovation approach. *Sustainable Production and Consumption*. 2023;43:34-45. DOI: 10.1016/j.spc.2023.10.011.

[28] Yu B, Yang X, Wu X. Study on spatial spillover effects and influencing factors of carbon emissions in county areas of Ha-Chang city group: Evidence from NPP-VIIRS nightlight data. *Acta Scientiae Circumstantiae*. 2020;40:697–706.

[29] Hao R, et al. Spatialization and Spatio-temporal Dynamics of Energy Consumption Carbon Emissions in China. *Environmental Science.* 2022;43:5305-14. DOI: 10.13227/j.hjkx.202112066.

[30] Chen Y, et al. Spatio-temporal Evolution and Influencing Factors of Carbon Emissions in Shaanxi Province. *China Environmental Science*. 2024;44:1826–39. DOI: 10.19674/j.cnki.issn1000-6923.20231127.058.

[31] Qin J, Gong N. The estimation of the carbon dioxide emission and driving factors in China based on machine learning methods. *Sustainable Production and Consumption.* 2022;33:218-229. DOI: 10.1016/j.spc.2022.06.027.

[32] Bai Z, Kuang H, Yang J. Promoting or inhibiting? Influence of railway container transportation on regional economic development. *Chinese Geographical Science*. 2024;34:1175-1190. DOI: 10.1007/s11769-024-1462-5.

[33] Bai Z, et al. Evolution of spatial and temporal patterns of railway container transportation: A case study of China cities. *Frontiers in Public Health*. 2022;10. DOI: 10.3389/fpubh.2022.1087234.

[34] Zhang N, Zhang Y, Chen H. Spatial correlation network structure of carbon emission efficiency of railway transportation in China and its influencing factors. *Sustainability*. 2023;15:9393. DOI: 10.3390/su15129393.

[35] Yan J, Feng J, Chen B. Research on the impact of urban ecological infrastructure on carbon emissions in china. *Acta ecologica sinic*. 2024;44:1-14. DOI: 10.20103/j.stxb.202211133271.

[36] Shan Y, et al. China CO2 emission accounts 1997–2015. *Sci Data* 2018;5:170201. DOI: 10.1038/sdata.2017.201.

[37] Wang C, et al. Analysis of urban carbon balance based on land use dynamics in the Beijing-Tianjin-Hebei region, China. *Journal of Cleaner Production.* 2021;281:125138. DOI: 10.1016/j.jclepro.2020.125138.

[38] Elhorst JP. Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*. 2010;5:9-28. DOI: 10.1080/17421770903541772.

[39] Li H, Calder CA, Cressie N. Beyond Moran's I: Testing for spatial dependence based on the spatial autoregressive model. *Geographical Analysis.* 2007;39:357–75. DOI: 10.1111/j.1538-4632.2007.00708.x.

[40] Tian C, Yang D. An Empirical Analysis of the Impact of Transportation Structure on Transportation Carbon Emissions. *Transport Research,* 2022;8:10-18+39. DOI: 10.16503/j.cnki.2095-9931.2022.06.002.