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Research article

Temporal-spatial analysis of transportation CO_2 emissions in China: Clustering and policy recommendations

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A R T I C L E I N F O

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A B S T R A C T

Reducing transportation-related carbon dioxide (CO_2) emissions in China poses significant challenges due to the sector's growth potential and variations among provinces and transportation modes. This study utilizes the bottom-up approach and the Logarithmic Mean Divisia Index (LMDI) decomposition method to calculate transportation CO_2 emissions and explores the temporal-spatial differences across Chinese provinces. The results reveal that national transportation CO_2 emissions increased by 50.14% from 2010 to 2019, and emissions from private cars present the fastest growth among all transportation modes by 254% over the decade. Spatially, higher emissions are found in eastern provinces, and neighboring provinces notably distinguish from each other in terms of the emission proportion of different modes and the factor analysis from LMDI. Regarding the heterogeneity of the spatial emission characteristics, a cluster-based evaluation method is proposed for the 31 provinces according to the emission structure and the LMDI decomposition. Four clusters are derived, each featuring varied emission distribution and driving factors. Correspondingly, policy recommendations are proposed to address the characteristics of each cluster, such as controlling car ownership, promoting integrated transport modes, improving fuel economy, and electrifying urban transportation services. The cluster-based analysis method can provide more specific suggestions to province targeting its emission characteristics rather than its location, which is one of the major contributions of this study.

1. Introduction

Transportation is a significant contributor to carbon dioxide (CO_2) emissions, which have adverse effects on the environment and human health [1,2]. According to the International Energy Agency (IEA), fuel combustion from transportation accounted for approximately 24.5% of global CO_2 emissions in 2019, making it the second-largest sector. As a fast-growing economy and the world's largest carbon emitter, China faces enormous pressure to harmonize economic growth and carbon emissions. In China, the transport sector contributed 9.1% of national CO_2 emissions in 2019 [3]. As China's economy continues to grow, so does its transportation sector, resulting in a considerable increase in CO_2 emissions.

In order to reconcile this inherent contradiction, numerous emerging studies on CO_2 emissions reduction from transportation in China have been carried out. Despite the emergence of several studies addressing CO_2 emissions reduction within China's transportation sector [4,5], there are evident gaps in the existing research that warrant further investigation. Most studies employ either top-down methodologies [6,7], focusing on overall or specific modes of transportation [8–10], which pose challenges when attempting

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Nomenclature

Abbreviations

CO_2	carbon dioxide
GDP	gross domestic product
GTP	gross transportation product
IEA	International Energy Agency
LMDI	Logarithmic Mean Divisia Index
MaaS	Mobility-as-a-Service
Mt	million tons
TOD	transit-oriented-development

Symbols

C	the total transportation CO_2 emissions
C^0	the total transportation CO_2 emissions in 0 year
C^t	the total transportation CO_2 emissions in t year
$C_{ownership}$	the ownership transportation CO_2 emissions
$C_{turnover}$	the turnover transportation CO_2 emissions
c_i	the cluster to which it belongs
$d(c,\mu)$	the sum of the squared errors
D_{xk}	the relative contribution of kth influencing factor to the total transportation CO_2 emission
D_i	the mileage of the ith type vehicle
EC	total energy consumption of the transportation sector
ED	economic development factor
EE	energy use efficiency factor
E_i	the ith energy consumption
EI	CO_2 emission intensity factor
F_i	the ith energy CO_2 emission factor
M	the total number of samples
P	the scale of population development
P	population factor
s_i	the ith sample
TE	transportation economic share factor
T_i	the turnover for ith transportation mode
TI_{ij}	the energy intensity for ith transportation mode using the jth energy
TS	traffic CO_2 emission structure factor
V_i	the holding capacity of ith type vehicle
x_k	the kth influencing factor
μ_{ci}	the centroid of the cluster
ΔC_{xk}	the contribution of kth influencing factor to the change in total transportation CO_2 emissions from year 0 to target year t

comprehensive analyses across provinces and modes. Conversely, bottom-up approaches often concentrate on specific regions or individual transportation modes, limiting their scope to nationwide analyses across China's 31 provinces [11,12]. This results in a lack of in-depth exploration of the varied carbon emission structures among transportation modes across provinces in their decomposition analyses [13,14]. Furthermore, the predominant focus on historical-phase factors tends to overlook the significance of a provincial-level classification based on emission characteristics [15], hindering the development of precise, targeted emission reduction strategies.

Addressing these constraints, this study introduces a novel three-step clustering framework to tailor emission reduction strategies specific to China's transportation sector. It begins by employing a bottom-up model to compute CO_2 emissions for each province, encompassing various transportation modes. Subsequently, the Logarithmic Mean Divisia Index (LMDI) method identifies six influential factors affecting transportation CO_2 emissions. Finally, leveraging the K-means clustering algorithm, this study categorizes the 31 Chinese provinces based on their unique emission characteristics, providing custom policy recommendations aligned with individual emission profiles and socio-economic development. This focused approach shows promise in significantly contributing to China's efforts to reduce its overall CO_2 footprint and combat climate change, offering invaluable insights for policymakers and researchers dedicated to climate change mitigation efforts.

2. Literature review

To establish an eco-friendly transportation network in China and mitigate the concerning rise in carbon emissions within the transportation sector, a myriad of studies have proposed pragmatic recommendations from diverse angles, systematically organized in Table 1. Understanding emission characteristics plays a pivotal role in devising targeted emission reduction strategies, which these studies initiate through transportation CO_2 emission calculations. These models, varying in calculation scopes [16], encompass top-down [17,18], bottom-up [11,19], and hybrid bottom-up-top-down models [13,20]. To discern the driving factors of transportation CO_2 emissions, decomposition analysis methods were also employed, such as panel model [6,17], GWR-STIRPAT model [21,22], econometric method [23,24], and LMDI model [14,18]. Among them, LMDI model is widely used in the transportation field due to its residual-free decomposition, applicability, and ease of use and interpretation [14,25]. With the help of LMDI, emission factors, transport energy intensity, transport share effects, economic growth and population factors on transportation CO_2, energy structure effect, industrial structure factor, and travel propensity factor, traffic CO_2 structure factor were considered as major influence factors by various scholars [9,14,26].

While delving into historical-phase factors and distinct characteristics of transportation modes can inform potential policy recommendations for CO_2 emission reduction, the complex emissions landscape across China's provinces reveals significant disparities. Studies, such as that of Li et al., underscore the varied structure of transportation CO_2 emissions and socio-economic development across provinces, even among neighboring regions [13]. This diversity poses a substantial challenge in formulating a comprehensive strategy for CO_2 emission reduction across the transportation sector [7].

Traditionally, Chinese provinces have been categorized into east, central, and west based on their geographical and economic positions, guiding the formulation of emission reduction strategies for each region [18,21]. However, while cluster analysis has been effective in other domains such as electricity [32] and industry [15,33], its implementation in transportation, as observed in the work by Tian et al., didn't significantly diversify policy recommendations due to simpler classifications [29]. Consequently, there remains a gap in recommending targeted provincial emission reduction strategies within the transportation sector.

To bridge this gap, this research employs a comprehensive provincial-level model to calculate transportation-related CO_2 emissions. Employing the LMDI method and conducting cluster analysis across all 31 provinces, the study aims to analyze the factors influencing both national and provincial transportation-related CO_2 emissions in-depth. The primary goal is to provide technical analysis and policy recommendations supporting efforts to reduce CO_2 emissions within provincial transportation systems.

Table 1
Review of transportation CO_2 emissions researches in China.

Calculation methods	Analysis Method	Scale and Time	Transportation modes	Cluster	Source
Top-Down	Laspeyres complete decomposition approach, PLSR	China 1995–2006	Road freight	None	Wang et al. [8]
	Panel model	30 provinces in China 2000–2015	Total transportation	Geographical location	Lin et al. [17]
	Tapio, LMDI	30 provinces in China 2006–2015	Total transportation	Geographical location	Bai et al. [18]
	Updated emissions factors	30 provinces in China 2000–2012	Total transportation	None	Shan et al. [27]
	Dynamic panel quantile regression	30 provinces in China 2000–2016	Total transportation	None	Huang et al. [6]
	Tapio, LMDI	4 cities 2000–2016	Total transportation	None	Wang et al. [14]
	Tapio	Jiangsu 1995–2012	Total transportation	None	Wang et al. [10]
	STIRPAT, GTWR	30 provinces in China 2003–2017	Total transportation	Geographical location	Liu et al. [7]
Bttom-up	Gompertz function	31 provinces in China 2015–2050	9 vehicle types, 4 fuel types	None	Peng et al. [28]
	Moran's Iindex, M-R spatial decomposition model	Central Plains of China 2019	37 vehicle types, 3 fuel types	The Moran's Iindex	Zhao et al. [4]
		31 provinces in China 2000–2011	5 freight modes	Overall GHGs emission characteristics	Tian et al. [29]
	Moran's Iindex, GWR- STIRPAT Model	31 provinces in China 1988–2016	4 freight modes	Geographical location	Lv et al. [21]
	LMDI	Shanghai and Tokyo 1986–2009	8 urban transport modes	None	Luo et al. [26]
	PLSR Validation	7 cities 2000–2014	4 urban passenger transportation	None	Yuan et al. [5]
Bttom-up and Top-Down	Gini coefficient, Theil index, Moran index, LMDI	341 cities in China 2002–2013	4 transportation modes	Geographical and socio-economic factors	Li et al. [13]
		Beijing 2002–2013	4 urban passenger transport modes	None	Wang et al. [30]
	LMDI	31 provinces in China 1980–2007	4 passenger transport modes	Geographical location	Loo et al. [31]

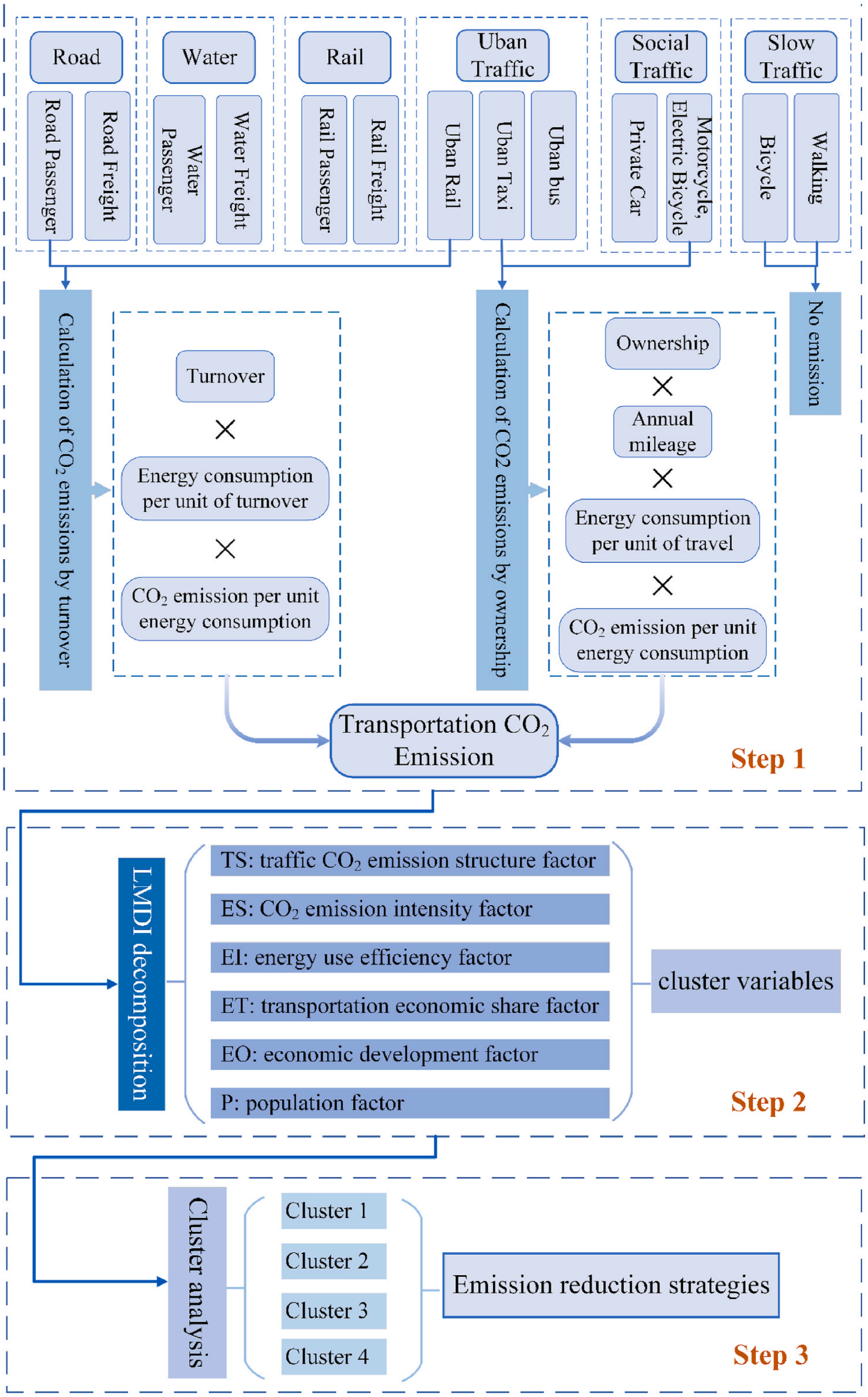

Fig. 1. The flow chart of the transportation CO_2 emission calculation and analysis.

3. Methodology

Fig. 1 delineates the procedural framework for the provincial transportation CO_2 emission reduction strategy recommendation method, which encompasses three fundamental steps. Firstly, it involves establishing a provincial transportation CO2 emission calculation model using available data, allowing for the computation of transportation-related CO_2 emissions across each province from 2010 to 2019. Secondly, the application of the LMDI model facilitates the decomposition and analysis of both national and provincial transportation CO_2 emissions. Finally, the six factors derived from the LMDI analysis serve as cluster variables to categorize the 31 provinces into four clusters. Each cluster undergoes a comprehensive analysis, culminating in the formulation of targeted transportation emission reduction policies. The detailed methodologies for these three steps are extensively outlined in the subsequent sections.

3.1. Transportation CO_2 emission calculation

Transportation CO_2 emissions is a product of the total energy consumption and the relevant CO_2 emission factors, as Eq. (1).

$$C = \sum_{i=1}^{n} E_i F_i \tag{1}$$

where, C is the total transportation CO_2 emissions, E_i is the energy consumption of the ith type, and F_i is the energy CO_2 emission factor of the ith type.

In order to analyze the inter features of the transportation CO_2 emissions, the total energy consumption should be decomposed into various traffic modes, and thus the "bottom-up" calculation method was employed. Based on the data collected from the transportation statical yearbook, the transportation CO_2 emission calculation can be conducted by two methods: the turnover method and the ownership method.

The turnover method is applicable to intensive transport mode such as freight and railway transport, of which the CO_2 emissions are counted per transported unit per kilometer. Turnover method calculates CO_2 emissions from the corresponding sectors using Eq. (2)

$$C_{turnover} = \sum_{ij} T_i \times TI_{ij} \times F_j \tag{2}$$

where, C_{turnover} is the turnover transportation CO_2 emissions, i is the traffic mode (e.g. road, waterway, air, rail, etc.); j is the energy type (e.g. gasoline, standard coal, electricity, etc.); T_i is the turnover for ith transportation mode (which can be obtained from annual

Table 2
CO_2 emission calculation data source.

Calculation of Emissions Through Turnover				
Traffic Modes	Turnover		Energy Consumption Per Unit of Turnover	CO_2 Emission Per Unit Energy Consumption
Road Freight	The statistical yearbooks of each province. (2011–2020) [35]		The China Statistical Yearbook. (2011–2020) [36]	The Guide to Provincial Greenhouse Gas Inventories (NDRC Climate [2011] No. 1041) [37] The BP China CO_2 Emissions Calculator [38].
Road Passenger	The statistical yearbooks of each province. (2011–2020) [35]		The China Statistical Yearbook. (2011–2020) [36]	
Water Freight	The statistical yearbooks of each province. (2011–2020) [35]		The China Statistical Yearbook. (2011–2020) [36]	
Water Passenger	The statistical yearbooks of each province. (2011–2020) [35]		The China Statistical Yearbook. (2011–2020) [36]	
Rail Freight	The statistical yearbooks of each province. (2011–2020) [35]		The Railway Statistical Bulletin. (2011–2020) [39]	
Rail Passenger	The statistical yearbooks of each province. (2011–2020) [35]		The Railway Statistical Bulletin. (2011–2020) [39]	
Urban Rail	The China Transport Statistical. (2011–2020) [40]		The Urban Rail Transportation Statistics and Analysis Report. (2011–2020) [39]	
Calculation of Emissions Through Ownership				
Traffic Modes	**Ownership**	**Annual Mileage**	**Energy Consumption Per Unit of Travel**	CO_2 **Emission Per Unit Energy Consumption**
Private Car	The statistical yearbooks of each province. (2011–2020) [35]	An updated emission inventory of vehicular VOCs/IVOCs in China [41]	The China Energy Conservation and New Energy Vehicle Development Research Report. (2015–2017) [41] The Announcement of the Average Fuel Consumption of Chinese Passenger Vehicle Enterprises [42]. The China Mobile Source Environmental Management Annual Report. (2011–2020) [43]	The Guide to Provincial Greenhouse Gas Inventories. (NDRC Climate [2011] No. 1041) [37] The BP China CO_2 Emissions Calculator [38].
Urban Taxi	The China Transport Statistical Yearbook. (2011–2020) [40]			
Urban Bus	The China Transport Statistical Yearbook. (2011–2020) [40]		The China Statistical Yearbook. (2011–2020) [36]	

statistics yearbook); TI_{ij} is the energy intensity for *i*th transportation mode using the *j*th energy; F_i is the CO_2 emission factors for *j*th energy.

For the ownership transportation CO_2 emissions, the data available in the statical yearbook is the holding capacity of the vehicles. Consequently, the ownership transportation CO_2 emission can be calculated by the vehicles holding capacity, vehicle mileages, the vehicles energy efficiency and the CO_2 emission factors, and it can be written as Eq. (3).

$$C_{ownership} = \sum_{ij} V_i \times D_i \times E_{ij} \times F_j \tag{3}$$

where, $C_{\mathrm{ownership}}$ is the ownership transportation CO_2 emissions, *i* is the traffic mode (e.g., private cars, taxis, buses, and urban rail transit, etc.), *j* is the energy type (e.g., gasoline, aviation fuel, electricity, etc.), V_i is the holding capacity of *i*th type vehicle, D_i is the mileage of the ith type vehicle, E_{ij} is the energy efficiency for the *i*th type vehicle using *j*th type energy, and F_j is the CO_2 emission factors for *j*th energy.

Finally, the total transportation CO_2 emissions can be calculated as Eq. (4):

$$C = C_{turnover} + C_{ownership} \tag{4}$$

3.2. Decomposition model for transportation CO_2 emissions

Based on Kaya's extended constant equation, the transportation CO_2 emissions can be decomposed into various influencing factors, and it can be written as Eq. (5) [34].

$$C = \sum_{i,j}^{n} C_{ij} = \sum_{i,j}^{n} \frac{C_{ij}}{C_j} \times \frac{C_j}{EC_j} \times \frac{EC_j}{GTP_j} \times \frac{GTP_j}{GDP_j} \times \frac{GDP_j}{P_j} \times P_j \tag{5}$$

where, *EC* is total energy consumption of the transportation sector; *GTP* is the gross transportation product; *GDP* is provincial gross domestic product; *P* is the scale of population development, *i* is transport mode, *j* is province.

As the influencing factors $\frac{C_{ij}}{C_j}, \frac{C_j}{EC_j}, \frac{EC_j}{GTP_j}, \frac{GTP_j}{GDP_j}, \frac{GDP_j}{P_j}, P_j$ in Eq. (5) all have physical meanings, thus, Eq. (5) can be rewritten as Eq. (6):

$$C = \sum_{i,j}^{n} TS_{ij} \times EI_j \times EE_j \times TE_j \times ED_j \times P_j \tag{6}$$

where $TS_{ij} = C_{ij}/C_j$ is traffic CO_2 emission structure factor (*TS*), $EI_j = C_j/EC_j$ is CO_2 emission intensity factor (*EI*), $EE_j = EC_j/\ GTP_j$ is energy use efficiency factor (*EE*), $TE_j = GTP_j/GDP_j$ is transportation economic share factor (*TE*), $ED_j = GDP_j/P_j$ is economic development factor (*ED*), P_j is the population factor (*P*).

To identify the influence factor contribution ratio on the total transportation CO_2 emission, the aggregate changes from $C^0 = \sum_i x^0_{1,i} x^0_{2,i} \cdots x^0_{n,i}$ in year *0* to $C^t = \sum_i x^t_{1,i} x^t_{2,i} \cdots x^t_{n,i}$ in year *t* can be calculated. It can be decomposed by two methods, namely the multiplicative decomposition method and the additive decomposition method. In this study, we employed the additive decomposition method, which is written as:

$$\Delta C_{tot} = C^t - C^0 = \Delta C_{x_1} + \Delta C_{x_2} + \cdots + \Delta C_{x_n} \tag{7}$$

In Eq. (7), the effect of the kth factor on the transportation CO_2 emissions in the right side can be written as Eq. (8):

$$\Delta C_{x_k} = \sum_i \frac{C^t_i - C^0_i}{\ln C^t_i - \ln C^0_i} \ln \left(\frac{x^T_{k,i}}{x^0_{k,i}} \right) \tag{8}$$

where, x_k is the kth influencing factor, including *TS*, *EI*, *EE*, *TE*, *ED* and *P*, ΔC_{x_k} is the contribution of kth influencing factor to the total transportation CO_2 emissions change from year *0* to target year *t*.

Besides that, the relative effect of *k*th factor on the total transportation CO_2 emissions can be calculated as Eq. (9):

$$D_{x_k} = \frac{\Delta C_{x_k}}{\Delta C_{tot}} \tag{9}$$

3.3. Cluster-based analysis of CO_2 emissions and socio-economic development

The K-means method is utilized to analyze the transportation CO_2 emission characters in 31 provinces and cities of China in a cluster base. The emission proportion of different transportation sectors (denoted as TS_{ij}), and five LMDI-derived factors, $EI_j EE_j$, TE_j, ED_j, and P_j spanning 10 years (2010–2019), were utilized as clustering feature vector for 31 provinces. Prior to clustering, the data is normalized to the same magnitude, and the outliers are filtered out. To determine the optimal number of clusters, K values ranging from 1 to 10 are tested, and the elbow method is used to determine the final K value. Finally, K-means is employed to cluster the 31 provinces.

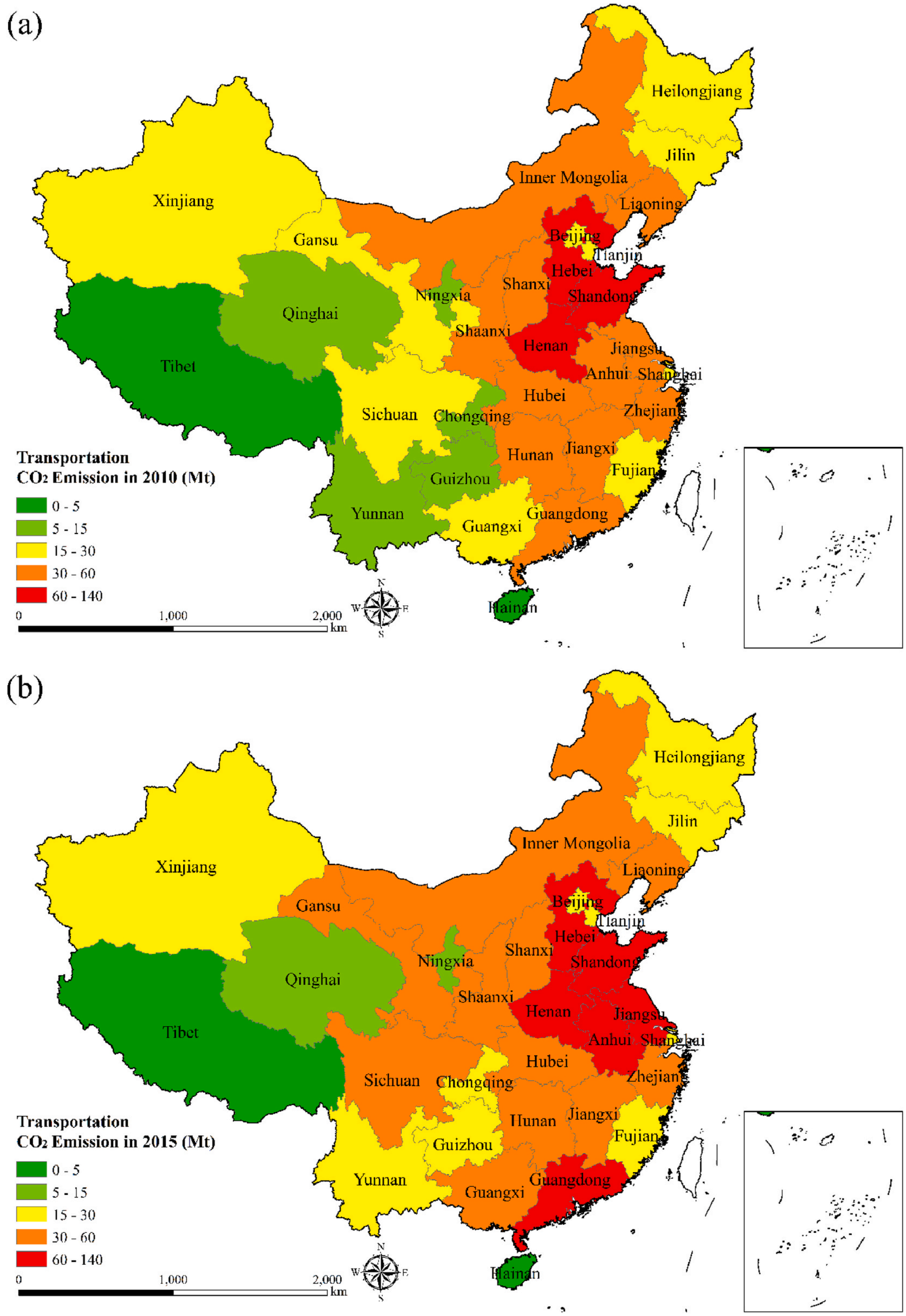

Fig. 2. Temporal distribution of provincial transportation CO_2 emissions, (a) provincial transportation CO_2 emissions in 2010, (b) provincial transportation CO_2 emissions in 2015, (c) provincial transportation CO_2 emissions in 2019

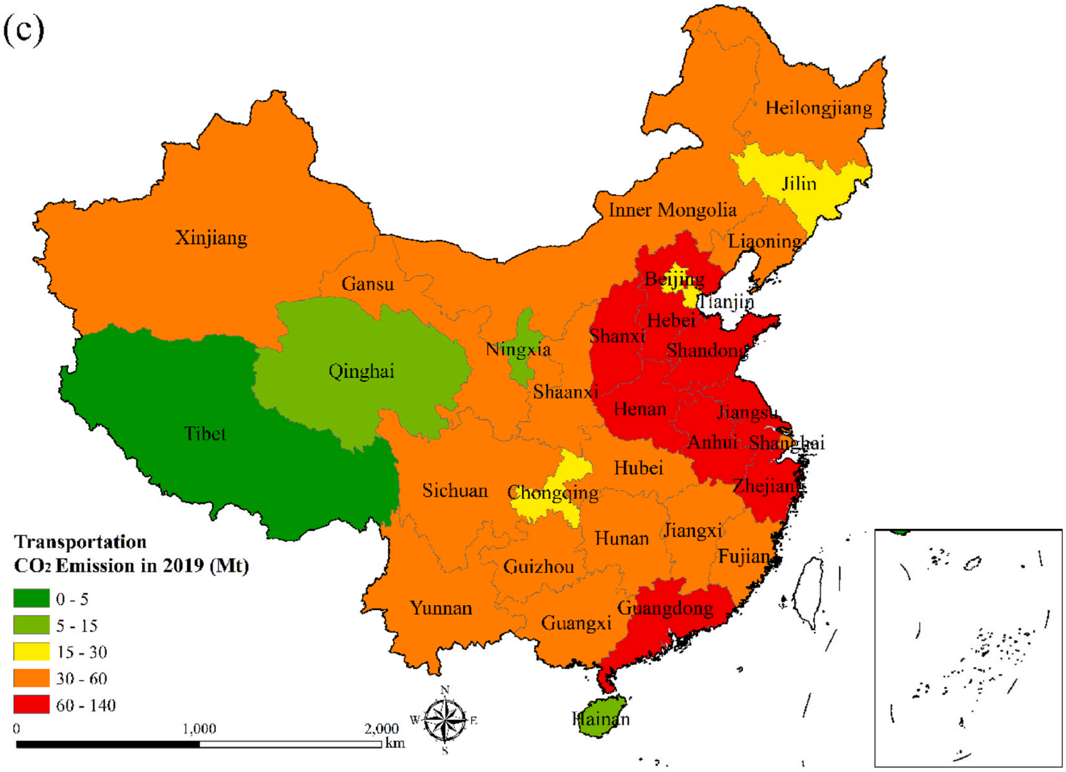

Fig. 2. (*continued*).

4. Date source collection and data analysis

To accurately calculate transportation CO_2 emissions, reliable traffic data is crucial, which can be classified into four main categories: transportation activity level data, energy efficiency data for various transportation modes, CO_2 emissions factors data for various energy sources, and LMDI analysis data. To ensure the accuracy of the data, information was primarily sourced from official yearbooks and reports, with detailed references listed in Table 2. It's important to note that the data in Table 2 covers the period from

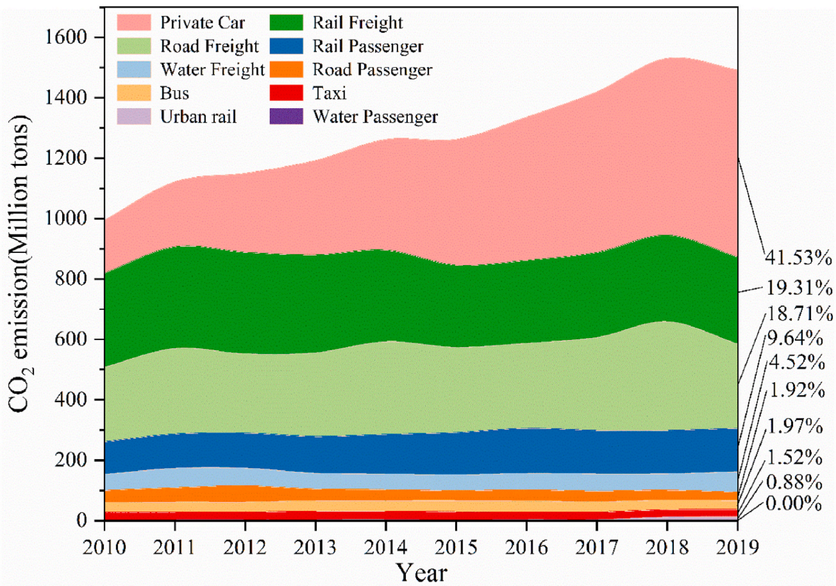

Fig. 3. Trends in CO_2 by transportation sectors during 10 years.

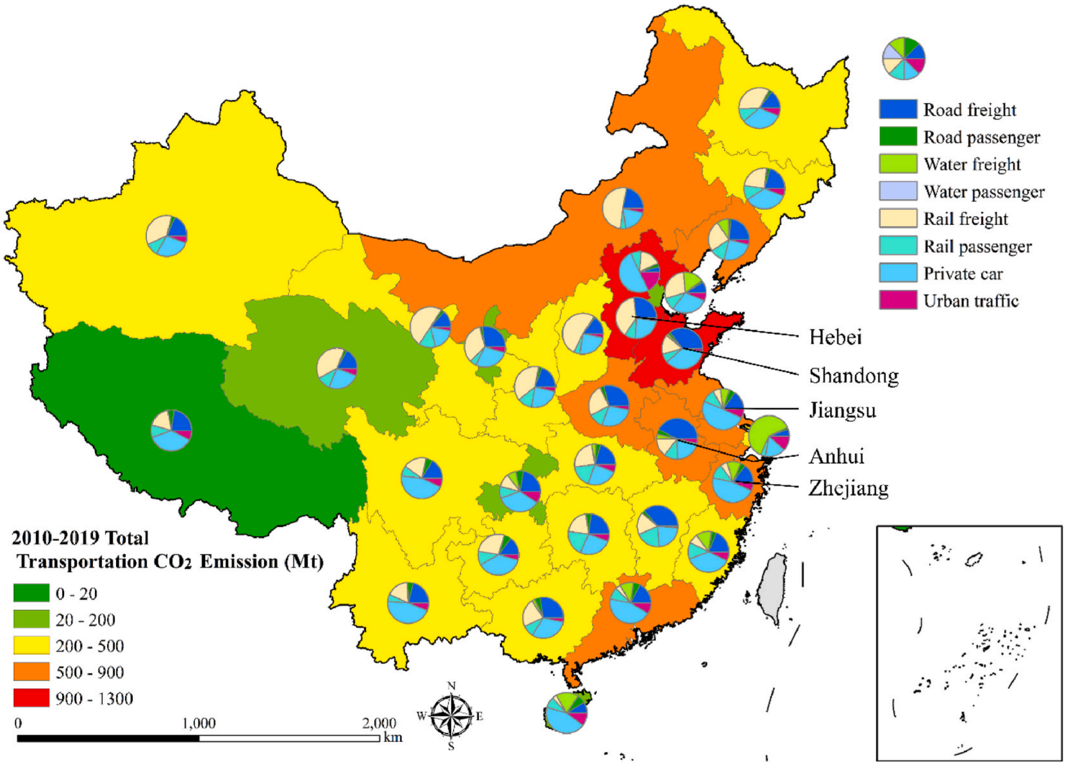

Fig. 4. CO_2 emission structure of transportation in Provinces from 2010 to 2019.

2011 to 2020 due to the typical inclusion of CO_2 emission data in the statistical yearbook of the subsequent year.

The transportation activity level data is of utmost importance for CO_2 emissions calculation, which includes turnover and holding capacity of various transportation modes and the corresponding emission factors. Data on operational passenger and freight transportation turnover for highways, waterways, and railroads, as well as private car holding capacity, were obtained from the 2011–2020 statistical yearbooks of every province in China [35]. Meanwhile, data on operating mileage of rail transportation, buses, and taxis were sourced from the 2011–2020 China Transport Statistical Yearbook [40]. The annual operating mileage of private cars and taxis was obtained from Liu et al.'s research results [41].

The energy efficiency data for different transportation modes is also critical, which was obtained from various official reports. For example, the China Statistical Yearbook 2011–2020 [36] provides data on energy efficiency of highway, waterway passenger and freight transportation, and bus. For railroad passenger and freight transportation, the Railway Statistical Bulletin 2011–2020 [39] was used. Data on the total vehicle electric energy consumption of urban rail transportation was obtained from the 2011–2020 Urban Rail Transportation Statistics and Analysis Report [44]. To calculate the energy efficiency of private cars and taxis, several reports, such as the China Energy Conservation and New Energy Vehicle Development Research Report (2015–2017) [45], the Announcement of the Average Fuel Consumption of Chinese Passenger Vehicle Enterprises (2018–2020) [42], and the annual percentage of vehicles with different emission standards from the China Mobile Source Environmental Management Annual Report [43], were referenced.

Data on CO_2 emissions factors for various energy sources was also collected from different sources, including the BP China CO_2 Emissions Calculator [38] and the Guide to Provincial Greenhouse Gas Inventories [37]. Additionally, regional grid CO_2 emission factors were obtained from data published by the Ministry of Environment and Ecology of the People's Republic of China and the National Center for Climate Strategy [36,46].

Finally, to apply the LMDI decomposition model for the analysis, necessary data, such as GDP, population, GDP per capita, economic structure, the gross transportation product (GTP), and total energy consumption in transportation, storage, and postal industry, were collected. These data were gathered from the 2011–2020 Provincial Statistical Yearbooks [35] and the China Statistical Yearbook [36]. It's worth noting that GTP is represented as the total values of the transport, storage, and postal sector. By gathering and analyzing data from four categories, transportation CO_2 emissions can be calculated and decomposed, and effective strategies to reduce them can be developed.

5. Results and discussions

5.1. Temporal-spatial distribution of provincial transportation CO_2 emissions

Transportation CO_2 emissions for all provinces in China from 2010 to 2019 were calculated. The total CO_2 emissions from transportation during this period amounted to 12,755.54 million tons for the entire country, excluding Hong Kong, Macau, and Taiwan due to limited data availability. In Fig. 2, the spatial distribution of provincial transportation CO_2 emissions is visually depicted for the years 2010, 2015, and 2019. Over the decade from 2010 to 2019, China observed a substantial rise in total CO_2 emissions from transportation, fueled by the country's rapid economic growth and burgeoning transportation demands. This surge marked an increase from 993.53 million tons in 2010 to 1491.67 million tons in 2019, reflecting a noteworthy 50.14% growth over the ten-year period.

Additionally, the figure reveals a noticeable trend of transportation CO_2 emissions gradually shifting from coastal areas towards inland regions, essentially from east to west, a pattern well-documented in prior research [18,21]. This shift predominantly roots in the rapid economic advancements of China's coastal provinces, distinguished by well-established transportation infrastructure and sustained high demand for transportation services, consequently resulting in elevated CO_2 emissions from transportation in these coastal zones. Simultaneously, the implementation of China's Western Development Strategy has triggered a rapid upswing in CO_2 emissions from transportation in the western regions, signifying the potential for a substantial increase in China's future transportation CO_2 emissions.

In Fig. 3, an analysis of the evolving trends in transportation CO_2 emissions across various sectors is presented. While there have been improvements in the energy efficiency of private vehicles due to advancements in engine technology and stricter emission standards, the CO_2 emissions of private cars surged significantly by 254% over the decade. This growth was propelled by the rising living standards and increased ownership of private vehicles, constituting 41.53% of total private vehicle emissions in 2019. Urban transport modes such as buses, taxis, and urban rail also exhibited growth, with CO_2 emissions increasing by 6.52 million tons (10.75%) over the decade. This rise can be attributed to accelerating urbanization and robust policies promoting public transport.

Despite advancements in energy efficiency for high-speed trains, CO_2 emissions from railway passenger transport increased by 33.79% from 2010 to 2019. This escalation primarily resulted from the continuous enhancement and expansion of the high-speed rail network at a national level, alongside increased promotion of railway travel. Freight modes—water, road, and rail freight—contributed significantly to the total CO_2 emissions, accounting for 42.37% during this period. Notably, road freight witnessed a 13.09% increase in the past decade, constituting the highest proportion (44.64%) of emissions within the freight sector, attributable to the extensive expressway network in China and the convenience of door-to-door service.

Fig. 4 provides a visual representation of the spatial distribution of total provincial transportation CO_2 emissions over the ten-year period. It is evident that the provinces surrounding Beijing exhibited the highest CO_2 emissions. This can be attributed to Beijing's role as a fossil energy hub and its substantial demand for heavy freight transportation in China. Conversely, Tibet, Hainan, Qinghai, and Ningxia recorded the lowest emissions due to their abundant renewable energy resources and lower transportation demands compared to other provinces.

While transportation serves as a means of connecting all provinces, the structure of transportation CO_2 emissions varies

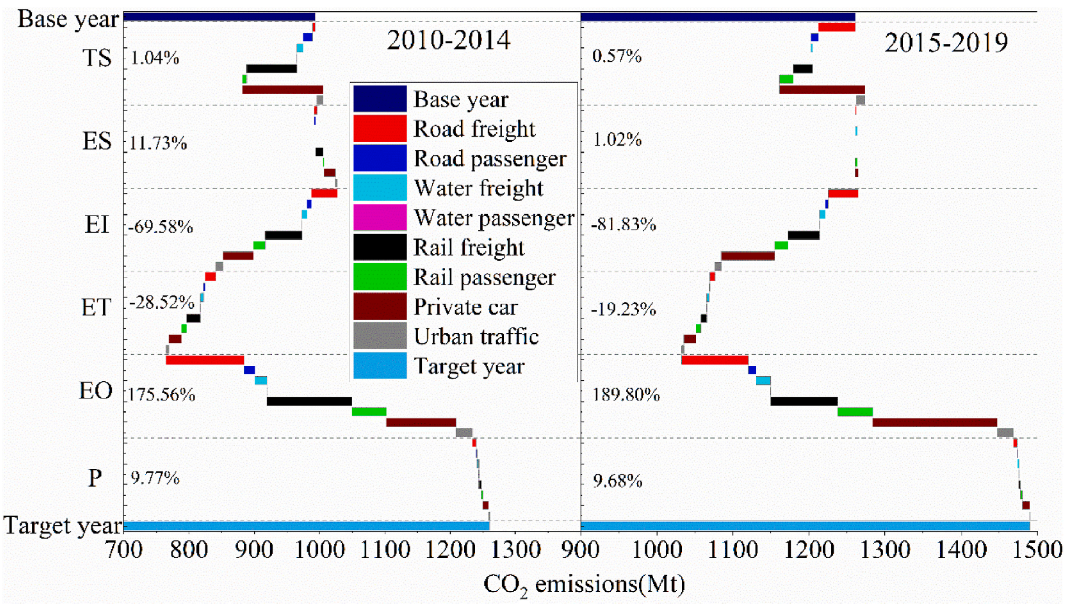

Fig. 5. Driving Factors for Temporal-Spatial Differences in Provincial Transportation CO_2 Emissions in 2010–2014 period and 2015–2019 period. The two periods share the same legend.

significantly among them, as depicted in Fig. 4. Even neighboring provinces display notable differences in their CO_2 emission structures. For instance, Jiangsu Province and Anhui Province in the Eastern region and Yangtze River Delta area demonstrate contrasting emission profiles. In Jiangsu, private cars contribute the most to CO_2 emissions, whereas in Anhui, road freight plays a dominant role. Similarly, Hebei and Shandong Provinces exhibit substantial disparities in their CO_2 emission structures, with rail freight being prominent in Hebei, while private cars and road freight hold greater significance in Shandong. Conversely, some provinces exhibit similar CO_2 emission structures, such as Jiangsu and Zhejiang Provinces, showing the close relationship between transportation CO_2 emissions and economic characteristics.

Based on these findings, it can be concluded that there is a strong correlation between transportation CO_2 emissions, economic characteristics, and technological development. The rapid growth of the economy leads to increased transportation demand, which, in turn, contributes to higher CO_2 emissions. While technological advancements can help reduce emissions, their effectiveness may be limited in offsetting the growth in demand. Therefore, additional measures and strategies are necessary to address the environmental impact of transportation. Furthermore, national or local policies play a crucial role in shaping transportation CO_2 emissions. Policy interventions, such as the implementation of the “truck-to-rail" policy in 2018, can have a significant impact on reducing CO_2 emissions in the road freight sector at a national level. These policies play a crucial role in promoting sustainable transportation practices and mitigating the environmental impact of transportation activities.

In summary, transportation CO_2 emissions are influenced by economic growth, economic structure, technological advancements, and policy interventions. To effectively reduce these emissions, a comprehensive approach is required that combines sustainable economic development, innovative technologies, and supportive policies aimed at promoting environmentally friendly transportation systems.

5.2. *Driving factors for temporal-spatial differences in provincial transportation CO_2 emissions*

5.2.1. *LMDI analysis in different time spans*

The provincial transportation CO_2 emissions in China display notable variations both temporally and spatially. By applying the LMDI decomposition method, insights into the temporal-spatial disparities in national transportation CO_2 emissions are revealed in Fig. 5. Apart with the potential driving factors contributed to the total CO_2 emissions, the contribution of potential driving factors on the CO_2 emissions of various traffic modes for different periods were also calculated and illustrated in Fig. 5. Compared with the period of 2010–2014, although the contribution of these influencing factors followed a similar trend, the degreed of the impact varies across different factors for both the total emission and different transportation sectors due to the decarbonization policy and technology development during the period of 2015–2019.

Fig. 6. Provincial transportation CO_2 emission cluster distribution.

The economic development (*ED*) significantly impacts transportation CO_2 emissions during both the 2010–2014 and 2015–2019 periods, leading to increased emissions across various transportation modes, notably road freight, rail freight, rail passenger, and private cars. The expansion of high-speed rail infrastructure and the increasing living standards contribute to this effect. It is crucial to focus on controlling private car emissions while promoting economic development, considering the continued growth of private car ownership. Measures such as license control, electric vehicle promotion, and the railway and water transportation infrastructure improvement can be implemented.

The population (*P*) and emission intensity (*EI*) have limited influence on transportation CO_2 emissions. Both factors show a weakening trend from 2010 to 2019, with the declining population growth rate diminishing the role of *P* in emission growth. On the other hand, referring to *EI*, continuous efforts to improve vehicle emission standards have reduced CO_2 emissions from private cars, road passenger, and freight transportation, particularly during the 2015–2019 period. Electrification of the railway system has also contributed to the reducing driving effect of *EI*. Further emission reduction can be achieved through research and development of energy utilization efficiency, implementation of supportive policies, and their adoption in the commercial transportation sector.

The impact of the Traffic Structure (*TS*) on transportation CO_2 emissions is generally minimal but varies across different transportation modes. It increases CO_2 emissions from private cars while reducing emissions in other sectors. Thus, enhancing public transportation and shifting to public commuting options are essential. *TS* factor played a significant role in reducing CO_2 emissions from railway freight during the 2010–2014 period, but its effect weakened during 2015–2019. Conversely, it had a stronger reduction effect on road freight for 2015–2019 compared to 2010–2014. Although the *TS* factor contributes relatively little to the total transportation CO_2 emissions, its varying performance across different traffic sectors provides evidence for the development of relevant decarbonization policies. By optimizing the traffic structure, transportation emissions can be effectively reduced, contributing to overall decarbonization efforts.

The Energy use Efficiency (*EE*) and Transportation Economic share (*TE*) are key drivers in reducing transportation CO_2 emissions. Improving energy use efficiency through EE factor leads to emissions reduction, particularly in private cars due to the implementation of emission standards. Investing in research and development, supportive policies, and implementation in the commercial transportation sector is recommended. *TE*'s inhibitory effect has diminished due to insufficient transport capacity, low organization and efficiency, and inadequate infrastructure. Optimization of transportation speed, information intelligence, and eco-friendly approaches are crucial to control CO_2 emissions and counteract the weakening effect of *TE*.

5.2.2. LMDI effects in different provinces

By analyzing the trends of driving factors for transportation CO_2 emissions in the Eastern, Central, Western, and Northeastern provinces of China, it is evident that the *ED* emerges as the only factor promoting emissions in all provinces in China, the details can be found in Supplementary Material 1. However, the promoting effect of the economic factor has declined in the northern regions due to recent economic growth slowdown, while the southern provinces have maintained a relatively fast growth rate. Notably, Anhui Province stands out for effectively controlling transportation CO_2 emissions despite significant economic growth, thanks to measures such as optimizing transportation infrastructure and service structure.

The factors of *P*, *EI* and *TS* have slight promoting or inhibiting effects on transportation CO_2 emissions across different provinces. The population (*P*) inhibits emissions in most northern provinces due to population outflow, whereas active economic provinces in the south and developing regions in the west experience a growth effect. The *EI* fluctuates across the 31 provinces, primarily driven by regions with rapid economic growth and consequently a significant increase in private car ownership. The *TS* adjustment has a significant impact on the CO_2 emissions of various sectors, while its influence on overall emissions is relatively small across most provinces, because the overall emissions keep in stable. Adjusting transportation structures, promoting public transportation, and shifting towards rail or water transportation can mitigate the promoting effect of *EI* on transportation CO_2 emissions.

Table 3
Features of four clusters, including emission structure and decomposition factors.

Cluster Center	National Average Level	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Road Freight	22.63%	18.14%	19.44%	24.63%	4.86%
Road Passenger	3.01%	5.02%	2.85%	2.09%	2.14%
Water Freight	4.45%	6.35%	2.24%	1.95%	30.40%
Water Passenger	0.00%	0.00%	0.00%	0.00%	0.00%
Rail Freight	23.62%	12.78%	29.64%	32.36%	8.64%
Rail Passenger	10.27%	9.61%	13.37%	9.79%	6.04%
Private Car	31.04%	41.09%	26.96%	25.61%	33.24%
Urban Traffic	4.97%	7.01%	5.49%	3.57%	14.68%
EI (ton/ton standard coal)	3.72	2.76	3.19	5.28	1.29
EE (ton standard coal/ten thousand yuan)	1.44	1.35	1.84	1.14	2.47
TE (%)	4.94	4.19	4.56	6.15	3.06
ED (thousand yuan/person)	49.58	49.79	41.03	43.15	112.74
P (million person)	43.22	49.93	38.62	42.78	22.82

Note: * the cluster center contains the average CO_2 shares for 2010–2019 for the eight transportation sectors in the transportation CO_2 emission structure factor and the other five influencing factors.

Regarding the two main factors that inhibit transportation CO_2 emissions, *EE* and *TE*, their performance varies across provinces. Over the past decade, most provinces have seen improvements in transportation energy efficiency, which has curbed the growth of CO_2 emissions. Among all the provinces, the most significant changes occurred in Anhui and Hebei. *EE* changed from a promoting effect in the 2010–2014 period to an inhibiting effect in the 2015–2019 period in Anhui due to the improvement of the transportation efficiency, while the reverse is true for Hebei due to the industrial recovery and industry transfer. *TE* demonstrates a strong inhibiting effect in provinces where the transportation industry has already developed due to limited transportation investments. However, in provinces with rapidly developing transportation infrastructure, such as Shandong and Henan, promoting effect of *TE* is revealed. Therefore, as the demand for infrastructure construction decreases, the inhibiting effect of *TE* factor is expected to be strengthened.

In conclusion, the driving factors for transportation CO_2 emissions exhibit different trends across provinces. Economic development remains the primary promoting factor, but its effect varies due to provincial economic growth variations. *P*, *TS* and *EI* have slight promoting or inhibiting effects across various provinces, while *EE* and *TE* play significant roles in curbing emissions. Understanding these driving factors and their provincial variations is crucial for formulating effective policies and strategies to mitigate transportation CO_2 emissions in different provinces.

5.3. Clustering analysis and policy recommendations for provincial transportation CO_2 emissions

According to the aforementioned analysis, provinces exhibit varied characteristics in terms of transportation CO_2 emissions and associated decomposition factors. To develop targeted decarbonization policies, provinces were classified into four clusters based on the similarity of their decomposition factors using the elbow method. The results were shown in Fig. 6 and Table 3.

Cluster 1 consists mainly of developed regions or regions in a rapid development stage. This cluster is characterized by a high proportion of CO_2 emissions from private cars (41.09%), with the population factor a significant contributor above the national average level. Additionally, some provinces in this cluster, such as Tibet, are constrained by natural geographic characteristics, limiting the development of specific transportation modes other than road traffic. Therefore, policies to improve the service of integrated transport modes and restrict the use of road transport can be proposed, and the following policy recommendations are suggested: first, implementing measures to control car usage, such as congestion pricing, carpooling incentives, and restrictions on vehicle ownership; second, improving the convenience and accessibility of greener transportation modes, including expanding and enhancing railway and public transit networks; in addition, encouraging the adoption of electric and hybrid vehicles through incentives, subsidies, and charging infrastructure development; finally, implementing vehicle scrappage policies to improve overall fuel efficiency and promote the use of cleaner vehicles.

Different from *Cluster 1* featured on high emissions from private vehicles, *Cluster 2* stands out for its high proportion of CO_2 emissions from railway transport, particularly railway passengers, surpassing the national average level, which attributes to the presence of a well-developed railway infrastructure network in these regions. The *EE* factor has a major negative impact on total transport emissions in this cluster. To reduce emissions in similar provinces of *Cluster 2*, actions to improve the energy efficiency of railway system are highly encouraged. At the same time, the following policy recommendations are suggested, including upgrading the fuel standard, improving railway operation efficiency, and railway electrification.

Cluster 3 exhibits similar CO_2 proportions in railway transport as *Cluster 2*, with rail freight reaching an even higher proportion at 32.36%. Another noteworthy feature of *Cluster 3* is the proportion of the road freight sector, contributing to 24.63% of the total provincial emissions and higher than the national average level by 8.82%. This may be contributed by the economic structure of these provinces featuring on high proportions of industry and agriculture, both requiring intensive freight resources. Regarding regions with similar features of *Cluster 3*, policies should focus on reducing the emissions of bulky freight and improving the share of integrated freight modes, such as 1) to improve the fuel economy standards and promote the use of cleaner energy trucks for the road freight sector, and 2) to encourage the shift from road freight to rail freight by investing in railway construction and optimizing scheduling.

Cluster 4 differs from the other clusters, exhibiting extremely high CO_2 emissions from the urban transport sector, representing the CO_2 distribution in large municipalities. In this cluster, the decomposition factors of *EE* and *ED* have a significant impact on total emissions, exceeding the national average level. However, the effects of the other three factors are negligible compared to the other clusters. The electrification of urban traffic, the prioritization of public transit and the promotion of active modes can correspondingly lead to reduced CO_2 emissions in such regions. Policy recommendations can be proposed from four aspects: 1) the electrification of urban transit services, including buses, taxis, and other public transportation vehicles, to reduce emissions from *EI* factor; 2) implementing transit-oriented-development (TOD) urban planning strategies to reduce the need for long-distance commuting and to promote active transportation modes; 3) introducing mobility management initiatives, such as Mobility-as-a-Service (MaaS) [47–49], to provide integrated and sustainable transportation options for urban residents; and 4) incentivizing the use of green travelling behavior, such as the Carbon Credit program [50,51].

5.4. Implications of the results and limitations

The findings of this study stand to significantly influence the landscape of provincial transportation CO_2 emission policies. By segmenting Chinese provinces through the k-means method, a comprehensive framework has emerged, providing specific strategies tailored to curtail CO_2 emissions within the transportation sector. This granular approach offers a sophisticated roadmap, empowering policymakers and researchers to access and adapt validated strategies from provinces sharing similarities within the same cluster. This targeted methodology represents a promising avenue, offering a nuanced, effective means to mitigate and reduce CO_2 emissions in transportation, presenting an invaluable resource for stakeholders actively engaged in climate change mitigation efforts.

Nonetheless, it's crucial to acknowledge the limitations that could affect the robustness of these conclusions. The reliance on national averages due to the absence of province-specific CO_2 emission factors introduces a potential bias in estimating provincial transportation CO_2 emissions. This discrepancy could significantly impact the overall characters of provincial CO_2 emissions, especially if provincial factors markedly differ from national averages. To bolster the accuracy and reliability of future analyses, there's a pressing need to broaden the CO_2 emission factor database. By expanding this dataset, future assessments can achieve a more refined and precise estimation of provincial transportation CO_2 emissions.

Addressing these limitations holds paramount importance in refining future policy recommendations and strategies tailored to abating transportation-related CO_2 emissions. By fortifying the methodology and data sources, subsequent efforts can better guide and support policymakers and researchers in their endeavors toward sustainable climate action.

6. Conclusion

This research introduces a novel clustering framework aimed at formulating province-specific strategies for reducing CO_2 emissions within China's transportation sector. Employing a bottom-up model for temporal-spatial analysis, the study identifies six key driving factors using the LMDI method to understand the intricate dynamics influencing CO_2 emissions. The subsequent K-means clustering method categorizes China's provinces into four clusters, each tailored to specific policy recommendations.

The study uncovered a notable surge of 31.04% in China's transportation CO_2 emissions from 2010 to 2019, predominantly driven by private cars. Spatial analysis reveals distinct regional patterns, with higher emissions in the east compared to the west, showcasing varied emission structures among provinces. Notably, economic development emerged as a pivotal driver of CO_2 emissions, especially prominent in coastal and riverine areas, while energy intensity played a crucial role, notably within private car segments.

These findings underscore the significant roles of economic development and energy intensity in shaping emission trends across diverse transportation modes and provinces. The clustering approach, categorizing provinces into four distinct groups, suggests tailored strategies for emission reduction. Policymakers and researchers can leverage similarities within clusters to adapt proven strategies, enhancing the effectiveness of emission reduction initiatives.

To further validate and refine these findings, future research will concentrate on evaluating proposed policies through scenario simulations. Analyzing the economic and social impacts of these policies, alongside exploring innovative technological solutions within the transportation sector, will offer a comprehensive assessment of the feasibility of specific policy actions.

Ethical approval

The data collected for this project received the necessary clearance from the University Ethics Review board and was collected with the consent of the participants involved in the study.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

CRediT authorship contribution statement

Linfeng Zhang: Writing – review & editing, Writing – original draft, Conceptualization. **Jiaran Wei:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Ran Tu:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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