



# Spatiotemporal evolution trend and decoupling type identification of transport carbon emissions from economic development in China

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## Abstract

Carbon emissions are a major concern in China, and transportation is an important part of it. In this paper, data on China's 30 provinces' transport carbon emissions from 2005 to 2019 were selected to construct a spatial autocorrelation model and identified the decoupling types, which revealed the relationship between transport carbon emissions and economic development. This study suggests a regulation strategy for provincial transport carbon emissions in China based on the contribution rates of transport carbon emission variables. According to the findings, transport carbon emissions of China indicated a slow rise from 2005 to 2019, the annual growth rate has fluctuated downward, and petroleum products have been the most major source. The geographical correlation of transport carbon emissions has gradually improved, and the transport carbon emission intensity has become more significant. Differences in the transport carbon emission intensity slightly increased, which were significantly regionally correlated. There were seven forms of decoupling between yearly provincial transport carbon emissions and economic development, with weak decoupling accounting for the largest proportion, 45.24%. Decoupling was achieved in 83.33% of the provinces in the period of 2005–2019. As a consequence of factor decomposition, the energy intensity, transport intensity, and economic structure played an overall inhibitory role, while the carbon emission intensity, economic scale, and population played promoting roles. The economic scale was the most important influencing factor.

**Keywords** Transport carbon emissions · Spatiotemporal evolution · Economic decoupling · Contribution rates of influencing factors

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## Highlights

- China's transport carbon emissions indicated a slow rise from 2005 to 2019; the annual growth rate of carbon emissions has fluctuated downward.
- The geographical correlation of transport carbon emissions has gradually improved, and the transport carbon emission intensity has become more significant.
- There were seven decoupling types between the annual provincial transportation carbon emissions and economic development in China, with weak decoupling accounting for the largest proportion.
- Economic scale was the main driving factor of traffic carbon emissions.

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## Introduction

Carbon emissions have become a global concern. The Global Energy Review: Carbon Emissions 2021 study from the International Energy Agency (IEA) showed that global carbon emissions from energy combustion and industrial processes firmly recovered in 2021, increasing 6% annually to 36.3 billion tons (Chen et al. 2023). Transportation was responsible for 22–25% of global carbon emissions (Bhat and Ordóñez Garcia 2021; Demircan Cakar et al. 2021; Heidari et al. 2022; Oladunni et al. 2022; Zhu et al. 2021) and 29% of energy consumption (Sardar et al. 2022; Xu

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et al. 2021). According to the 2016 Paris Climate Agreement, which was signed by the world's top carbon emitter, China, peak carbon emissions would be reached by 2030. According to the China Statistical Yearbook, the energy consumption of the transport sector was 413.09 million tons of standard coal in 2020, and China's total energy consumption was 4983.14 million tons of standard coal, with the transport sector accounting for about 8.29%. In 2020, the GDP of the transportation industry was 4156.17 billion yuan, and China's total GDP was 101,598.62 billion yuan. The transportation sector accounts for only 4.09%. An important area for study is increasing the economic effectiveness of carbon emissions. It is important to study the relationship between transport carbon emissions and the economy, and analyze the factors influencing provincial transportation in China to reduce emissions of transportation. Transport carbon emissions are impacted by transportation logistics, China's provincial transportation links are becoming increasingly close, but the economic development levels vary significantly, and the economic benefits of transport carbon emissions also differ; coordinated regional development is essential for lowering carbon emissions and improving the transportation economy. Studying the spatiotemporal evolution and economic effectiveness of transportation-related greenhouse gas emissions in China is beneficial for developing emission-reduction strategies to reduce energy consumption, increase the effectiveness of regional transportation-related emissions, and achieve sustainable economic growth.

"Top-down" and "bottom-up" research methodologies are frequently utilized to measure carbon emissions, while "bottom-up" approaches use data such as vehicle type, driving distance, unit fuel consumption, and corresponding carbon emission factor data to calculate carbon emissions; "top-down" strategies rely on converting energy use. The Bayesian structural equation model (BSEM) focuses on raw observations and relies less on asymptotic theory, making it better suited for obtaining reliable results (Lu et al. 2020). The approach of ecological network input–output interval fuzzy linear programming (EIFP) is used to investigate the transfers of transportation CO<sub>2</sub> emissions (Zhu et al. 2021). In research addressing zero-carbon urban policy, a unique version of the best–worst method (BWM) may effectively handle expert preferences when comparing paired criteria (Pamucar et al. 2021). Some scholars have used support vector machine (SVM), and cross-validation models or effectively constructed gradient boosting regression (GBR) models combined with social and economic characteristics, resulting in prediction effects with greater significance (Li et al. 2022). The DNE21 model (dynamic new earth 21 plus) (Akimoto et al. 2022) can be used to assess climate change mitigation measures for energy system cost control. Studying the consequences of demographic and economic variables on carbon emissions involves using the STIRPAT

model (the stochastic influences by regression on population, affluence, and technology) (Oladunni et al. 2022; Sardar et al. 2022). LEAP (long-range energy alternative planning system) model is built on scenarios for policy creation and represents energy consumption and environmental factors and is suitable for analyzing and evaluating implementation effects (Zhao et al. 2021). The autoregressive distributed lag (ARDL) method works well for relatively small samples (Solaymani 2022). The system dynamics model is a complex open-parameter structure that is used to analyze carbon dioxide emission concentrations (Heidari et al. 2022); the model of LMDI (logarithmic mean division index) (Ma et al. 2020; Meng and Li 2020; Nnadiriri et al. 2021; Wang et al. 2020a, 2020c) is a typical technique for examining the variables that affect carbon emissions. This model is simple to explain and widely used and is not limited by zero values or residual values; in addition, the results are easily understood (Huang and Ling 2021; Meng and Li 2020; Wang et al. 2018; Zhang et al. 2022). The Tapio decoupling model is widely employed to evaluate the relationship between the energy efficiency of the economy and carbon emissions (Chen et al. 2020; Ma et al. 2020; Wang et al. 2020a, 2020c). For the analysis of spatial correlations and clustering intensities, several researchers have used the Moran's index (Wang et al. 2020b; Cao et al. 2019; Yaacob et al. 2020) and geographic weighted regression (GWR) to examine the geographical associations between the same variable and several locations, increasing the simulation's degree of fit in comparison to the linear regression model (Kilian et al. 2022; Xu et al. 2021).

Researchers have been looked at the variables affecting traffic-related carbon emissions. The economic scale and the macroeconomic and policy guidance significantly impact transport carbon emissions (Cao et al. 2019; Huang and Ling 2021; Oladunni et al. 2022), and studies have shown that the biggest influences on greenhouse gas emissions are growth in the population and the economy (Oladunni et al. 2022). The industry structure (Meng and Li 2020), energy intensity (Wang et al. 2020c, 2022, 2018), sociocultural system, economic development (Aminzadegan et al. 2022), and public support (Long et al. 2021) all impact transport carbon emissions (Xu et al. 2021). Transport services and communications technologies also directly impact carbon emissions and are increased by internet use (Kwakwa et al. 2022). Reasonably formulating policies and carbon trading prices are the primary directions of carbon emissions studies (Fleschutz et al. 2021). Different modes of passenger transport and the reasonable development planning of public transport systems have regulating effects on transport carbon emissions (Sardar et al. 2022; Noussan et al. 2022; Dujmović et al. 2022; Veludo et al. 2021). The shared travel mode (Tikoudis et al. 2021) and highway transportation proportion

(Wimbadi et al. 2021) can lower carbon emissions associated with transportation (Dujmović et al. 2022). The promotion of low-emissions vehicle (LEV) and bus rapid transit (BRT) systems can aid in the switch to low-carbon urban transportation (Wimbadi et al. 2021). The system's energy structure has a significant impact on carbon emissions, and the primary source of carbon emissions related to transportation is fossil fuels (Kwakwa et al. 2022; Zhu et al. 2021). The electrification of transportation networks is the greatest way to reduce carbon emissions from fuel and gasoline (Akimoto et al. 2022; Bhat and Ordóñez Garcia 2021), and the electricity demand is predicted to nearly double by 2050 (Potrč et al. 2022). The efficiency of transportation's carbon emissions is increased by the introduction of new technology (Demircan Cakar et al. 2021; Lu et al. 2020; Umar et al. 2020); energy hydrogen-based synthetic fuels and bioenergy can be used as alternatives to fossil fuels, and carbon dioxide removal (CDR) technology can offset carbon dioxide emissions (Akimoto et al. 2022). Some scholars have looked at the impact of electricity-dependent energy carriers (Gustafsson et al. 2021); however, electric bus batteries also cause differences in average carbon emissions by region (McGrath et al. 2022). New anti-fouling coating technologies can save fuel (Farkas et al. 2021); machine learning algorithms are used to forecast the effectiveness and demand of carbon emissions associated with transportation. (Ağbulut 2022, Ghahramani and Pilla 2021, Li et al. 2022), and deep learning (DL) models have predicted that Turkey's transportation sector's energy demand and carbon emissions will rise by 3.4 times over the next decade (Ağbulut 2022).

Research on transport carbon emissions have focused mainly on statistical analyses and have explored emissions only from the national or provincial perspective (Kilian et al. 2022; Nnadiri et al. 2021; Pani et al. 2021); specifically, most analyses of transport carbon emissions in China have been performed in provinces such as Guangdong (Zhao et al. 2021), Shanghai (Zhu et al. 2022), and Zhejiang (Liu et al. 2023), while less research has explored spatial factors and regional transportation drivers. On the other hand, there is the absence of analyses of the economic efficiency of transport carbon emissions in China. In this paper, the study's research focus is the transportation-related carbon emissions of 30 Chinese provinces from 2005 to 2019. First, we develop a model to calculate transport carbon emissions in order to analyze spatiotemporal shifts in transport carbon emissions and the intensity of transportation carbon emissions in China's province. Second, we analyze the spatial pattern evolution trend of transport carbon emissions in China. Finally, we identify the decoupling types of transport carbon emissions and economic development and reveal the relationship between transport carbon emissions intensity and economic development.

## Methods

### Sources of data

The data for 30 Chinese provinces from 2005 to 2019 were used to this study. The China Statistical Yearbook's traffic data classifications were used to classify the carbon emissions of transportation in this study, which include the transportation, storage, postal, and telecommunications service sectors. According to Industrial classification for national economic activities (UNSD:2006, International standard industrial classification of all economic activities, NEQ), the transportation, storage, postal, and telecommunications service sectors include railway transport, road transport, water transport, air transport, pipeline transport, multimodal transport, transport agency industry, loading, unloading, warehousing industry, and postal industry. In this study, the carbon content per unit fuel  $C$  (T/TJ), carbon oxidation rate  $R$  (%), and the electric carbon emission factor  $EF$  are derived from the Guidelines for the Compilation of Provincial Greenhouse Gas Inventories (Trial). Fossil fuel consumption, electricity consumption, and average low calorific value of energy  $ALC$  (kJ/kg) are all from the China Energy Source Statistical Yearbook. GDP data, population data, and freight turnover data are from the China Statistical Yearbook. Production of electricity, coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and liquefied petroleum gas are used as calculation standards when calculating transport carbon emissions, as these products cover approximately 90% of transport carbon emissions. The nine fossil energy sources and power metrics described above are chosen for this work. Electricity does not directly produce carbon emissions but primarily from the energy that thermal power plants consume (Demircan Cakar et al. 2021; Lian et al. 2020). Each province's transportation-related carbon emission data was computed based on the method for calculating carbon emissions. The calculated carbon emission results were compared with the Carbon Emission Accounts and Datasets (CEADs) in China, and the calculated data were basically consistent (except for the carbon emission energy consumption of power production not included in CEADs), thus verifying the validity of the calculated data.

### Carbon emission and carbon emission intensity measurement of transportation

The Intergovernmental Panel on Climate Change's (IPCC) fundamental formula for accounting for carbon states that greenhouse gas (GHG) emissions are equal to the product of the activity data (AD) and the emission factor (EF). The main equation is expressed as follows (Wang et al. 2022):

$$CT = \sum_{i=1}^9 EC_i \times EF_i \times \frac{44}{12} \quad (1)$$

where  $CT$  represents carbon emissions ( $10^4$  t),  $EC_i$  represents the Class- $i$  primary energy consumption,  $EF_i$  represents the coefficient of the Class- $i$  primary energy, and  $44/12$  represents the molecular weight ratio of  $CO_2$ . The following formula can be created from the previously mentioned one (Liu et al. 2022):

$$CT = \sum_{i=1}^9 FC_i \times ALC_i \times C_i \times R_i \times \frac{44}{12} + EC_i \times EF_i \quad (2)$$

Transportation-related carbon emissions are calculated as the total carbon emissions from fossil energy use and electricity production. The letter  $i$  stands for the several kinds of fossil fuels;  $ALC$  (kJ/kg) stands for average low calorific value, while  $FC$  (kg  $CO_2$ /kg) stands for the carbon emission coefficient.  $R$  stands for carbon rate (%),  $C$  (T/TJ) is for carbon content,  $EC$  for electric consumption (kWh); and  $EF$  represents the electric carbon emission factor (kg  $CO_2$ /kWh).

$$CI_i = \frac{C_i}{E_i} \quad (3)$$

The carbon emission intensity in this study is defined as the carbon emissions per unit of energy used and the carbon emissions' energy efficiency. The letter  $i$  stands for the 30 provinces;  $CI$  stands for the carbon emission intensity,  $C$  for those emissions ( $10^4$  t), and  $E$  for overall energy used for transportation ( $10^4$  t) (Li et al. 2023).

In order to examine the features of the transport carbon intensity distribution across 30 Chinese provinces, the Theil model is employed. The change coefficient of the regional transportation sector's carbon emission intensity is measured by  $CV_t$ . The regional province  $i$ 's logarithmic deviation average of the transportation sector's carbon emission intensity is designated as  $GE_0$ . The Thiel indicator for region- $i$  transportation carbon emission intensity is called  $GE_1$  (Wang et al. 2020a):

$$CV_t = \frac{\sqrt{\frac{1}{n} \sum_i (y_i - \bar{y})^2}}{\bar{y}} \quad (4)$$

$$GE_0 = \frac{1}{n} \sum_{i=1}^n \ln \frac{y_i}{\bar{y}} \quad (5)$$

$$GE_1 = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{\bar{y}} \ln \frac{y_i}{\bar{y}} \quad (6)$$

where  $y_i$  is the transport carbon emission intensity,  $\bar{y}$  is the average transport carbon emission intensity, and  $n$  is the number of provinces.

### Tapio decoupling model

The link between transportation-related carbon emissions and local economic growth is measured by the Tapio decoupling index model. The main models are expressed as follows (Wang et al. 2020a):

$$e = \frac{\%CO_2}{\%GDP} = \frac{\Delta CO_2 / CO_2^0}{\Delta GDP / GDP^0} = \frac{(CO_2^t - CO_2^0) / CO_2^0}{(GDP^t - GDP^0) / GDP^0} \quad (7)$$

where  $e$  refers to the decoupling coefficient. Traffic GDP in target year  $t$ , transport carbon emissions in target year  $t$ , and carbon emissions in base year  $0$  are represented by  $GDP^t$ ,  $CO_2^t$  and  $CO_2^0$ , respectively.  $GDP^0$  is the transportation sector's production value in the base year. The difference between the transport sector's overall production from base year  $0$  to goal year  $t$  is  $\Delta GDP$ , while the difference between the sector's total carbon emissions from target year  $t$  to base year  $0$  is  $\Delta CO_2$ . The growth rate of total carbon emissions is represented by  $\%CO_2$ , while the growth rate of the transportation sector's total output value is represented by  $\%GDP$ .

### Logarithmic mean deviation index (LMDI)

Carbon emissions from transportation are broken down using the LMDI decomposition method. The main formula is expressed as follows (Zhang et al. 2022):

$$C_i = \frac{C_i}{E_i} \times \frac{E_i}{T_i} \times \frac{T_i}{G_{ti}} \times \frac{G_{ti}}{G_i} \times \frac{G_i}{P_i} \times P_i \quad (8)$$

The letter  $i$  stands for the 30 provinces, where  $C$  equals the sum of transportation-related carbon emissions,  $E$  equals the energy consumption,  $T$  is the volume of freight turnover ( $10^4$  t),  $G_t$  equals the GDP value of the transportation sector ( $10^4$  CNY),  $G$  equals the gross national product ( $10^4$  CNY),  $P$  equals the population ( $10^4$ ), and the equation can be further manipulated as follows (Zhang et al. 2022):

$$CI_i = \frac{C_i}{E_i}; EI_i = \frac{E_i}{T_i}; TI_i = \frac{T_i}{G_{ti}}; EC_i = \frac{G_{ti}}{G_i}; GC_i = \frac{G_i}{P_i}; P_i = P_i \quad (9)$$

This article defines the following parameters: carbon emission intensity ( $CI$ ) represents the carbon emissions per unit of energy consumption; energy intensity ( $EI$ ) represents the energy consumption per unit of freight turnover; transport intensity ( $TI$ ) represents the freight turnover volume per unit of economic in transportation; economic structure ( $EC$ ) represents the proportion of economic in transportation to the total



economic output value; economic scale ( $GC$ ) represents the gross economic product per unit of population; population ( $P$ ) represents the total population value (Zhang et al. 2022). The following equation is thus obtained:

$$C_i^t - C_i^0 = \Delta C_i = \Delta CI_i + \Delta EI_i + \Delta TI_i + \Delta EC_i + \Delta G_i + \Delta P_i \tag{10}$$

$$\Delta CI_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{CI_i^t}{CI_i^0} \tag{11}$$

$$\Delta EI_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{EI_i^t}{EI_i^0} \tag{12}$$

$$\Delta TI_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{TI_i^t}{TI_i^0} \tag{13}$$

$$\Delta EC_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{EC_i^t}{EC_i^0} \tag{14}$$

$$\Delta GC_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{GC_i^t}{GC_i^0} \tag{15}$$

$$\Delta P_i = \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \times \ln \frac{P_i^t}{P_i^0} \tag{16}$$

where  $C_t$  and  $C_0$  stand for the transport carbon emission values for the target year  $t$  and base year  $0$ , respectively, and  $\Delta C$  represents the change in transport carbon emission between the two years, and the other values represent the impact values for the target year  $t$  and base year  $0$  (Li et al. 2023; Wang et al. 2020c).

**Geospatial weighted model (GWR)**

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)x_{jk} + \varepsilon_i, i = 1, 2, \dots, n \tag{17}$$

where  $(u_i, v_i)$  is the  $i$ th sample point’s location (such as its latitude and longitude), and  $\beta_k(u_i, v_i)$  is the  $k$ th regression parameter, and  $\varepsilon_i$  is the random error of the  $i$ th sample point. The Gauss function method is a continuous, monotonically decreasing function between  $w_{ij}$  and  $d_{ij}$ ; this function can overcome the discontinuity of the above spatial weight function (Wang et al. 2018). It has the following function form:

$$W_{ij} = \exp\left(-\left(d_{ij}/b\right)^2\right) \tag{18}$$

The continuous monotonically declining function between data point  $W_{ij}$  and  $d_{ij}$  is represented by comparing the distance between data point  $j$  and regression point  $i$ ,  $d_{ij}$ , using the aforementioned equation:

$$AIC = -2\ln\left(\hat{\theta}_L, x\right) + 2q \tag{19}$$

where  $\hat{\theta}_L$  is the theta maximum likelihood estimation.

$$AICc = 2n\ln(\hat{\sigma}) + n\ln(2\pi) + n\frac{n + tr(S)}{n - 2 - tr(S)} \tag{20}$$

where  $AICc$  stands for the “corrected” AIC estimate,  $n$  denotes the size of the sample point,  $\hat{\sigma}$  denotes the error term estimation standard deviation, and  $tr(S)$  denotes the trace of the bandwidth-dependent  $S$  matrix of the GWR. AIC is beneficial for evaluating whether the GWR model simulates data better than the OLS model.

**Results**

**Spatiotemporal evolution of provincial transport carbon emissions and the carbon emission intensity in China**

**Spatiotemporal evolution of provincial transport carbon emissions in China**

The carbon emissions from transportation in 30 Chinese provinces from 2005 to 2019 were computed by this study. The average carbon emissions of 30 provinces from 2005 to 2019 showed an overall rising trend but decreased in 2013, as seen in Fig. 1. From 2005 to 2019, the total carbon emissions from transportation rose from 39,025.93 ( $10^4$  t)

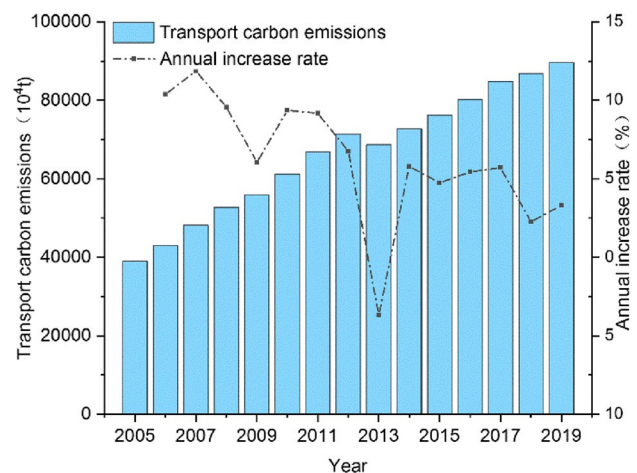


Fig. 1 Transport carbon emissions and increase rate of year

to 89,718.57 ( $10^4$  t), and the average province carbon emissions grew with an average annual growth rate of 9.28% from 1300.86 ( $10^4$  t) in 2005 to 2990.62 ( $10^4$  t) in 2019. The growth rate of carbon emissions exhibited a pattern of changing downward, even though carbon emissions grew during the research period, carbon emissions from transportation increased annually at a pace that varied from 10.39% in 2005–2006 to 3.32% in 2018–2019. From 2008 to 2009, 2012 to 2013, and 2017 to 2018, the annual growth rate declined significantly. Depending on the five-year periodic calculation, the total carbon emissions during 2015–2019 increased by 74.80% compared to those during 2005–2009, while the average yearly growth rate of transportation-related carbon emissions fell by 59.19%. This demonstrates how China succeeded in reducing emissions and conserving energy. Due to the effects of the 2008 financial crisis on the transportation sector, the pace of increase in transportation-related carbon emissions has decreased. The economy as a whole slowed down in 2012–2013, while the pace of growth in transportation-related carbon emissions was  $-3.70\%$ . After 2017, energy-saving and emissions-reduction efforts stepped up, and the growth rate of transport carbon emissions from 2017 to 2019 fell to 2.83%.

The transportation sector's carbon emissions were influenced by changes in energy consumption and overall carbon emissions from all energy sources between 2005 and 2019. In China's transportation, petroleum products were the largest source of carbon emissions, with gasoline, kerosene, diesel, fuel oil, and other petroleum products accounting for a sizable share of carbon emissions. As seen in Fig. 2, diesel and gasoline produced the highest transport carbon emissions, accounting for 42.23% and 19.68% of the total. Over time, the energy structure of transport carbon emissions changed. The proportion of carbon emissions from coal and petroleum products decreased from 5.96% and 82.81% in 2005 to 1.80% and 76.47% in 2019, and the proportion of carbon emissions from diesel and gasoline also decreased, dropping from 41.40% and 25.54% in 2005 to 38.03% and 18.70% in 2019. The carbon emissions from electricity production increased from 4238.65 ( $10^4$  t) in 2005 to 17,006.78 ( $10^4$  t) in 2019, transport carbon emissions climbed from 10.86% in 2005 to 18.96% in 2019, while natural gas transport carbon emissions increased from 142.73 ( $10^4$  t) in 2005 to 2490.53 ( $10^4$  t) in 2019, the contribution of this factor increased from 0.37% in 2005 to 2.78% in 2019, indicating that the transport sector was implementing technological innovations during this time, and the growth of transportation energy was moving in the direction of new energy sources like electricity and gas.

The 30 provinces' levels of transport carbon emissions vary significantly. Guangdong, Shandong, Shanghai, Liaoning, and Jiangsu are among the top five, with yearly average carbon emissions of 5954.50 ( $10^4$  t), 5106.85 ( $10^4$  t),

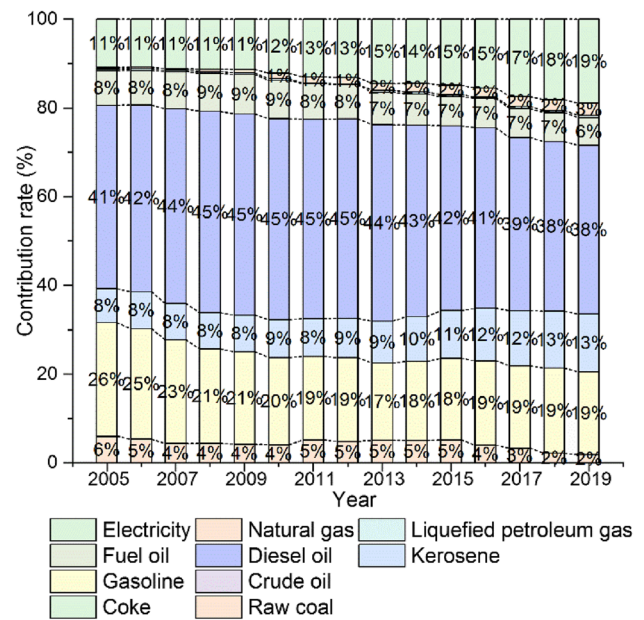


Fig. 2 Proportion of transport carbon emissions per energy source

4450.74 ( $10^4$  t), 3676.36 ( $10^4$  t), and 3613.95 ( $10^4$  t); Tianjin, Gansu, Hainan, Ningxia, and Qinghai are in the bottom five, with average annual carbon emissions of 1120.11 ( $10^4$  t), 1094.01 ( $10^4$  t), 560.21 ( $10^4$  t), 369.21 ( $10^4$  t), and 294.40 ( $10^4$  t). The average annual carbon emissions of Guangdong were 20.23 times that of Qinghai. The provinces with the top five average annual growth rates were Qinghai (37.08%), Anhui (21.61%), Fujian (17.50%), Guizhou (17.14%), and Jiangxi (14.89%). Shanghai (6.71%), Liaoning (5.24%), Inner Mongolia (4.53%), Shandong (4.38%), and Ningxia (3.96%) were among the five regions with the lowest average annual growth rates, as seen in Fig. 3. Provinces with large traditional transport carbon emissions, such as Shandong and Liaoning, have implemented relevant policies for industrial adjustment and achieved remarkable results. Qinghai, which has low carbon emissions, is developing transportation, with a high growth rate.

In 2005, 2010, 2015, and 2019, the spatial pattern of China's transport carbon emissions changed significantly, as seen in Fig. 4. In 2005, the highest carbon emissions were in Guangdong, Shandong, and Shanghai, with carbon emissions of 3980.21 ( $10^4$  t), 3632.45 ( $10^4$  t), and 2943.05 ( $10^4$  t). The higher carbon emissions were in Liaoning, Hubei, Jiangsu, Hebei, and Zhejiang. Transport carbon emissions showed spatial aggregation; the eastern region had a high concentration of carbon emissions, which progressively dropped as they moved westward. In 2010, the carbon emission growth rate of Hebei decreased and that of Inner Mongolia was up to 106.59% compared to 2005. In 2015, Guangdong, Shandong, Shanghai, Jiangsu, and Liaoning all saw an increase in their transport-related carbon emissions, forming

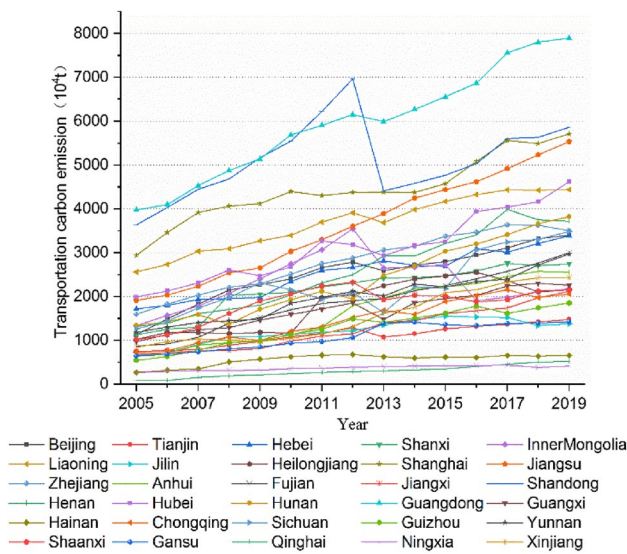


Fig. 3 Transport carbon emissions of provinces in China

spatial aggregation with Zhejiang, Hubei, Henan, Hunan, Beijing, Inner Mongolia, and Hebei, and North China, East China, and Central China all have quite large carbon emissions. In 2019, the growth rates of carbon emissions in Inner Mongolia slowed down, while that in Sichuan increased significantly, reaching 3486.06 ( $10^4$  t). East and Central China are still concentrated regions with high carbon emissions. From 2005 to 2019, the classification of carbon emissions in Inner Mongolia and Shaanxi decreased and the growth rates of carbon emissions in Jiangsu, Anhui, Henan, Hunan, and Sichuan were relatively high. The growth rate of carbon emissions in North China slowed over time.

**Spatiotemporal evolution of the carbon emission intensity of provincial transportation in China**

Since the energy consumption of each province differs, carbon emissions cannot objectively describe the carbon emission efficiency of transportation. The carbon emission

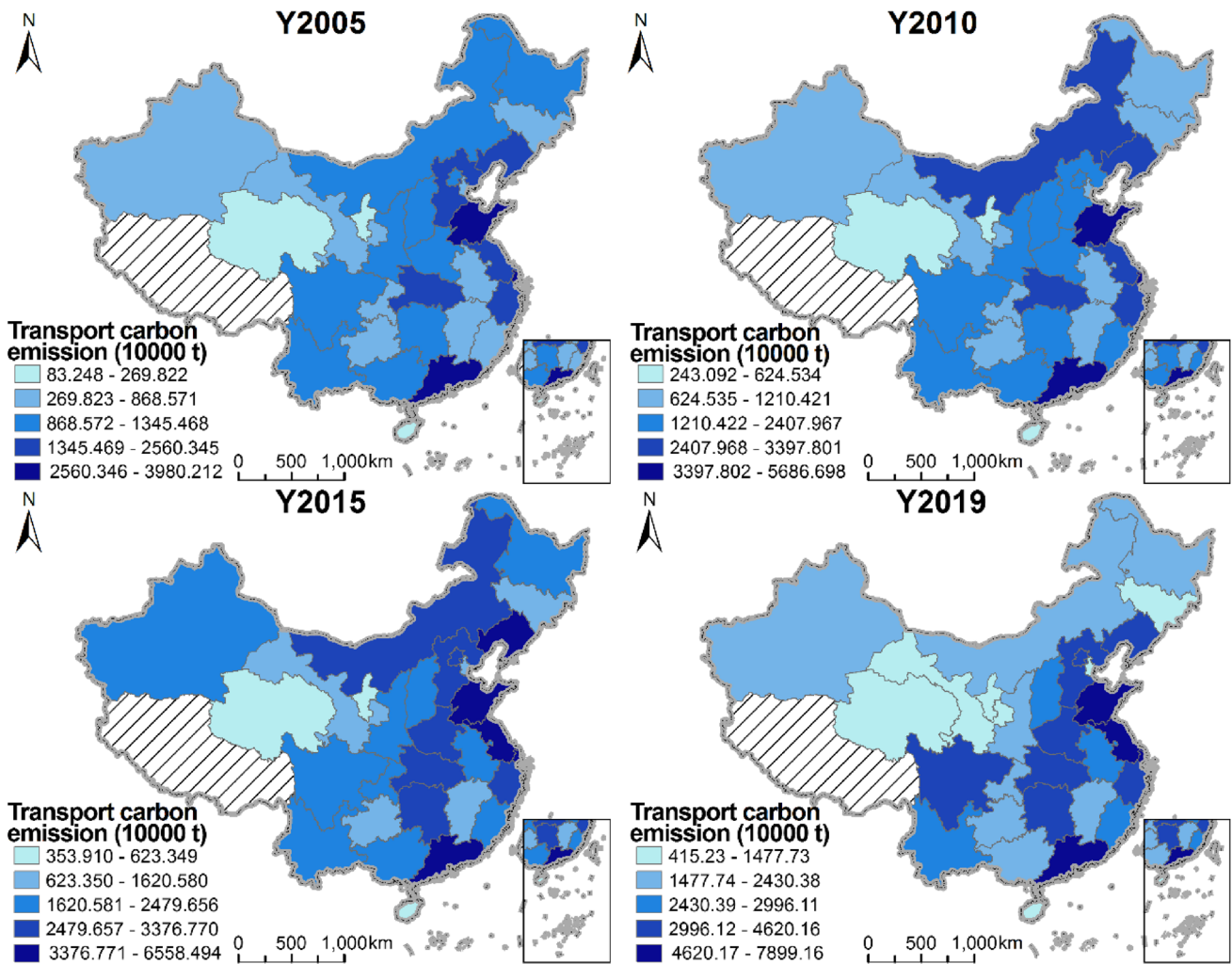


Fig. 4 Spatial distribution of transport carbon emissions in 2005, 2010, 2015 and 2019



intensity in this study is defined as the carbon emissions per unit of energy used and the carbon emissions' energy efficiency. Figures 5, 6 indicate the annual average transportation carbon emission intensity value and growth rate from 2005 to 2019. Although China's total transport carbon emission intensity remains steady, there is a significant variation between its regions. The average transport carbon emission intensities of the 30 provinces in 2005, 2010, 2015, and 2019 were 2.33, 2.32, 2.35, and 2.40. The growth rate showed slight fluctuations and decreased in 2009, 2012, 2014, and 2018. Hebei, Shanxi, Gansu, Tianjin, and Shaanxi have the highest average carbon emission intensity levels, while the lowest are Guangxi, Guangdong, Xinjiang, Chongqing, and Hainan. The largest declines in average carbon emission intensity occurred in Chongqing (−4.22%), Ningxia (−5.69%), Shanxi (−7.51%), Guizhou (−9.87%), and Jilin (−11.14%) from 2005 to 2019. The highest growth rates were in Tianjin (28.56%), Hebei (17.29%), Shandong (17.06%), Inner Mongolia (12.75%), and Zhejiang (11.62%).

With the exception of North China, Fig. 7 demonstrates that the global transportation sector's overall carbon emission intensity was steady, with most of the values staying between 2.1 and 2.5. North, East, Central, South, and Northwest China all increased from 2005 to 2019, with North China of the highest growth rate at 10.76%. In Northeast China and Southwest China, the decreases were 2.78% and 3.52%. Southwest China's carbon emission intensity was lowest between 2017 and 2019, whereas it declined in Northeast China and Central China, with the largest decrease of 5.06% in Central China. North China has a much higher than average carbon emission intensity for transportation, as this region mainly relies on energy production and has a high transportation integration degree and a large demand for road freight transport, leading to the high transportation level of carbon emission intensity. The economic

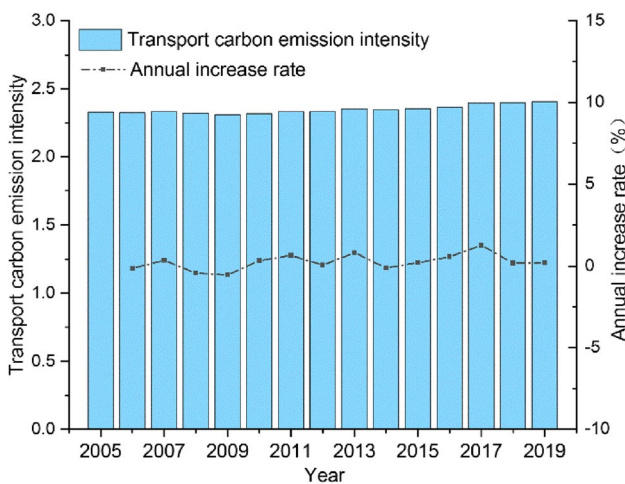


Fig. 5 Transport carbon emission intensity and increase rate of year

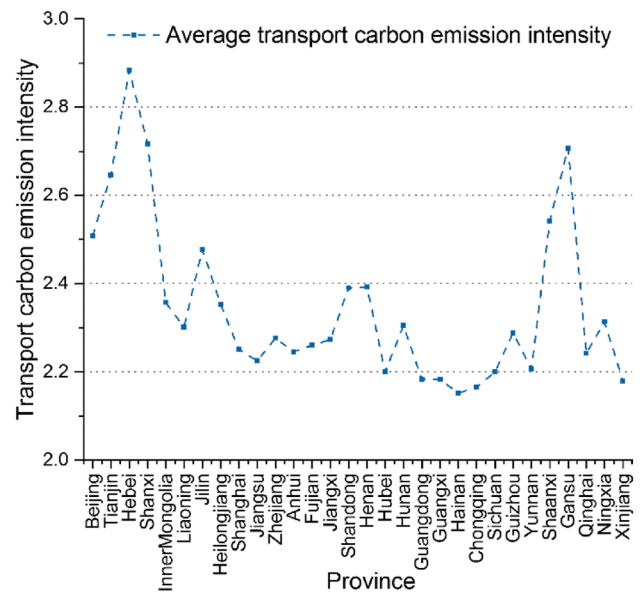


Fig. 6 Average transport carbon emission intensity of provinces in China

development of North China is good, and energy conservation and emission reductions should be strengthened. A number of energy-saving and emission-reduction programs have recently been implemented in East China. Jiangsu, Shanghai, Zhejiang, and other provinces introduced dozens of “dual carbon”-related policies in recent years. In Southwest and Northeast China, transport carbon emission intensity showed a downward trend, decreasing from 2.29 and 2.44 in 2005 to 2.21 and 2.38 in 2019. The average value of Southwest China and South China showed flat trends, with similar development trends, and the overall carbon intensity in these regions was lower than that in other regions.

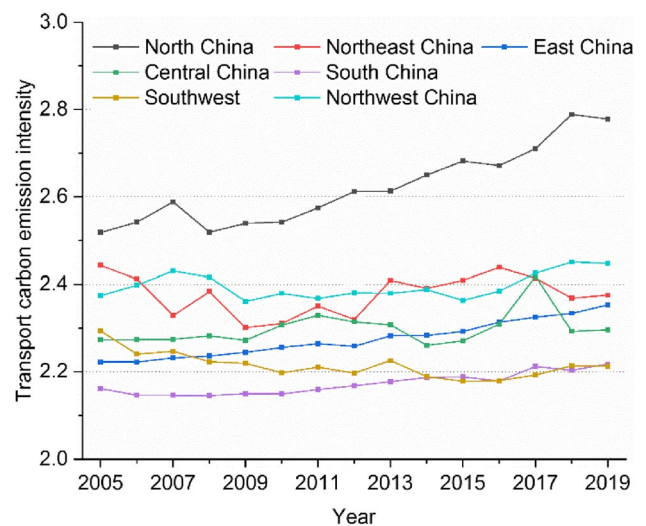


Fig. 7 Carbon emission intensity of regional transportation in China



In Northwest and East China, the traffic carbon intensity remained stable but increased. The intensity of carbon emissions in Northeast and Central China fluctuated in a “W” pattern, with a large fluctuation range. From 2007 to 2008 and 2013 to 2017, there were clear changes in the transportation sector’s carbon emission intensity, and increased significantly compared to other regions, indicating that energy-saving measures for transport carbon emissions should be strengthened continuously in Northeast and Central China.

### Spatial correlation analysis of the spatial pattern of transport carbon emissions and the carbon emission intensity in China

#### Analysis of the spatial correlation of transport carbon emissions

Analysis of spatial correlations reflects the spatial correlations of carbon emissions across regions and carbon emissions’ spatial aggregation features (Wang et al. 2020b). In this study, the spatial autocorrelation analysis of transport carbon emissions was conducted using global Moran’s *I*. The

results showed that from 2005 to 2019, despite being positive, the Moran index of all transportation-related carbon emissions failed to pass the significance test at the 5% level. The spatial association steadily got stronger as time went on. There was a significant regional association between the intensity of transportation’s carbon emissions from 2005 to 2019. Each province’s carbon emission intensity had a substantial spatial association, and the significance level was greater than 99%. Due to the significant relationship between the spatial distribution of the transportation economy’s development level, the emission intensity of provinces in China were affected by geographical factors.

A global space cannot reflect the aggregation characteristics between provinces. On this basis, Anselin local Moran’s *I* is used to analyze the spatial aggregation characteristics of transport carbon emissions. The regional pattern of transport carbon emissions changes, as depicted in Fig. 8, and the transport links between different provinces are usually negatively correlated with distance. Regional traffic development differences are obvious. In the spatial clustering analysis of transportation carbon emissions, high-high cluster indicates that provincial transportation has been

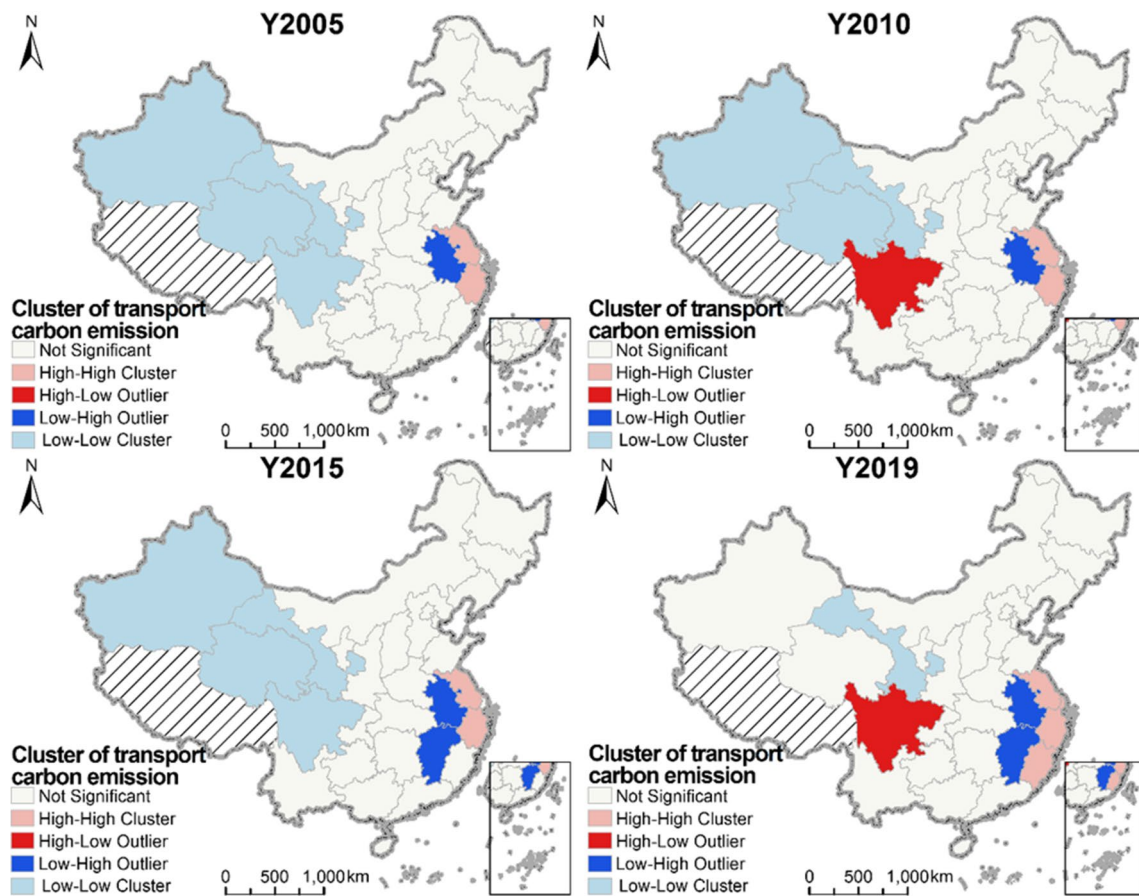


Fig. 8 Spatial autocorrelation of transport carbon emissions in 2005, 2010, 2015, and 2019

strengthened, forming a high level of regional transportation carbon emissions; high-low cluster refers to the provinces with high carbon emission levels adjacent to the provinces with low-carbon emission levels, which are mainly found in localized economic centers; low–high cluster refers to the provinces with low carbon emissions adjacent to the provinces with high carbon emissions, which are often manifested in the peripheral regions with high carbon emissions; and low-low cluster refers to the concentrated distribution of low-carbon emission provinces, generally in regions with a lower level of economic development. According to the spatial analysis, in 2005, 2010, 2015, and 2019, the proportions of “high-high cluster” were 6.67%, 6.67%, 6.67%, and 13.33%, mainly in Jiangsu and Zhejiang provinces. In 2019, Shanghai and Fujian also showed the clustering type. The proportion of the “low-low cluster” was most significant, at 16.67%, 13.33%, 16.67%, and 6.67% in Xinjiang, Qinghai, and Gansu in Northwest China. The generation of spatial aggregation indicates that the regional traffic performance increases and that spatial adjacency enhances transportation, reduces transportation costs, and forms an aggregated distribution of transport carbon emissions. Overall, traffic

emissions have relatively low spatial correlations, and clustering is not significant.

A significant spatial association exists between transport carbon emission intensity, reflecting the viability of spatial analysis of regional energy efficiency and carbon emissions, as shown in Fig. 9. For carbon emission intensity, high-high cluster indicates the clustering of provinces with high carbon emission intensity values but low-energy utilization, high-low cluster indicates that provinces with high carbon emission intensity are neighboring provinces with low carbon emission intensity; low–high aggregation indicates that provinces with low-carbon emission intensity are surrounded by provinces with high carbon emission intensity; and low-low cluster represents the provinces with low carbon emission intensity values and high carbon emission energy efficiency have created a scale effect. In 2005 and 2010, the high concentrations were located mainly in Beijing, Tianjin, Shanxi, Ningxia, and Shaanxi, accounting for 13.33% and 20%. The low concentrations were placed in Fujian, Jiangxi, Guangdong, Guangxi, and Hainan, accounting for 20% and 26.67% in 2005 and 2010. In 2015, Inner Mongolia, Jilin, Hebei, Beijing, Tianjin, Shanxi, and Shandong showed high

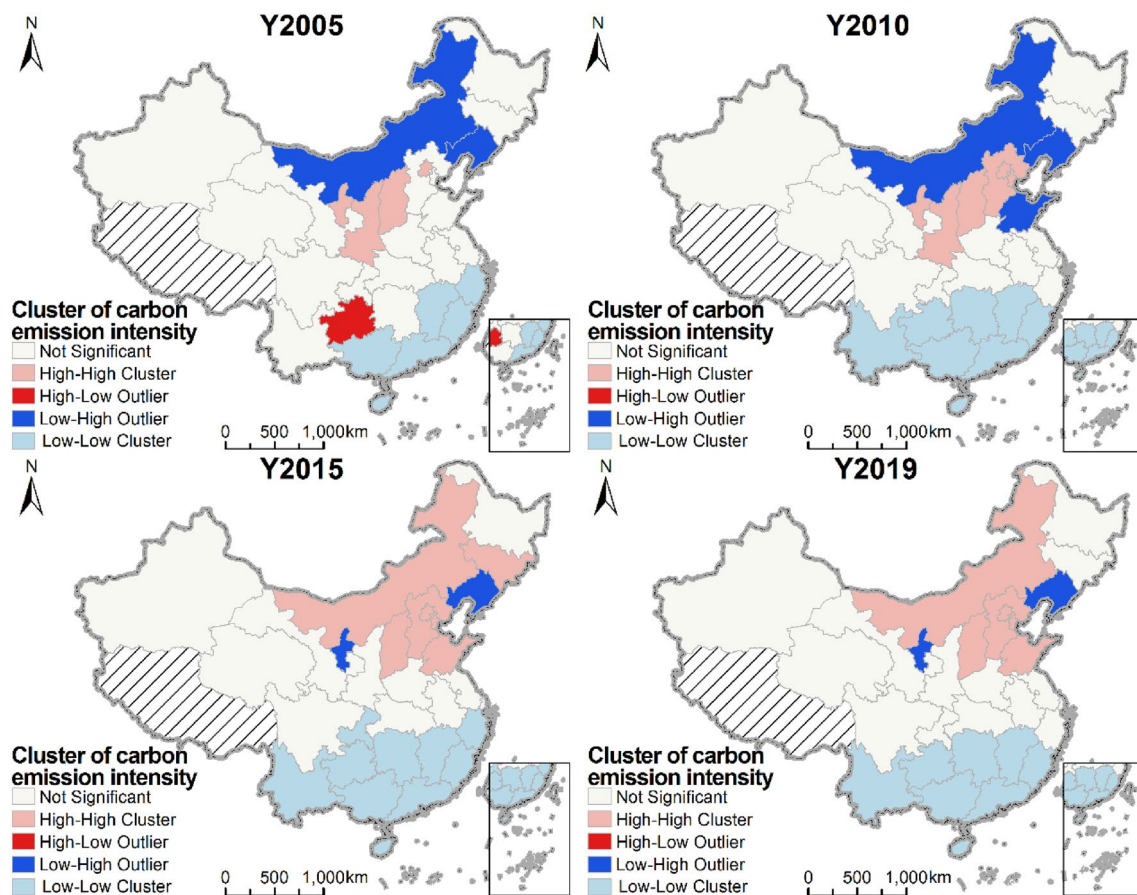
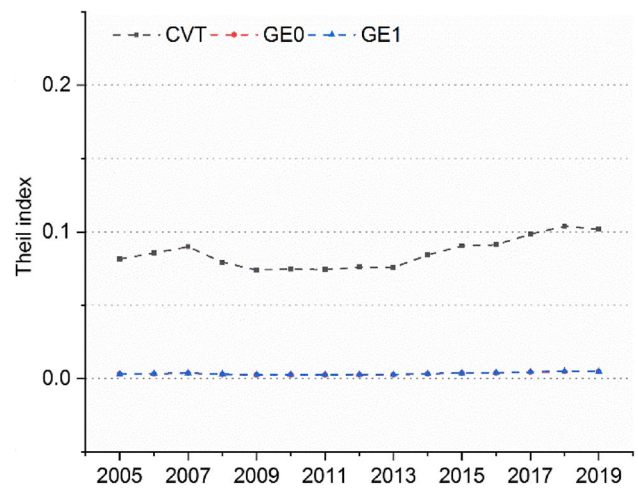


Fig. 9 Spatial autocorrelation of transport carbon emission intensity in 2005, 2010, 2015, and 2019

aggregation, and low aggregation expanded to Chongqing. In 2019, high carbon emission intensity regions were concentrated in Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, and Shandong, accounting for 20%, while low regions were still concentrated in Fujian, Jiangxi, Hunan, Guizhou, Guangdong, Guangxi, and Hainan. In general, the efficiency of converting energy into carbon emission intensity is low in some parts of North China; targeted energy conservation and emission reduction initiatives are required since transportation is a major factor in the economic growth of these areas. The economic development of Northeast China depends on energy development and industrial production, and efficiency improvement is not significant. Although North China's general economic level is high and transportation clearly produces a lot of carbon emissions, the country's energy consumption efficiency is not very high. More energy conservation and emission reduction efforts are needed. Southwest and South China have mainly low aggregation, indicating that the energy efficiency ratio is relatively ideal and that the development of regional transportation energy conservation and emission reduction should be strengthened continuously. In South China, the establishment of a green transportation system build the foundation for the efficient transport of carbon. Southwest China is rich in hydropower resources, and tourism promotes the development of low-energy transportation.

#### Differences in transport carbon emission intensity among provinces

The Theil index is an important tool used to analyze differences in the regional income level to measure the relationship between intergroup gaps and the total gap (Wang et al. 2020a, c). The standard deviation and logarithmic deviation mean of transport carbon emission intensity in 30 provinces from 2005 to 2019 were calculated to quantitatively describe the distribution features of the intensity of transportation-related carbon emissions in 30 Chinese provinces. The standard deviation reflects the dispersion degree of transport carbon emissions. The larger  $GE_0$  and  $GE_1$  are, the larger  $CV_t$  is. The intensity of transport carbon emissions tended to stabilize, but the difference increased, which showed an overall fluctuating trend. As shown in Fig. 10, the  $GE_1$ ,  $GE_0$ , and  $CV_t$  values of the transport carbon emission intensity in 30 provinces of China increased from 0.003, 0.003, and 0.082 in 2005 to 0.005, 0.005, and 0.102 in 2019, indicating that the differences of transport carbon emission intensity in China were increasing.  $CV_t$  showed a fluctuating trend, with significant fluctuations from 2013 to 2019.  $GE_0$  and  $GE_1$  showed stable trends, increasing slightly in 2007 and 2018. The differentiation of the overall carbon emission intensity was stable at a low value, and the differences between the developments of transport sectors in provinces were small.



**Fig. 10** Change of correlation coefficient of transport carbon emission intensity in China

The average correlation coefficient of the regional carbon emission intensity decreased significantly, indicating a correlation among regions. In Northwest and North China, there were also significant variations in transportation-related carbon emissions and energy efficiency. The low level of  $GV_t$  in Southwest China shows that the level of carbon emission intensity in this region was relatively balanced, the regional energy efficiency was at a reasonable stage of development, and the regional development differences were relatively small.

#### Decoupling of economic development and provincial transport carbon emissions in China

To evaluate the economic effect of carbon emissions and formulate emissions-reducing measures in line with regional development, to explain the connection between province transportation-related carbon emissions and local economic growth, we utilized a subject index. There are eight categories of Tapio decoupling models (Wang et al. 2020a): (1) Expansion negative decoupling,  $e > 1.2$ : the carbon emission growth rate of transportation is higher than that of GDP, the level of economic efficiency is not high. (2) Recessive decoupling,  $e > 1.2$ : the carbon emissions of transportation is reduced faster than GDP, suggesting a slowdown in the economy. (3) Weak decoupling: the GDP growth rate of transportation is higher than that of carbon emissions,  $0 < e < 0.8$ : economic development is becoming more energy efficient. (4) Weak negative decoupling,  $0 < e < 0.8$ : the GDP of transportation is reduced faster than carbon emissions; economic growth is weakened. (5) Strong decoupling,  $e < 0$ , is the best economic model since it results in an increase in transportation GDP with a drop in carbon emissions. (6) Strong negative decoupling ( $e < 0$ ) results in an increase in



transport carbon emissions with a drop in GDP, indicating a state of strong decline. (7) Recessive coupling,  $0.8 < e < 1.2$ : GDP and carbon emission growth in transportation are similar, regarding the state of the economy and carbon emissions. (8) Expansion coupling,  $0.8 < e < 1.2$ : the reduction in carbon emissions from transportation is similar to GDP and shows that there is a high association between GDP and carbon emissions.

We estimate the yearly decoupling of transportation-related carbon emissions in 30 provinces in this article. The results showed seven decoupling types. Weak decoupling accounted for the largest proportion of 45.24%; this was followed by expansion negative decoupling at 20.71%, recessive coupling at 13.33%, strong decoupling at 11.43%, strong negative decoupling at 6.67%, weak negative decoupling at 1.67%, and recessive decoupling at 0.95%. The proportion of weak decoupling was high, indicating that the economic development energy efficiency improved. From 2005 to 2006, both the transport carbon emission level and transportation industry GDP increased, and most provinces showed weak decoupling. Expansion negative decoupling occurred in Beijing, Shanxi, Heilongjiang, Jiangxi, and

other provinces, indicating that the economic development of these provinces was inefficient expansion. In 2018–2019, transport carbon emissions and the GDP increased in most provinces. Zhejiang, Anhui, Henan, and Guangxi showed strong decoupling, which was an ideal economic development state. The strong negative decoupling observed in Jilin and Qinghai indicated that the economic energy efficiency in these provinces was low, and the economic development of the provinces needs to transform into energy savings and high efficiency. The number of strong negative decoupling regions decreased, while the number of decouple regions increased, and the decoupling elastic gaps between different regions were narrowing. Figure 11 shows the decoupling states during the 5-year period and the full observation period. The entire research region oscillates between expansion negative decoupling, weak decoupling and recessive coupling between 2005 and 2009. From 2010 to 2014, four coupling types were experienced, including expansion negative decoupling, strong decoupling, weak decoupling, and recessive coupling. Among them, the number of provinces with expansion negative decoupling decreased, with strong decoupling increased. From 2015 to 2019, the

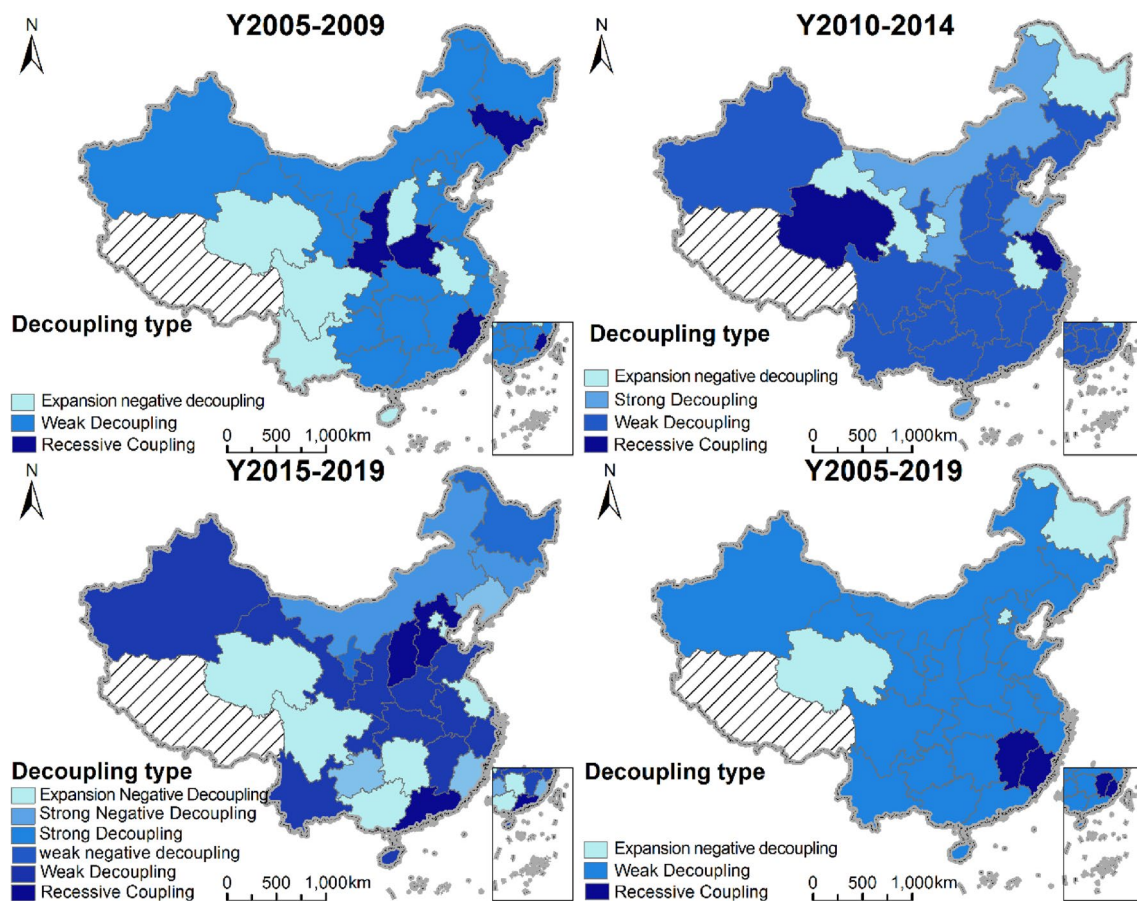


Fig. 11 Economic decoupling types of 5-year periodic transport Carbon emissions



decoupling types increased, with expansion negative decoupling accounting for 23.33% and weak decoupling accounting for 43.33%. Most provinces have realized the economic decoupling. In general, from 2005 to 2019, 83.33% of provinces realized weak decoupling; only Beijing, Qinghai, and Heilongjiang experienced expansion negative decoupling; and Jiangxi and Fujian experienced recessive coupling. The decoupling elasticity gaps of 30 provinces in China were narrowing, and transport carbon emissions tended to correspond to low-carbon economies.

The correlation of the provincial decoupling state space is significant, and the decoupling types of adjacent regions are similar. As seen in Fig. 12, we study the regional decoupling state, and the results are as follows: North China presented a decoupling state, with strong decoupling in 2012–2013 and 2015–2016 but strong negative decoupling in 2013–2015 and 2017–2018, indicating significant fluctuations in the economic efficiency. In 2018–2019, weak negative decoupling appeared, indicating that economic efficiency needs to be steadily improved. A variety of decoupling states appeared in Northeast China, accounting for 71.43%, among which weak decoupling states accounted for 50%, indicating that the dependence of the transportation GDP on energy was reduced. In 2005–2006, 2010–2011, 2013–2014, and 2018–2019, recessive coupling occurred, accounting for 28.57%. The decoupling states of East China and South China were similar, with the recessive coupling state appearing in only 2 years and the strong negative decoupling state appearing in one year; in addition, the energy demand of the transportation economy was low. The reason for this may be that East China and South China are economically developed, attach high importance to reducing carbon emissions, and introduce several regional emission reduction policies. There were a variety of negative decoupling states in central China, among which the proportion of expansion negative

decoupling was 28.57%, transport carbon emissions persisted in fluctuating terms of economic effectiveness, and economic energy efficiency need to be constantly increased. The southwest and northwest regions give consideration to the growth of the tertiary industry and tourism, with 78.57% and 85.71% in the decoupling state. Fluctuations occurred in 2006–2007, 2013–2014, 2015–2016, and 2017–2018, indicating a state of expansion negative decoupling that may have been related to regional economic changes in that year. It is proven that regional decoupling is greatly affected by the economic environment.

## Discussion

### Spatial differentiation and contribution rate analyses of transport carbon emission factors

#### Spatiotemporal heterogeneity analysis of transport carbon emission factors

The study’s findings demonstrate transport carbon emissions’ spatial agglomeration impact and economic energy efficiency are related. Combined with the research literature, in this paper, we select carbon emission intensity, energy intensity, transport intensity, economic structure, economic scale, population, and economic intensity as the influencing elements. The data were first standardized, and an OLS linear regression model was used for factor screening. The findings revealed that the economic structure, economic scale, population, and economic intensity of carbon emissions were the most significant factors each year, and there was no multicollinearity. The  $R^2$  values modified in 2005, 2010, 2015, and 2019 were 0.83, 0.86, 0.84, and 0.89, according to the GWR model calculation findings, respectively, and with time, the influencing factors of the traffic explanatory power gradually enhanced the carbon emissions space, and the economy and population were some of the most important influencing factors.

As shown in Fig. 13, the economic structure has an impact on spatial promotion, and the influence coefficient of the carbon emission intensity fluctuated greatly over time. From 2010 to 2015, the spatial regression coefficient of the economic structure increased, and the coefficient decreased in 2019. In 2005, Guangdong, Fujian, Zhejiang, Shanghai, Jiangsu, Anhui, and Jiangxi had the highest spatial impact coefficients, distributed in East China and South China. In 2010, Inner Mongolia, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, and Zhejiang had the highest spatial impact coefficients, from North China and East China. Liaoning, Jilin, and Heilongjiang in Northeast of China showed the highest spatial impact coefficients in 2015. In 2019, Xinjiang, Qinghai, Guizhou, Yunnan, Guangxi, and

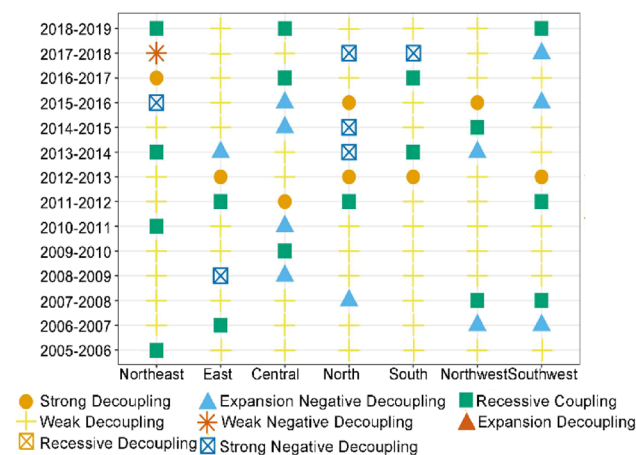


Fig. 12 Economic decoupling types of regional transportation carbon emissions

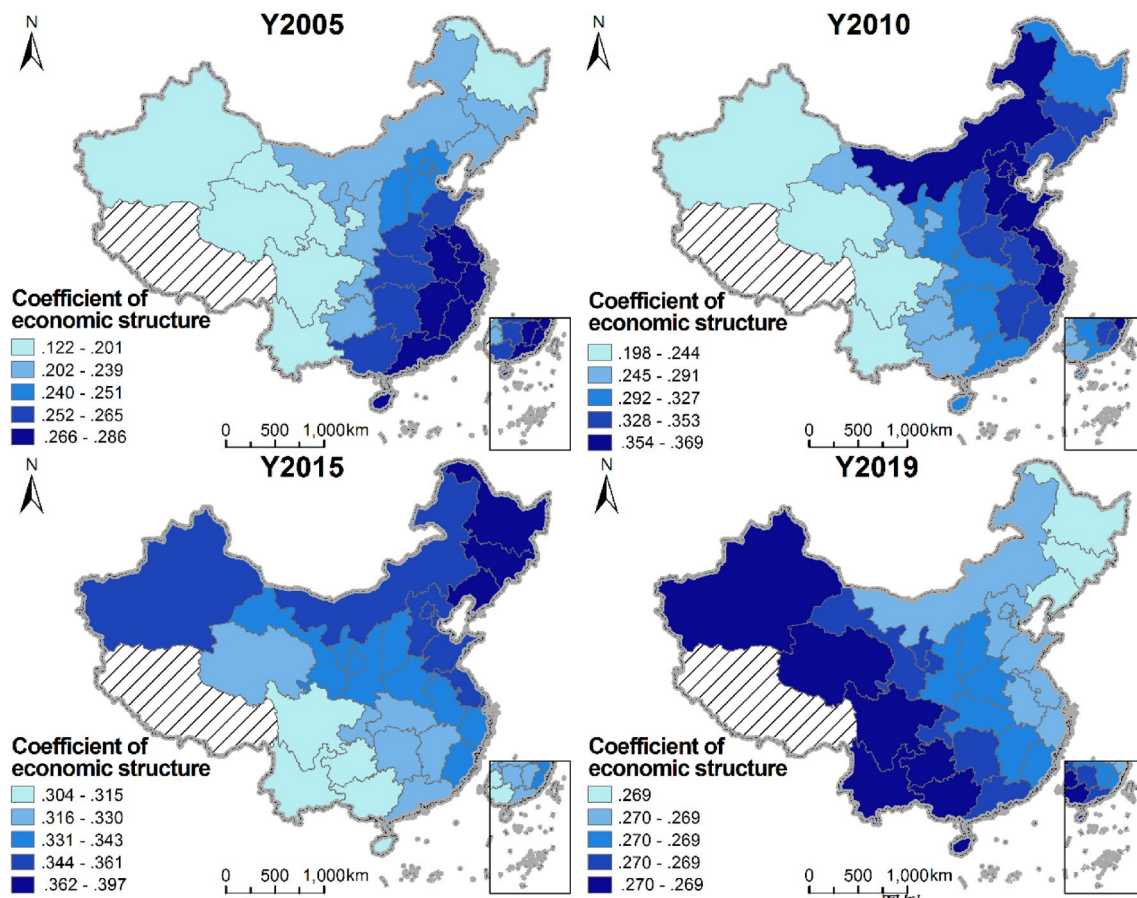


Fig. 13 Spatial distribution of economic structure

Hainan were the most significant regions in Northwest, Southwest, and South China. Overall, the spatial influence of the economic structure developed from east to west.

Figure 14 demonstrates the influence of the economic scale, which is significant in Guangdong, Guangxi, and Hainan and gradually strengthens from north to south. From 2005 to 2019, the per-capita GDP of 30 provinces increased by 328.78%, while the carbon emissions from transportation increased by only 129.89%. The rapid growth of the per-capita GDP increased the impact of the economic scale from transportation, because transportation is an important embodiment of the economic capacity. From 2005 to 2019, the economic scale in South China and Southwest China showed a strong spatial influence.

The spatial influence of the population is similar to that of the economic scale, which had a broad promoting impact on transport carbon emissions in all regions. As shown in Fig. 15, the effect of the population was weaker in the western region and stronger in the eastern region, mainly affecting Shandong, Shanghai, Zhejiang and Fujian. East China was the largest economy affected by the population, while Northwest and Southwest China were less affected.

The spatial regression coefficient of the population was the largest among the influencing factors. In 2005, 2010, 2015, and 2019, the average spatial coefficients of the population were 0.93, 0.91, 1.02, and 1.02.

The economic intensity reflects the carbon emissions per unit of GDP from transportation, and its influence gradually increased from west to east. Northeast China was dominated by heavy industry, with road and railway transportation as the main modes of transportation, and this increased the impact of the economic intensity on transport carbon emissions. Figure 16 demonstrates the traffic volumes in the southwest and northwest regions were relatively low, and the influence of the economic intensity was small.

#### Contribution rate of transport carbon emission factors

Carbon emission intensity, energy intensity, transport intensity, economic structure, economic scale, and population were chosen as the primary decomposition components in accordance with the decomposition model. The findings in Tables 1 and 2 demonstrate that the aforementioned variables have diverse effects on changes in transport carbon

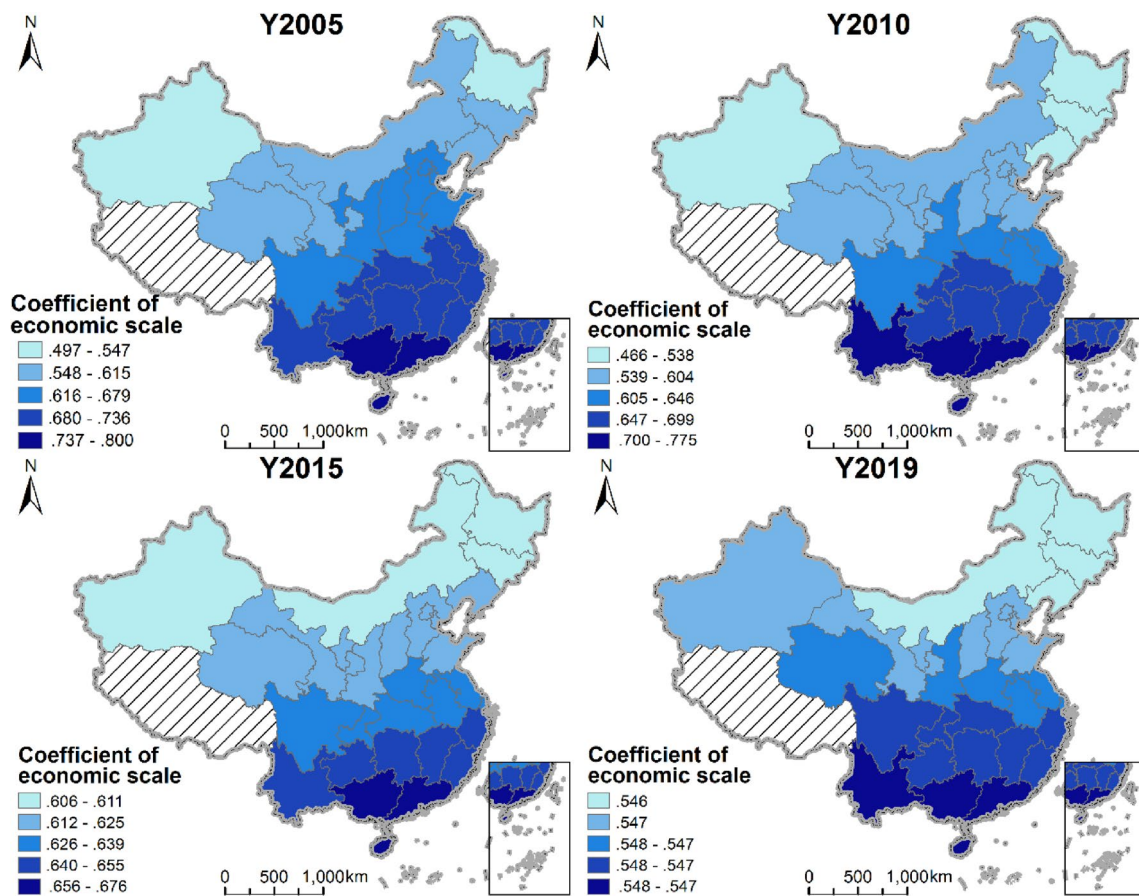


Fig. 14 Spatial regression coefficient of economic scale

emissions. From 2005 to 2019, the cumulative contributions were  $3139.16 (10^4 \text{ t})$ ,  $-14023.10 (10^4 \text{ t})$ ,  $-21103.40 (10^4 \text{ t})$ ,  $-16060.90 (10^4 \text{ t})$ ,  $91612.70 (10^4 \text{ t})$ , and  $7128.23 (10^4 \text{ t})$ , respectively. The energy intensity, transport intensity, and economic structure generally inhibit transport carbon emissions, while the carbon emission intensity, economic scale, and population generally promote transport carbon emissions, with average contribution rates of  $-27.40\%$ ,  $-4.123\%$ ,  $-31.38\%$ ,  $3.08\%$ ,  $89.92\%$ , and  $7.00\%$ , respectively. These results are consistent with related research conclusions (Nnadiri et al. 2021; Solaymani 2022; Zhu et al. 2022).

The carbon emission intensity generally promoted carbon emissions with fluctuations, with multiple positive and negative effects. The contribution of the carbon emission intensity increased significantly from 2016 to 2017, from  $292.69 (10^4 \text{ t})$  to  $1090.55 (10^4 \text{ t})$ . The carbon emission intensity had an inhibiting effect on Henan, Guizhou, Jilin, Shanxi, Chongqing, Ningxia, and Qinghai, and a promoting effect on other regions.

The contribution of the energy intensity increased from  $-213.16 (10^4 \text{ t})$  in 2005 to  $7563.50 (10^4 \text{ t})$  in 2019, and the contribution of carbon emission suppression

gradually increased, reducing transport carbon emissions by  $-14023.10 (10^4 \text{ t})$  in general, accounting for 27.40% of the total contribution of carbon emission suppression from 2005 to 2019. In 2008 and 2016, the domestic economy declined, and the contribution value of the energy intensity increased significantly, indicating that the energy intensity is closely related to the economy. In 2018–2019, the contribution value of the energy intensity changed from inhibiting to promoting, thus proving that the economic environment brings fluctuations in energy intensity. The energy intensity contributed to carbon emissions mainly in Guangdong, Hunan, Tianjin, Zhejiang, Inner Mongolia, and Shanghai.

The effect of transport intensity played a substantial role in fostering carbon emissions in 2008 and 2014, reducing transport carbon emissions by  $21103.41 (10^4 \text{ t})$  and accounting for 41.23% of the total inhibition contribution from 2005 to 2019, accounting for a large proportion and indicating that the contribution value had a suppressive impact on carbon emissions. The transport intensity contributed to carbon emissions mainly in Guangdong, Shandong, Yunnan, Hunan, and Tianjin.



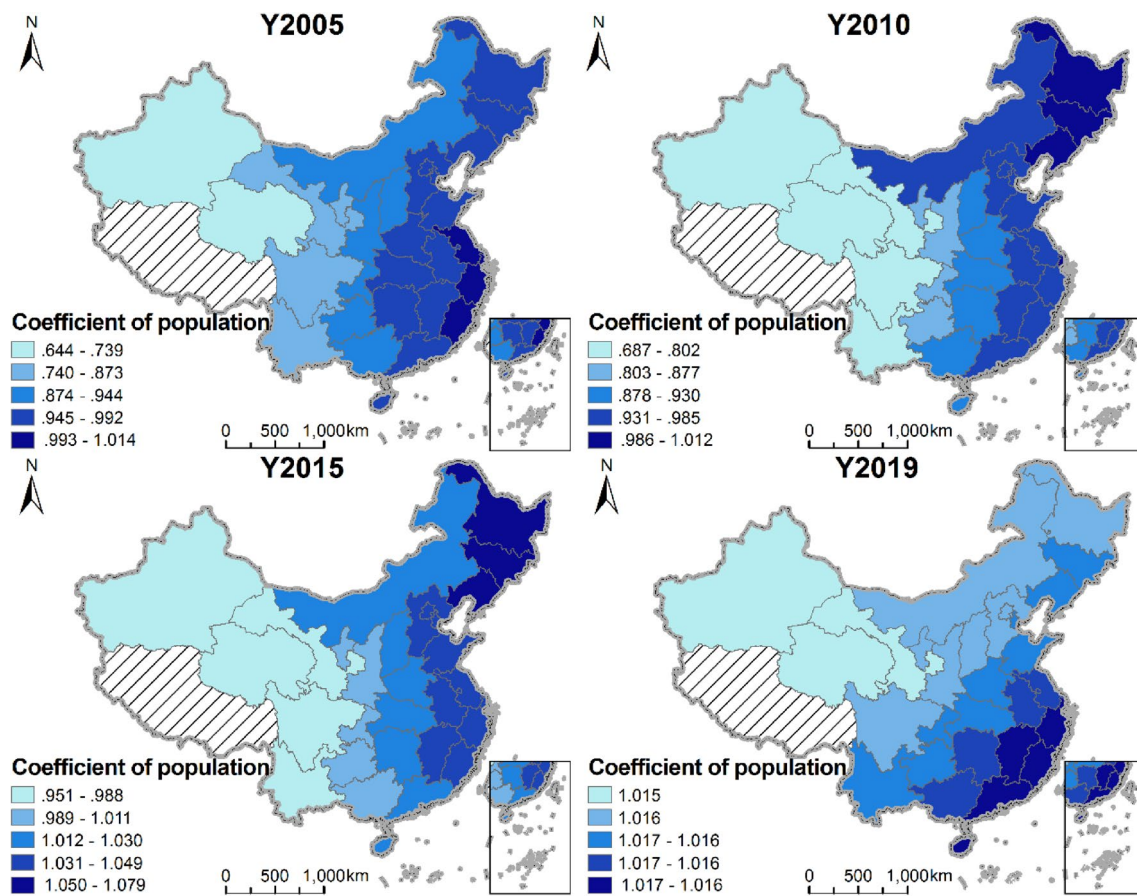


Fig. 15 Spatial regression coefficient of population

The number of years when the economic structure inhibited transport carbon emissions was the largest among the influencing factors. The overall inhibitory contribution value was  $-16060.90$  ( $10^4$  t), and the inhibitory contribution rate was 31.38%; increasing the proportion of transport GDP would not increase carbon emissions. The significance of increasing the economic effectiveness of carbon emissions is supported by this conclusion. Yunnan, Xinjiang, Henan, Hebei, Anhui, and Shandong's carbon emissions were encouraged by their economic structures, although the proportions were not very significant. The provinces with strong inhibition were Guangdong, Beijing, Fujian, Shanghai, and Sichuan.

With a total contribution rate of 89.92%, per-capita GDP significantly contributed to the growth of transport carbon emissions, and its change trend was basically consistent with that of carbon emissions. Due to the increasing demand for traffic volume, the economic scale and transport carbon emissions continue to increase. Guangdong, Shandong, Hubei, Jiangsu, and Shanghai all had average annual carbon emissions above 3 million tons, which

significantly increased the amount of carbon emissions from transportation.

The emission contributions of the population decreased from  $485.49$  ( $10^4$  t) to  $282.93$  ( $10^4$  t) from 2005 to 2019, with a decrease rate of 41.72%. The consumption potential of the population drives the development of urban transportation; Guangdong Province had the largest contribution of the population factor, with an average contribution value of  $126.20$  ( $10^4$  t) of carbon emissions. Guangdong, Shanghai, Beijing, Zhejiang, and other provinces with better economic development were more attractive to talent, and their large populations promoted carbon emissions. Figure 17 demonstrates the contribution rate of each influencing factor.

Among the contributions of the seven regions, the economic scale was the main factor promoting carbon emissions of all the regions. In North China and East China, the variables limiting carbon emissions were energy intensity, transport intensity, and economic structure, whereas the ones boosting carbon emissions were carbon intensity, economic scale, and population. Among the inhibiting factors, the energy intensity, transport intensity, and economic structure



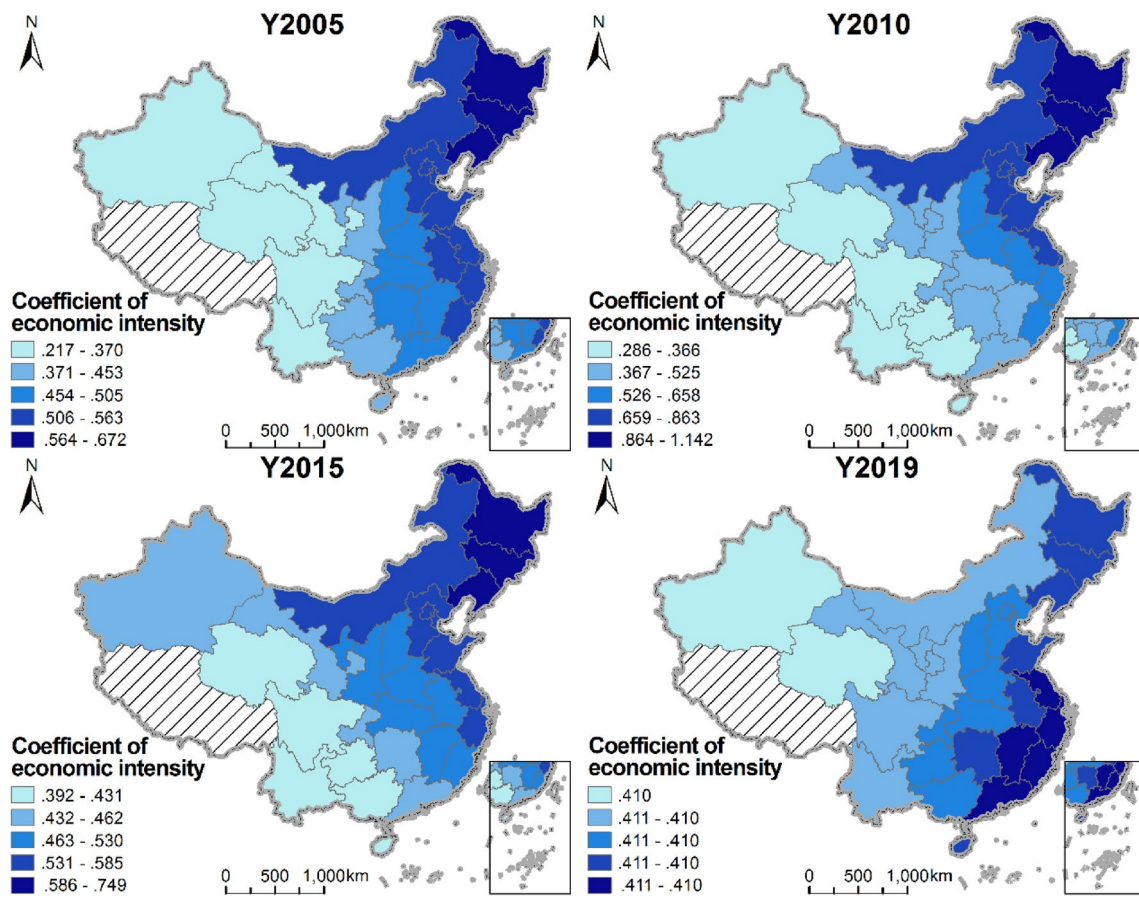


Fig. 16 Spatial regression coefficient of economic intensity

Table 1 Average contribution of influencing factors from 2005 to 2019

Year	CI	EI	TI	EC	GC	P	Total
2006	-41.6747	-213.156	-1943.4	-80.5357	5849.554	485.4895	4056.274
2007	129.7956	-285.841	-517.944	-2287.98	7514.26	562.1318	5114.417
2008	-112.125	-6911.91	5024.578	-2152.79	8147.925	615.5185	4611.194
2009	-93.181	-666.365	585.9902	-2780.79	5537.969	615.3555	3198.976
2010	157.5333	-4181.57	118.7295	-1344.93	9694.102	801.4623	5245.325
2011	520.9414	-3661.68	-242.462	-2362.73	10,621.91	742.6581	5618.643
2012	41.60946	-1476.29	-1194.27	131.1578	6429.377	591.4674	4523.054
2013	792.2815	891.5737	-9948.36	-522.308	5661.905	484.6355	-2640.27
2014	-164.851	-3744.43	3550.225	-1421.25	5275.974	488.8599	3984.526
2015	157.8327	7229.465	-8094.7	393.1431	3451.009	314.5834	3451.333
2016	292.6942	-256.627	359.4276	-1451.1	4729.829	460.9288	4135.151
2017	1090.551	-6188.91	1933.046	1055.492	6302.851	391.6184	4584.651
2018	84.10024	-2120.83	-863.058	-1812.4	6349.097	290.594	1927.507
2019	283.647	7563.497	-9871.2	-1423.91	6046.897	282.9316	2881.861

CI carbon emission intensity, EI energy intensity, TI transport intensity, EC economic structure, GC economic scale, P population

**Table 2** Average contribution of influencing factors in each province from 2005 to 2019

Province	CI	EI	TI	EC	GC	P
Beijing	0.18	852.04	-627.87	-1962.48	3248.81	761.38
Tianjin	287.44	2081.42	-2862.61	-10.18	970.25	261.74
Hebei	416.46	-1079.48	-853.89	353.41	2636.12	195.48
Shanxi	-89.81	-831.25	458.80	-710.26	2722.98	66.68
Inner Mongolia	345.52	-1644.69	-545.91	-660.98	3355.66	-3.57
Liaoning	87.80	-879.30	-352.11	-557.99	3570.39	10.62
Jilin	-90.10	-352.35	57.75	-74.53	1327.91	-151.56
Heilongjiang	48.40	917.57	-482.73	-565.08	1579.62	-360.08
Shanghai	93.62	-1546.94	-480.28	-1597.13	5206.90	1089.63
Jiangsu	44.47	-51.29	-695.96	-1261.47	5213.90	371.33
Zhejiang	341.12	-1682.77	-140.44	-696.38	3397.06	686.09
Anhui	86.18	38.37	-1480.02	304.50	2949.61	19.60
Fujian	29.37	-952.64	1298.59	-1620.83	3083.68	289.36
Jiangxi	43.86	140.45	-358.12	-470.75	2033.77	45.18
Shandong	864.46	-1024.19	-4281.86	39.68	6179.16	449.81
Henan	-155.40	102.36	-1820.48	405.72	3706.50	158.26
Hubei	76.83	-1473.95	-1620.59	-156.75	5680.83	125.02
Hunan	107.17	2461.12	-2956.29	-953.68	3725.47	92.79
Guangdong	291.56	-8276.14	5002.81	-2102.26	7236.22	1766.76
Guangxi	18.88	-508.99	-320.98	-467.58	2444.89	119.45
Hainan	20.87	-284.53	-88.41	-240.66	871.51	107.29
Chongqing	-28.24	-719.07	14.10	-690.94	2553.91	199.08
Sichuan	80.22	-28.94	-462.68	-1406.59	3986.96	55.81
Guizhou	-110.50	823.69	-1143.40	-919.13	2565.74	92.58
Yunnan	8.87	375.94	-3049.18	712.94	3639.00	102.15
Shaanxi	183.68	-1081.80	-655.86	-783.73	3331.17	129.69
Gansu	62.91	-91.51	-277.84	-384.02	1497.56	-20.74
Qinghai	-9.43	327.13	-256.27	-36.55	384.65	22.58
Ningxia	-18.22	-99.11	-173.05	-199.39	569.28	68.64
Xinjiang	100.99	465.79	-1948.62	652.16	1943.15	377.18

CI carbon emission intensity, EI energy intensity, TI transport intensity, EC economic structure, GC economic scale, P population

accounted for a similar proportion in East China, but in North and Central China, transport intensity is the biggest inhibitor. In Northeast China, the energy intensity, transport intensity, economic structure, and population inhibited carbon emissions, accounting for 11.26%, 27.85%, 42.93%, and 17.96%, respectively. In South China, the main factors inhibiting carbon emissions was energy intensity, accounting for 76.34%. In the southwest and northwest areas, transport intensity and economic structure were the major inhibiting influence. The proportions of factors between these two regions were similar.

Combined with the contribution rate of 5-year period, the development trend of the main influencing factors could be seen. In different periods, the carbon intensity, economic structure, economic scale, and population contribution rates were stable, and energy intensity and transport intensity fluctuated greatly. From 2015 to 2019, in the last 5 years,

the contribution rate of the period was consistent with the overall contribution trend, the recent economic structure, economic scale, and population contribution rate stability, and contributing impacts of carbon emission intensity increased. The rate of energy intensity inhibition fell, but the rate of transport intensity inhibition rose, indicating that the proportion of renewable energy gradually increased and that the energy-saving measures of freight transport need to be strengthened, as Fig. 18 shows.

### Transport carbon emission regulation approach

Based on the spatiotemporal characteristics of transportation carbon emissions and the types of economic decoupling and the influencing factors of provinces in China, this paper suggests to strengthen the macroeconomic policy regulation and control, realize the integration and coordinated development

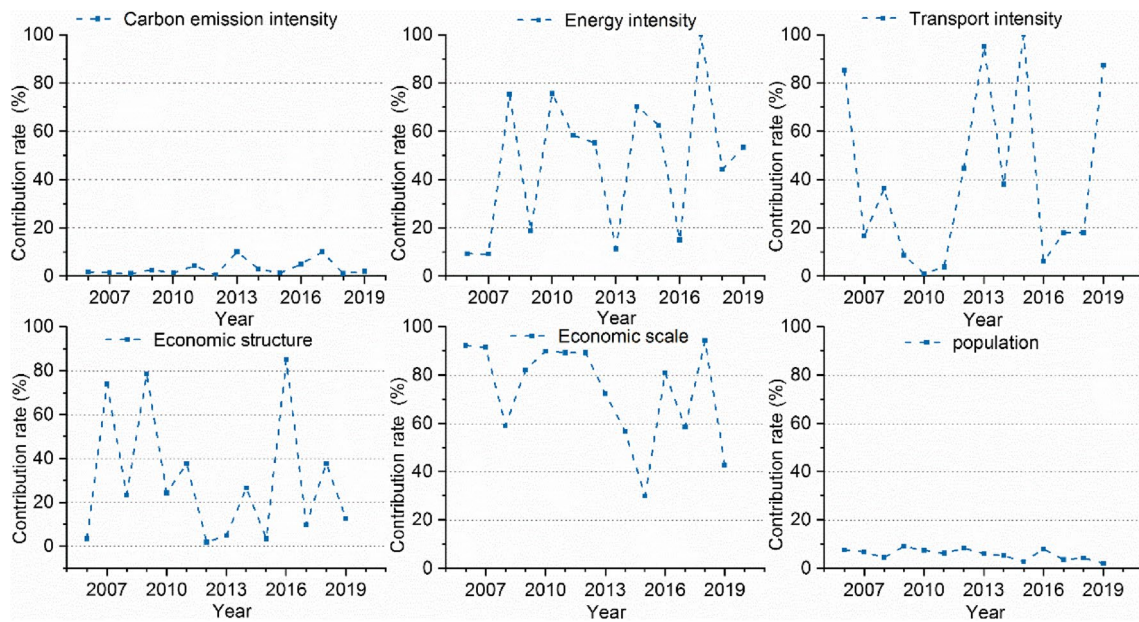


Fig. 17 Contribution rate of each influencing factor

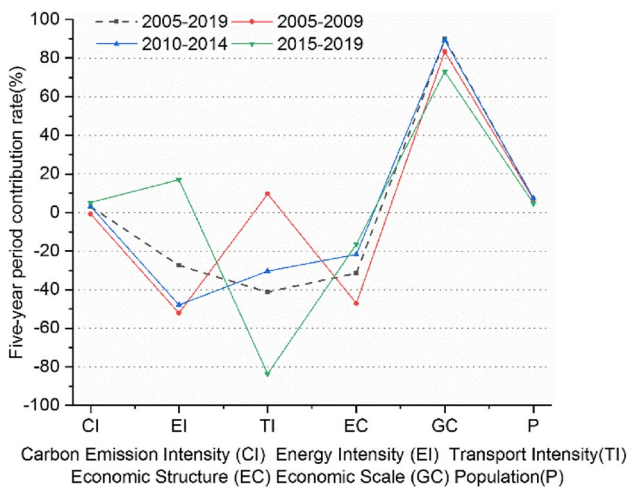


Fig. 18 Contribution rate of each influencing factor in 5-year period

of regional transportation resources, optimize the structure of transportation and energy, and vigorously develop the transportation technology, and make accurate suggestions on carbon emission reduction.

### Strengthening macro-scale controls and optimizing the economic efficiency

Macro-policy regulation is crucial since economic growth is the key factor determining transportation-related carbon emissions. A balance between carbon emission restrictions and economic development should be considered in an economic expansion (Inkinen and Hämäläinen 2020). The

economic scale is significant variables encouraging carbon emissions, while the economic structure is the main factor blocking carbon emissions, only by optimizing the economic energy efficiency and realizing the decoupling of the carbon emission economy can we gradually complete China's economic model change and advance superior economic and social development. First, we should improve the urban transport structure, transform the mode of transport, optimize the transport planning, strengthen the transport and traffic efficiency, increase the proportion of long-distance rail transport and bus rapid transit, and reduce the use of aircraft and private cars and other inefficient means of carrying passengers (Noussan et al. 2022) to comprehensively improve the economic efficiency of transport. Second, the average marginal emission reduction cost of transportation should be reduced; we should rely on low-carbon standard systems and economic demonstration zones, establish the provincial development priority framework (Pamucar et al. 2021), and encourage the regional and staged implementation of China's effective and low-carbon economic development model.

### Improving the energy structure and developing new technical forces in the transportation

The International Energy Agency (IEA) published the Roadmap for Carbon Neutrality in China's Energy System in September 2021, emphasized that the primary forces behind China's emission reductions come from improving energy efficiency, expanding renewable energy, and reducing coal use. Adjusting the energy structure, reducing the

consumption of fuels such as fuel oil and diesel, and increasing the utilization rate of renewable energy sources are important ways to reduce transport carbon emissions. First, we will help upgrade the industrial structure; minimize the energy-intensive, polluting, and high-emission industries; and strengthen the use of solar energy, geothermal energy, bioenergy, electricity, and hydrogen-based synthetic fuels. Second, we should encourage technological innovation, accelerate the introduction of innovative technology, and improve energy efficiency, vigorously develop new energy transportation, and gradually transition to low-carbon transportation development.

### Achieving low-carbon transportation development through regional cooperation

Low-carbon transport systems require regional cooperation, close logistical links with surrounding cities, enhanced economic exchanges and demand cooperation, the optimization of the transport structure, and the formulation of regional development policies. North China and East China had high economic efficiencies, but the energy carbon emission conversion rates still needed to be strengthened in these areas. We should continue strengthening the technical force, increase the transportation sector's GDP output's energy efficiency, and boost the energy utilization rate. Reducing carbon emissions in Central China is significantly impacted by the transport intensity. Therefore, efficient freight transport should be developed to increase the proportion of the transport GDP. In Northeast China, the economic structure and transport intensity inhibit carbon emissions, the freight routes and industrial structure should be improved, and the transportation economy should be enhanced. In South China, energy intensity is the main inhibiting factor; policies should focus on strengthening the low-carbon energy mode. In Southwest and Northwest China, improving the transport intensity and economic structure can effectively curb carbon emissions; Northwest China has great potential for solar energy and onshore wind energy resources and sufficient available land; these resources can be used to realize the local consumption of clean energy through industrial transformation. The southwest region is rich in natural gas reserves; consequently, we need to improve infrastructure building and modify this region's energy consumption structure.

## Conclusions

Measuring and analyzing the spatiotemporal characteristics and economic energy efficiency of carbon emissions from transportation are important for formulating effective policies for energy conservation and emission reduction. Based

on China's provincial carbon emission data from 2005 to 2019, this paper systematically analyzes spatiotemporal characteristics and regional differences, and proposes regional synergistic development as an effective way to improve China's transportation energy and economic efficiency. The main conclusions are as follows:

China's provincial carbon emissions indicated a slow rise from 2005 to 2019; the annual growth rate has fluctuated downward. Petroleum products have been the most major source, clean energy sources including electricity and natural gas climbed in percentage. The levels of transport carbon emissions among the 30 provinces varied significantly. Guangdong, Shanghai, and other areas in East and South China show higher carbon emissions, while Lower carbon emissions from transportation in northwest regions such as Ningxia and Qinghai. Qinghai, Anhui, and Fujian provinces had higher carbon emissions growth rates, while Inner Mongolia, Shandong, and Ningxia had lower growth rates. The total carbon emissions from transportation have a strong correlation with provincial economic development, while the carbon emission intensity is not. Carbon emissions from transportation show a trend of "eastern > western," and carbon emission intensity shows a trend of "northern > central > southern."

A positive spatial correlation was seen for transport carbon emissions. The geographical correlation of transport carbon emissions has gradually improved, and the transport carbon emission intensity was more significant. High-high clusters of transport carbon emission were manifested in the east, while low-low clusters were in the west. Jiangsu and Zhejiang were the sites of the high-high clusters, while low-low clusters were found in Xinjiang, Qinghai, and Gansu. High-high clusters of carbon emission intensity manifested mainly in the north of Hebei, Beijing, Tianjin, and Shanxi, while low-low clusters were found in the south of Fujian, Jiangxi, Hunan, Guizhou, Guangdong, Guangxi, Hainan, and Yunnan.

Differences of the transport carbon emission intensity slightly increased, that were significantly regionally correlated. There were seven forms of decoupling between yearly provincial transport carbon emissions and economic development, 83.33% of provinces realized decoupling, with weak decoupling accounting for the largest proportion, 45.24%. During 2005–2019, the number of regions experiencing expansion coupling and expansion negative decoupling decreased, while the number of decoupled regions increased and the decoupling elasticity gaps between different regions narrowed, and the GDP of transportation's reliance on energy decreased.

The energy intensity, transport intensity, and economic structure played an overall inhibitory role, while the carbon emission intensity, economic scale, and population played promoting roles. Economic scale was the most important



influencing factor, with a total contribution rate of 89.92%. The energy intensity, transport intensity, and economic structure were the key deterrents to carbon emissions in North and East China. The main factors inhibiting carbon emissions in Northeast and Central China were the transport intensity and economic structure. The main inhibitor of carbon emissions in South China was energy intensity. In Southwest and Northwest China, the main factors inhibiting carbon emissions were energy intensity, transportation intensity, and economic structure.

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**Data availability** All data materials analyzed during this study are included in this published article.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

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