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Yu, Bolin; Xu, Zhenci; Du, Congcong; Xu, Jinghang; Pan, Yuling; Zhou, Junfang; Shan, Yuli

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Original Articles

Spatiotemporal evolution and drivers of carbon inequalities in urban agglomeration: An MLD-IDA inequality indicator decomposition

Bolin Yu[a,b], Zhenci Xu[b,*], Congcong Du[c], Jinghang Xu[d], Yuling Pan[e], Junfang Zhou[f], Yuli Shan[d,g,*]

[a] School of Economics and Management, Wuhan University, Wuhan 430072, China
[b] Department of Geography, The University of Hong Kong, Hong Kong 999077, China
[c] Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China
[d] School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham B15 2TT, United Kingdom
[e] School of Economics and Management, China University of Mining and Technology, Xuzhou 221116, China
[f] School of Urban Design, Wuhan University, Wuhan 430070, China
[g] Integrated Research on Energy, Environment and Society (IREES), Energy and Sustainability Research Institute Groningen (ESRIG), University of Groningen, Groningen 9747 AG, the Netherlands

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ABSTRACT

Increasing countries are articulating ambitious goals of carbon neutrality. However, large inequalities in regional emissions within a country may hinder progress toward a carbon–neutral future, as the unequal distribution of reduction responsibilities among regions could impair just transition and exacerbate uneven development, which necessitates an in-depth understanding of the mechanism of multi-scale carbon inequalities within country, region, and city. Yet, the evolution of carbon inequalities within urban agglomerations and the differences between adjacent or distant urban agglomerations have not been well understood, especially in countries undergoing rapid urbanization. Using the data of 89 cities in China's Yangtze River Economic Belt (YREB) during 2006–2021, this paper quantifies carbon emissions inequality (CEI) at different scales in a systematic regional-urban agglomeration-city hierarchical structure. Then, under the integrated mean logarithmic deviation-logarithmic mean Divisia index (MLD-LMDI) decomposition framework, multi-scale CEIs are perfectly decomposed into six interrelated drivers, i.e., industrial emission structure, energy emission intensity, industrial energy mix, energy intensity, industrial structure, and economic development. The results show that economic development, energy intensity, and industrial energy mix disparities are the main determinants accounting for CEIs at different scales. The decreasing CEI in YREB is mainly due to the changes in industrial structure and economic development, while the energy intensity effect partially hinders the mitigation of CEI. In the upper reaches of the YREB, the energy intensity effect accounts for over 94% growth of CEI during 2006–2021, while the decline in CEIs in middle and lower reaches is primarily caused by the effects of industrial energy mix and industrial structure, respectively. Further spatial decomposition analysis reveals more refined city-level heterogeneous effects and emphasizes the prioritized emission reduction direction for each city. This paper offers implications for reducing carbon inequality and insights into coordinated carbon emissions mitigation at the regional level for a carbon–neutral future.

1. Introduction

Climate change is a global challenge with wide-ranging effects on society, the economy and the environment, involving ecosystems, health, human well-being, agricultural production, water availability, etc. (Crost et al., 2018; Pecl et al., 2017; Scholze et al., 2006). Climate change mitigation requires joint climate actions from the international community (Wang et al., 2023). To align with the sustainable development goals (SDGs) related to climate action, China proposed to achieve carbon peak by 2030 and carbon neutrality by 2060 (Pan and Dong,

* Corresponding authors at: School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham B15 2TT, United Kingdom (Yuli Shan).

E-mail addresses: xuzhenci@hku.hk (Z. Xu), y.shan@rug.nl, y.shan@bham.ac.uk (Y. Shan).

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2023b). However, carbon emissions vary considerably across China's regions (Lu et al., 2022), resulting in uneven distribution of emission reduction responsibilities and burdens, resource allocation, and hindering progress toward a carbon–neutral future.

The unequal regional carbon emissions in China necessitate comprehensive policies and strategies to ensure that emission reduction efforts not only make progress in low-emission regions but also assist high-emission regions in achieving their carbon reduction goals. The investigation of the carbon emissions inequality (CEI) and the associated drivers is the prerequisite for developing effective regionally coordinated emissions reduction policies. This, in turn, will enable regional cooperation in carbon reduction efforts and make progress towards the overarching national carbon neutrality objective.

In recent decades, China has undergone rapid urbanization, leading to the emergence of urban agglomerations and signifying a shift towards new economic and governance models (Zhang and Su, 2016). As a consequence, this urbanization wave has led to notable implications for resource utilization and environmental sustainability, underscoring the importance of city-level carbon mitigation efforts (Shan et al., 2022). The Yangtze River Economic Belt (YREB) along the Yangtze River (China's longest river and also the third longest river globally) is home to over 40 % of China's total population and economic output (NDRC, 2016) and has become an economic growth engine in China (Luo et al., 2020b). Covering 21.4 % of China's land area, the Yangtze River Basin spans 11 provinces or municipalities across the western, central, and eastern regions (Luo et al., 2022). The YREB encompasses three urban agglomerations located in its upper, middle, and lower reaches: the Chengdu-Chongqing (CY), Middle-Reach Yangtze River (MRYR), and Yangtze River Delta (YRD) urban agglomerations. These areas feature cities at different stages of development and exemplify the uncoordinated economic and societal growth in China. The collaborative carbon reduction of cities in the YREB not only plays a pivotal role in advancing the sustainable development of the Yangtze River Basin, it also stands as a significant exemplar of coordinated low-carbon development at the regional level in China.

This paper aims to reveal the spatiotemporal evolution of carbon emissions inequalities in urban agglomerations and elucidate the underlying influence mechanism. Specifically, several key questions remain to be addressed: (i) How are the inequalities in carbon emissions within urban agglomerations and between adjacent or distant urban agglomerations? (ii) What is the formation mechanism of multi-CEIs? And what contributes to the variations in CEIs? (iii) What are the predominant factors that either stimulate or mitigate carbon emissions in individual cities? Dealing with these questions holds great significance for designating targeted carbon mitigation policies. Using the city-level data from three national-level urban agglomerations in China's YREB between 2006 and 2021, this research employs a mean logarithmic deviation-index decomposition analysis (MLD-IDA) inequality indicator decomposition framework, in a multi-layer hierarchical structure of economic belt-urban agglomeration-city, to shed light on the drivers of regional inequalities in carbon emissions at different scales, thereby promoting coordinated carbon governance and sustainable development in China. Besides, this paper uncovers the causative factors behind differential carbon emissions within different cities of several urban agglomerations, contributing to advancing the national carbon neutrality goal.

The other sections are organized as follows. Section 2 provides a literature review. Section 3 describes the methodology and data. Section 4 presents the results and discussion of carbon emissions inequality in the YREB. Section 5 provides the results and discussion of carbon emission inequality at the urban agglomeration level. Section 6 offers a comparative analysis of carbon emissions at the city level. The final part concludes this study and gives some policy implications.

2. Literature review

Academic debate revolving around the driving factors of carbon emissions is persistent and controversial (Arto and Dietzenbacher, 2014; Rosa and Dietz, 2012; Yu et al., 2022). Natural disasters such as volcanic eruptions, forest fires, and earthquakes can release large amounts of carbon dioxide and other greenhouse gases (Yue and Gao, 2018). Meanwhile, ecosystems such as natural wetlands, grasslands, forests and oceans play a key role in the carbon cycle (Ribeiro et al., 2021). In addition to the abovementioned natural factors, it is believed that anthropogenic activities, including industrial processes (Xiao et al., 2022), land use change (Arneth et al., 2017), and fossil fuel burning (Yu et al., 2023b), also significantly influence carbon emissions. Various social and economic drivers of carbon emissions are studied in previous literature, such as industrial structure (Zhang et al., 2020), trade (Steinberger et al., 2012), green innovations (Xu et al., 2021), economic development (Rehman and Rehman, 2022), FDI (Pan et al., 2023a), technological progress (Milindi and Inglesi-Lotz, 2023), environmental regulation (Wang and Zhang, 2022), energy use (Yu et al., 2023a), etc.

Regression analysis and decomposition analysis are two widely used methods in driving factors analysis of carbon emissions. Most scholars employ econometric methods in the influencing factors analysis of carbon emissions (Dong et al., 2022; Khattak et al., 2022). However, in the econometric analysis, the inclusion of the residual fails to attribute carbon emissions to the major drivers and develop effective strategies to mitigate pollution. Moreover, due to differences in samples, variable selection, and estimation methods, many studies have reached controversial conclusions (Hassan et al., 2022; Li et al., 2021; Liu et al., 2021). A large number of carbon emissions-related research is carried out in the framework of decomposition analysis (Quan et al., 2020; Wang et al., 2019); especially, the logarithmic mean Divisia index (LMDI) method has been applied in many carbon emissions studies due to wide applicability and perfect decomposition form (Alajmi, 2021; Huang and Matsumoto, 2021). For example, Zhao et al. (2010) employ the LMDI method to investigate the drives of industrial carbon emissions in Shanghai during 1996–2007 and suggest that energy intensity, energy mix and industrial structure play a critical role in mitigating carbon emissions. With a significant amount of research focusing on the influencing factors of carbon emissions, there has been an increasing research interest in the influencing factors of carbon inequality.

One crucial issue related to carbon emissions is inequality. In existing literature, there has been significant research interest in environmental inequality among different groups based on income, race, class, and gender (Bindzar et al., 2021; Boyce et al., 2016; Downey and Hawkins, 2008; Newell, 2005; Sepehri et al., 2020). Besides, energy inequality has also received considerable attention (Bianco et al., 2021; Dong et al., 2018; Li et al., 2022; Liddle, 2010). Although lots of studies have investigated carbon emissions inequality (Bruckner et al., 2022; Chancel, 2022; Clarke-Sather et al., 2011; Duro and Padilla, 2006), these studies are mainly conducted from the country, regional, provincial, or industrial perspective; moreover, despite few studies on city-level carbon inequalities, there is a lack of comprehensive analysis of within and between urban agglomerations. The differences between adjacent or distant urban agglomerations have not been well understood, especially in countries undergoing rapid urbanization.

Regression analysis and decomposition analysis methods can be integrated with various inequality indexes to account for the mechanism of carbon inequalities. For example, Dong et al. (2020) apply a regression-based Shapley decomposition approach to address the question of what leads to China's haze pollution inequalities, however, this inequality decomposition framework is highly sensitive to the regression equation parameters and will still generate a residual term that leads to an incomplete explanation of inequalities. By contrast, factor decomposition doesn't generate residual and thus is a preferred method to combine with inequality indicators to study the drivers of the inequalities (Fan et al., 2020; Hou et al., 2024). Although some studies integrate the Theil index and the decomposition method of Shorrocks (1980), as stated by previous research (Chen et al., 2019; Luo et al., 2020a), simultaneously comparing and explaining the contributions of interaction terms and factors to inequality, however, can be difficult and ambiguous. In this paper, the inequality measurement (i.e., the mean logarithmic deviation) is incorporated into index decomposition analysis, which enables a full attribution of CEI to its drivers and a comparison of the magnitudes of various determinants' contributions.

To sum up, several deficiencies exist in previous literature. (1) Unraveling the spatial pattern of carbon emissions across regions is a critical prerequisite for realizing regionally coordinated carbon emissions reduction. While some studies have examined carbon inequality at the country, regional or industry level (Luo et al., 2020a; Remuzgo and Sarabia, 2015; Tian et al., 2021; Xu et al., 2022), little research comprehensively compares carbon emission inequalities within and between multiple coupled urban agglomerations. (2) Despite extensive research on the driving factors of carbon emissions, few studies focus on drivers of carbon inequality at the city level. The underlying socio-economic drivers of carbon emissions inequalities within and between urban agglomerations, however, are not well discussed, and scarce evidence exists on understanding the differences between adjacent or distant urban agglomerations. (3) Previous research rarely studies the spatial–temporal heterogeneity of carbon emissions across city, urban agglomeration, and regional levels simultaneously in an integrated framework, leading to a lack of understanding of the evolution mechanism of carbon emissions at different scales. These knowledge gaps impede the formulation of more effective and targeted strategies to mitigate carbon emissions in China, which motivates our study.

This paper focuses on carbon inequality and its underlying drivers on the temporal and spatial scales for the YREB as a whole, as well as for individual urban agglomerations and cities, considering their differentiated energy, economic, and environmental conditions. The integrated framework of this paper is illustrated in Fig. 1. The innovations of this paper consist of the following aspects. (1) Considering a nested economic belt-urban agglomeration-city hierarchical structure, this paper employs the mean logarithmic deviation (MLD) to measure the CEIs in urban agglomerations, and further reveals the evolution mechanisms of CEIs within and between urban agglomerations, distinguishing between upper, middle, and lower reaches of the YREB in China. (2) Little research investigates the influencing factors of carbon emission inequalities within urban agglomerations and between adjacent or distant urban agglomerations. To resolve this issue, this paper examines the socio-economic drivers of CEIs through an MLD-IDA approach framework, considering the upper, middle, and lower reaches of the YREB. Specifically, in factor decomposition, the carbon inequalities at different scales are fully attributed to the impacts of six drivers: industrial emission structure, energy emission intensity, energy mix, energy intensity, industrial structure, and economic development level. (3) Furthermore, this paper provides detailed evidence to explain the heterogeneous carbon emissions at the city level. The spatial index decomposition is conducted to clarify the differentiated conditions of carbon emissions from a city-level perspective. Noticeably, the case study in this paper can provide a reference for other countries or regions, especially those undergoing rapid urbanization, and the methodology is also applicable to the analysis of other research objects.

3. Methodology and data

This paper explores the socio-economic drivers of CEI through an MLD-IDA inequality indicator decomposition model. This approach aggregates the advantages of the MLD inequality measure and index decomposition analysis. As a generalized entropy index, the mean logarithmic deviation (MLD), with a logarithmic operator, can be well integrated into index decomposition analysis. MLD is additively decomposable, that is to say, the inequality measured by the MLD index can be expressed as the sum of within-region and between-region inequalities. In addition, the logarithmic mean Divisia index (LMDI) method, the most popular IDA method, has a concise decomposition form and wide applicability, effectively handles zero and negative values, and provides easily interpretable results without residuals. These make the MLD-IDA model particularly suitable, compared with other commonly used methods, for studying both the inequalities of carbon emissions within and between urban agglomerations and associated influencing factors simultaneously.

First, carbon emissions inequality in the YREB is measured by the MLD and then decomposed into within- and between-urban

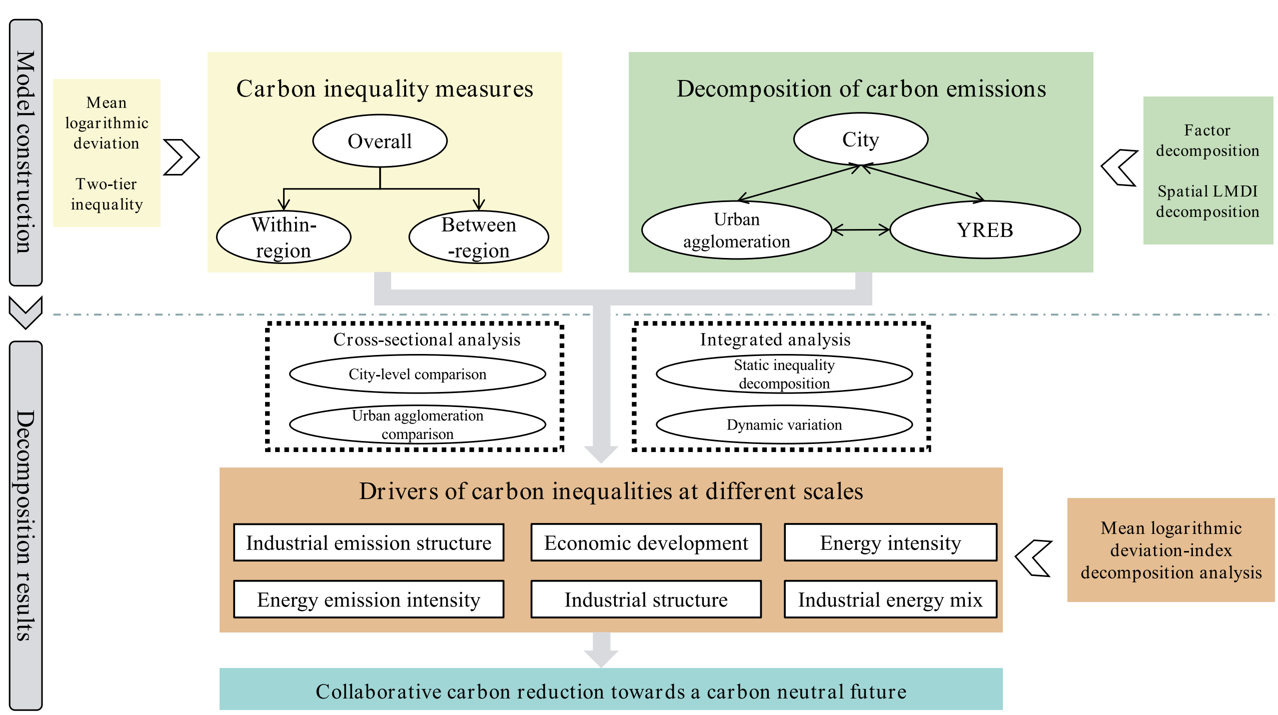


Fig. 1. Framework of this research.

agglomerations components. Second, the LMDI is used to reveal the influencing factors of carbon emissions and the results are then integrated into the MLD model, thereby examining the drivers of CEIs. Third, this paper accounts for the changes in carbon emissions inequalities during the study period.

3.1. Carbon emissions inequality decomposition through an MLD-IDA inequality indicator decomposition model

3.1.1. MLD measures for carbon emissions inequality

According to Dong et al. (2020), the overall inequality of carbon emissions among the YREB cities, as formulated using the MLD index, is as follows:

$$I = \sum_{i} \frac{1}{N} \times \ln\left(\frac{\bar{x}}{x_i}\right) \tag{1}$$

where I denotes the overall carbon emissions inequality (CEI) index, N is the number of cities. i indicates the i_{th} city; x represents carbon emissions per capita, and $\bar{x}$ represents the average carbon emissions per capita of all the YREB cities.

Considering the hierarchical structure in which a city is regarded as the component of each urban agglomeration, the sample is divided into the upper, middle, and lower reaches of the YREB given geographical proximity and development level (Luo et al., 2022). The bigger the *MLD* index, the larger the regional inequality of carbon emissions. *MLD* can be decomposed into two components as follows:

$$I = I_W + I_B \tag{2}$$

where I_W and I_B represent the within-urban agglomeration and between-urban agglomeration inequalities, respectively. The within-urban agglomeration inequality I_W can be calculated by:

$$I_W = \sum_{k=1}^{3} \frac{n_k}{N} \times I_k \tag{3}$$

where I_k denotes the inequality within the upper, middle, and lower reaches of the YREB ($k = 1,2,3$). n_k denotes the number of cities in urban agglomeration k ($n_1 = 41$ for the lower reaches, $n_2 = 36$ for the middle reaches, $n_3 = 12$ for upper reaches). I_k can be formulated as the following formula:

$$I_k = \sum_{i=1}^{n_k} \frac{1}{n_k} \times \ln\left(\frac{\bar{x}_k}{x_{k,i}}\right), k = 1,2,3 \tag{4}$$

The between-urban agglomeration inequality, I_B, can be given by:

$$I_B = \sum_{k=1}^{3} \frac{n_k}{N} \times \ln\left(\frac{\bar{x}}{\bar{x}_k}\right) \tag{5}$$

3.1.2. Influencing factors of carbon emissions inequalities

The Kaya identity is first used to decompose carbon emissions into several influencing factors in a multiplication form (Kaya, 1989). Due to concise principle, strong explanatory power, and no residual error, Kaya identity has been widely adopted and often combined with the index decomposition analysis in influencing factor analysis. Following the Kaya identity, we have:

$$\begin{aligned} CP &= \sum_{j} \frac{CE_j}{CE} \times \frac{CE}{E} \times \frac{E}{E_j} \times \frac{E_j}{GDP_j} \times \frac{GDP_j}{GDP} \times \frac{GDP}{P} \\ &= \sum_{j} IES_j \times EEI \times EM_j \times EI_j \times IS_j \times GP \end{aligned} \tag{6}$$

where CP denotes carbon emissions per capita. CE denotes total carbon emissions, j denotes the jth industry (primary, secondary, or tertiary industry), CE_j is carbon emissions in the jth industry. E is total energy use, E_j is energy use in the jth industry, GDP_j is the added value of the industry j, GDP is gross domestic product, P is the total population. *IES* denotes industrial emission structure that reflects the distribution of emissions by industry. *EEI* denotes energy emission intensity represented by the ratio of carbon emissions to energy use, which reflects the energy utilization structure of different energy sources. *EM* is the energy mix that reflects the distribution of energy consumption among different industries. *EI* denotes energy intensity, i.e., energy use per unit of added value. *IS* denotes industrial structure. *GP* is per capita *GDP*, representing economic development level.

The ratio of the YREB-wise average carbon emissions per capita (as the benchmark) to city-level carbon emissions per capita can be expressed as:

$$\begin{aligned} D^{u,i} = \frac{CP_u}{CP_i} &= \frac{\sum_j \frac{CE_{uj}}{CE_u} \times \frac{CE_u}{E_u} \times \frac{E_u}{E_{uj}} \times \frac{E_{uj}}{GDP_{uj}} \times \frac{GDP_{uj}}{GDP_u} \times \frac{GDP_u}{P_u}}{\sum_j \frac{CE_{ij}}{CE_i} \times \frac{CE_i}{E_i} \times \frac{E_i}{E_{ij}} \times \frac{E_{ij}}{GDP_{ij}} \times \frac{GDP_{ij}}{GDP_i} \times \frac{GDP_i}{P_i}} \\ &= D_{IES}^{u,i} \times D_{EEI}^{u,i} \times D_{EM}^{u,i} \times D_{EI}^{u,i} \times D_{IS}^{u,i} \times D_{GP}^{u,i} \end{aligned} \tag{7}$$

where i denotes the city, u denotes the benchmark, CP_u denotes the average carbon emissions per capita of all cities in the YREB. The above six factors on the right side of Eq. (7) can be given as:

$$D_{IES}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{IES^{uj}}{IES^{ij}}\right)\right) \tag{8a}$$

$$D_{EEI}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{EEI^{u}}{EEI^{i}}\right)\right) \tag{8b}$$

$$D_{EM}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{EM^{uj}}{EM^{ij}}\right)\right) \tag{8c}$$

$$D_{EI}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{EI^{uj}}{EI^{ij}}\right)\right) \tag{8d}$$

$$D_{IS}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{IS^{uj}}{IS^{ij}}\right)\right) \tag{8e}$$

$$D_{GP}^{u,i} = \exp\left(\sum_j w_{ij} \cdot \ln\left(\frac{GP^{u}}{GP^{i}}\right)\right) \tag{8f}$$

where

$$w_{ij} = \mathrm{L}\left(CE^{uj}/P^{u}, CE^{ij}/P^{i}\right) / L\left(CE^{u}/P^{u}, CE^{i}/P^{i}\right) \tag{8g}$$

$$L(a,b) = \begin{cases} \dfrac{a-b}{\ln a - \ln b}, ifa \neq b \\ a, ifa = b \end{cases} \tag{8h}$$

Integrating Eq. (1) and Eq. (7), we have

$$
\begin{aligned}
I &= \sum_i \frac{1}{N}\ln D_{IES}^{u,i} + \sum_i \frac{1}{N}\ln D_{EEI}^{u,i} + \sum_i \frac{1}{N}\ln D_{EM}^{u,i} + \sum_i \frac{1}{N}\ln D_{EI}^{u,i} + \sum_i \frac{1}{N}\ln D_{IS}^{u,i} + \sum_i \frac{1}{N}\ln D_{GP}^{u,i} \\
&= \sum_i\sum_j \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{IES^{uj}}{IES^{ij}}\right) + \sum_i\sum_j \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{EEI^{u}}{EEI^{i}}\right) + \sum_i\sum_j \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{EM^{uj}}{EM^{ij}}\right) \\
&\quad + \sum_i\sum_j \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{EI^{uj}}{EI^{ij}}\right) + \sum_i\sum_j \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{IS^{uj}}{IS^{ij}}\right) + \sum_i \frac{1}{N}\cdot w_{ij}\cdot \ln\left(\frac{GP^{u}}{GP^{i}}\right) \\
&= I(IES) + I(EEI) + I(EM) + I(EI) + I(IS) + I(GP)
\end{aligned}
\tag{9}
$$

Using a similar calculation process, the within-urban agglomeration and between-urban agglomeration inequalities are also decomposed as follows:

$$
\begin{aligned}
I_B &= \sum_k\sum_j \frac{n_k}{N} \times w_{kj} \times \left(\ln\left(\frac{IES^{uj}}{IES^{kj}}\right) + \ln\left(\frac{EEI^{u}}{EEI^{k}}\right) + \ln\left(\frac{EM^{uj}}{EM^{kj}}\right) \right. \\
&\quad \left. + \ln\left(\frac{EI^{uj}}{EI^{kj}}\right) + \ln\left(\frac{IS^{uj}}{IS^{kj}}\right) + \ln\left(\frac{GP^{u}}{GP^{k}}\right) \right) \\
&= I(IES)_B + I(EEI)_B + I(EM)_B + I(EI)_B + I(IS)_B + I(GP)_B
\end{aligned}
\tag{10}
$$

$$
\begin{aligned}
I_W &= \sum_k\sum_i\sum_j \frac{n_k}{N} \times \frac{1}{n_k} \times w_{ki,j} \times \left(\ln\left(\frac{IES^{k,j}}{IES^{ki,j}}\right) + \ln\left(\frac{EEI^{k}}{EEI^{ki}}\right) \right. \\
&\quad \left. + \ln\left(\frac{EM^{k,j}}{EM^{ki,j}}\right) + \ln\left(\frac{EI^{k,j}}{EI^{ki,j}}\right) + \ln\left(\frac{IS^{k,j}}{IS^{ki,j}}\right) + \ln\left(\frac{GP^{k}}{GP^{ki}}\right) \right) \\
&= I(IES)_W + I(EEI)_W + I(EM)_W + I(EI)_W + I(IS)_W + I(GP)_W
\end{aligned}
\tag{11}
$$

where n_k denotes the number of cities in each urban agglomeration. The above within-urban agglomeration component is the weighted average of three intraregional inequality indexes. In detail, when $k = 1, 2, 3$, the carbon inequalities within the upper (I_{UR}), middle (I_{MR}), and lower (I_{LR}) reaches of the YREB are shown in Eqs. (12)-(14), respectively:

$$
\begin{aligned}
I_{UR} &= \sum_i\sum_j \frac{1}{n_1} \times w_{UR,ij} \times \left(\ln\left(\frac{IES^{UR,j}}{IES^{UR,ij}}\right) + \ln\left(\frac{EEI^{UR}}{EEI^{UR,i}}\right) \right. \\
&\quad \left. + \ln\left(\frac{EM^{UR,j}}{EM^{UR,ij}}\right) + \ln\left(\frac{EI^{UR,j}}{EI^{UR,ij}}\right) + \ln\left(\frac{IS^{UR,j}}{IS^{UR,ij}}\right) + \ln\left(\frac{GP^{UR}}{GP^{UR,i}}\right) \right) \\
&= I(IES)_{UR} + I(EEI)_{UR} + I(EI)_{UR} + I(IS)_{UR} + I(GP)_{UR}
\end{aligned}
\tag{12}
$$

$$
\begin{aligned}
I_{MR} &= \sum_i\sum_j \frac{1}{n_2} \times w_{MR,ij} \times \left(\ln\left(\frac{IES^{MR,j}}{IES^{MR,ij}}\right) + \ln\left(\frac{EEI^{MR}}{EEI^{MR,i}}\right) \right. \\
&\quad \left. + \ln\left(\frac{EM^{MR,j}}{EM^{MR,ij}}\right) + \ln\left(\frac{EI^{MR,j}}{EI^{MR,ij}}\right) + \ln\left(\frac{IS^{MR,j}}{IS^{MR,ij}}\right) + \ln\left(\frac{GP^{MR}}{GP^{MR,i}}\right) \right) \\
&= I(IES)_{MR} + I(EEI)_{MR} + I(EM)_{MR} + I(EI)_{MR} + I(IS)_{MR} + I(GP)_{MR}
\end{aligned}
\tag{13}
$$

$$
\begin{aligned}
I_{LR} &= \sum_i\sum_j \frac{1}{n_3} \times w_{LR,ij} \times \left(\ln\left(\frac{IES^{LR,j}}{IES^{LR,ij}}\right) + \ln\left(\frac{EEI^{LR}}{EEI^{LR,i}}\right) \right. \\
&\quad \left. + \ln\left(\frac{EM^{LR,j}}{EM^{LR,ij}}\right) + \ln\left(\frac{EI^{LR,j}}{EI^{LR,ij}}\right) + \ln\left(\frac{IS^{LR,j}}{IS^{LR,ij}}\right) + \ln\left(\frac{GP^{LR}}{GP^{LR,i}}\right) \right) \\
&= I(IES)_{LR} + I(EEI)_{LR} + I(EM)_{LR} + I(EI)_{LR} + I(IS)_{LR} + I(GP)_{LR}
\end{aligned}
\tag{14}
$$

3.2. Accounting for the changes in carbon emissions inequalities

The change in overall carbon inequality can be expressed as:

$$
\begin{aligned}
I^t - I^0 &= \left(\sum_i \frac{1}{N}\ln D_{IES}^{u,i,t} + \sum_i \frac{1}{N}\ln D_{EEI}^{u,i,t} + \sum_i \frac{1}{N}\ln D_{EM}^{u,i,t} + \sum_i \frac{1}{N}\ln D_{EI}^{u,i,t} + \sum_i \frac{1}{N}\ln D_{IS}^{u,i,t} + \sum_i \frac{1}{N}\ln D_{GP}^{u,i,t} \right) \\
&\quad - \left(\sum_i \frac{1}{N}\ln D_{IES}^{u,i,0} + \sum_i \frac{1}{N}\ln D_{EEI}^{u,i,0} + \sum_i \frac{1}{N}\ln D_{EM}^{u,i,0} + \sum_i \frac{1}{N}\ln D_{EI}^{u,i,0} + \sum_i \frac{1}{N}\ln D_{IS}^{u,i,0} + \sum_i \frac{1}{N}\ln D_{GP}^{u,i,0} \right) \\
&= \Delta I_{IES} + \Delta I_{EEI} + \Delta I_{EM} + \Delta I_{EI} + \Delta I_{IS} + \Delta I_{GP}
\end{aligned}
\tag{15}
$$

$$\Delta \mathrm{I}_{IES} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{IES^{u,j,t}}{IES^{i,j,t}}\right) - w_{ij}^0 \ln\left(\frac{IES^{u,j,0}}{IES^{i,j,0}}\right) \right) \tag{16a}$$

$$\Delta \mathrm{I}_{EEI} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{EEI^{u,t}}{EEI^{i,t}}\right) - w_{ij}^0 \ln\left(\frac{EEI^{u,0}}{EEI^{i,0}}\right) \right) \tag{16b}$$

$$\Delta \mathrm{I}_{EM} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{EM^{u,j,t}}{EM^{i,j,t}}\right) - w_{ij}^0 \ln\left(\frac{EM^{u,j,0}}{EM^{i,j,0}}\right) \right) \tag{16c}$$

$$\Delta \mathrm{I}_{EI} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{EI^{u,j,t}}{EI^{i,j,t}}\right) - w_{ij}^0 \ln\left(\frac{EI^{u,j,0}}{EI^{i,j,0}}\right) \right) \tag{16d}$$

$$\Delta \mathrm{I}_{IS} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{IS^{u,j,t}}{IS^{i,j,t}}\right) - w_{ij}^0 \ln\left(\frac{IS^{u,j,0}}{IS^{i,j,0}}\right) \right) \tag{16e}$$

$$\Delta \mathrm{I}_{GP} = \frac{1}{N}\sum_i\sum_j \left(w_{ij}^t \ln\left(\frac{GP^{u,t}}{GP^{i,t}}\right) - w_{ij}^0 \ln\left(\frac{GP^{u,0}}{GP^{i,0}}\right) \right) \tag{16f}$$

Similarly, we can also account for the changes in carbon inequalities within upper, middle, and lower reaches of the YREB (i.e., ΔI_{UR}, ΔI_{MR}, and ΔI_{LR}).

Furthermore, the variation of the between-urban agglomeration carbon inequality (i.e., I_B) can be decomposed as follows:

$$I_B^t - I_B^0 = \Delta I_{IES,B} + \Delta I_{EEI,B} + \Delta I_{EM,B} + \Delta I_{EI,B} + \Delta I_{IS,B} + \Delta I_{GP,B} \tag{17}$$

$$\Delta \mathrm{I}_{IES,B} = \sum_k \sum_j \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{IES^{u,j,t}}{IES^{k,j,t}}\right) - w_{kj}^0 \ln\left(\frac{IES^{u,j,0}}{IES^{k,j,0}}\right) \right) \tag{18a}$$

$$\Delta \mathrm{I}_{EEI,B} = \sum_k \sum_j \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{EEI^{u,t}}{EEI^{k,t}}\right) - w_{kj}^0 \ln\left(\frac{EEI^{u,0}}{EEI^{k,0}}\right) \right) \tag{18b}$$

$$\Delta \mathrm{I}_{EM,B} = \sum_k \sum_j \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{EM^{u,j,t}}{EM^{k,j,t}}\right) - w_{kj}^0 \ln\left(\frac{EM^{u,j,0}}{EM^{k,j,0}}\right) \right) \tag{18c}$$

$$\Delta \mathrm{I}_{EI,B} = \sum_k \sum_j \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{EI^{u,j,t}}{EI^{k,j,t}}\right) - w_{kj}^0 \ln\left(\frac{EI^{u,j,0}}{EI^{k,j,0}}\right) \right) \tag{18d}$$

$$\Delta \mathrm{I}_{IS,B} = \sum_k \sum_j \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{IS^{u,j,t}}{IS^{k,j,t}}\right) - w_{kj}^0 \ln\left(\frac{IS^{u,j,0}}{IS^{k,j,0}}\right) \right) \tag{18e}$$

$$\Delta \mathrm{I}_{GP,B} = \sum_j \sum_k \frac{n_k}{N} \cdot \left(w_{kj}^t \ln\left(\frac{GP^{u,t}}{GP^{k,t}}\right) - w_{kj}^0 \ln\left(\frac{GP^{u,0}}{GP^{k,0}}\right) \right) \tag{18f}$$

The within-urban agglomeration carbon inequality (i.e., I_W) can be formulated as:

$$I_W^t - I_W^0 = \Delta I_{IES,W} + \Delta I_{EEI,W} + \Delta I_{EM,W} + \Delta I_{EI,W} + \Delta I_{IS,W} + \Delta I_{GP,W} \tag{19}$$

$$\Delta \mathrm{I}_{IES,W} = \sum_k \sum_i \sum_j \frac{1}{N} \cdot \left(w_{ki,\mathrm{j}}^t \ln\left(\frac{IES^{\mathrm{k,j},t}}{IES^{ki,\mathrm{j},t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{IES^{k,j,0}}{IES^{ki,j,0}}\right) \right) \tag{20a}$$

$$\Delta \mathrm{I}_{EEI,W} = \sum_k \sum_i \sum_j \frac{1}{N} \cdot \left(w_{\mathrm{ki,j}}^t \ln\left(\frac{EEI^{\mathrm{k},t}}{EEI^{\mathrm{ki},t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{EEI^{k,0}}{EEI^{\mathrm{ki},0}}\right) \right) \tag{20b}$$

$$\Delta \mathrm{I}_{EM,W} = \sum_k \sum_i \sum_j \frac{1}{N} \cdot \left(w_{\mathrm{ki,j}}^t \ln\left(\frac{EM^{\mathrm{k,j},t}}{EM^{ki,\mathrm{j},t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{EM^{k,j,0}}{EM^{ki,j,0}}\right) \right) \tag{20c}$$

$$\Delta \mathrm{I}_{EI,W} = \sum_k \sum_i \sum_j \frac{1}{N} \cdot \left(w_{\mathrm{ki,j}}^t \ln\left(\frac{EI^{\mathrm{k,j},t}}{EI^{ki,\mathrm{j},t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{EI^{k,j,0}}{EI^{ki,j,0}}\right) \right) \tag{20d}$$

$$\Delta \mathrm{I}_{IS,W} = \sum_k \sum_i \sum_j \frac{1}{N} \cdot \left(w_{\mathrm{ki,j}}^t \ln\left(\frac{IS^{\mathrm{k,j},t}}{IS^{ki,\mathrm{j},t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{IS^{k,j,0}}{IS^{ki,j,0}}\right) \right) \tag{20e}$$

$$\Delta \mathrm{I}_{GP,W} = \sum_k \sum_i \frac{1}{N} \cdot \left(w_{\mathrm{ki,j}}^t \ln\left(\frac{GP^{\mathrm{k},t}}{GP^{ki,t}}\right) - w_{ki,\mathrm{j}}^0 \ln\left(\frac{GP^{k,0}}{GP^{ki,0}}\right) \right) \tag{20f}$$

3.3. Data sources and summary statistics

3.3.1. Data sources

The sample in this paper covers 89 cities in China's Yangtze River Economic Belt spanning 2006–2021. The YREB covers 11 provinces and municipalities along the Yangtze River in China. Given the completeness of detailed energy and emissions data and the high resolution of sectoral disaggregation, the sample excludes Yunnan and Guizhou and includes 89 cities in Jiangsu, Zhejiang, Shanghai, Anhui, Hubei, Hunan, Jiangxi, Chongqing, and Sichuan. The data on energy consumption and carbon emissions are collected from Carbon Emission Accounts and Datasets for emerging economies (CEADs) (Guan et al., 2021; Shan et al., 2018; Shan et al., 2020). Population, GDP, and sectoral added values are derived from *China City Statistical Yearbook*.

3.3.2. Summary statistics

We look at the city-level carbon emissions in both aggregate and per capita terms. Fig. 2 shows the distribution of carbon emissions in 89 cities of China's YREB. 2006 and 2021 are selected as the representative years to present the evolution of emissions over time. From Fig. 2(a), we find that the areas with the highest emission are mainly provincial capitals such as Shanghai (165 Mt), Nanjing (95 Mt), Wuhan (94 Mt), and Chongqing (90 Mt). On the whole, most cities are classified into the low emission range in 2006. As shown in Fig. 2(b), in 2021, more cities fall into the higher emission interval, and high-emissions cities are concentrated in the lower reaches of the YREB. Besides, regional central cities such as Nanjing, Shanghai and Wuhan are surrounded by more high-emissions cities.

As shown in Fig. 3, this paper depicts both spatial differences and temporal evolution of carbon emissions per capita in cities of China's YREB. We have identified a distinct hierarchical distribution of per capita carbon emissions at the city level. High-emission cities are concentrated in downstream regions especially in the YRD urban agglomeration, with only a few cities in midstream areas exhibiting higher per capita emission levels. Conversely, per capita emissions in downstream areas are generally lower. In particular, high-emission cities are centered around Wuhan, Nanjing, and Shanghai, forming a concentration in the vicinity. In addition, the city-level per capita carbon emissions exhibit a significant increase from 2006 to 2021, with many cities transitioning from lower emission ranges to higher emission categories.

Based on Eqs. (1)-(5), this study quantifies the YREB's CEI and its components, including within-region and between-region inequalities. Fig. 4 shows the changes in overall inequality, within-urban agglomeration inequality, and between-urban agglomeration inequality between 2006 and 2021. We find that the within-urban agglomeration CEI makes up over 70 % of the overall CEI, establishing a significant dominance in the overall CEI. To be more specific, the overall CEI decreases with a 15 % decline rate, and the within-urban agglomeration CEI shows a similar changing trend with the overall CEI. However, the between-urban agglomeration inequality presents an increasing trend during 2006–2021, with a minor fluctuation.

4. Results and discussion of carbon emissions inequality in the YREB

The previous section describes in detail the spatiotemporal heterogeneity of carbon emissions in the YREB. To quantify the city-level carbon inequalities and how they are influenced by various factors, this study utilizes the LMDI-based inequality decomposition in Eqs. (6)-(14) to decompose CEIs at different scales into six factors, including industrial emission structure, energy emission intensity, industrial energy mix, energy intensity, industrial structure, and per capita GDP. We calculate the contribution magnitudes of various determinants in generating CEIs. Furthermore, we investigate the changes in CEIs and the associated drivers based on Eqs. (15)-(20). Here, the decomposition analysis is performed for the overall CEI in the YREB and its constituent components, i.e., both within-urban agglomeration and between-urban agglomeration inequalities.

4.1. Inequality decomposition analysis in the YREB

Fig. 5 shows the results of carbon inequality decomposition in the YREB. It is found that the contributions of economic development and industrial emission structure are positive in all years, while the contribution of energy intensity is positive in most years except for 2006–2009 and 2017. That implies that economic development disparity, energy intensity disparity and industrial emission structure disparity play a role in promoting CEI. Among these factors, the economic development effect is the major positive driver of the YREB's CEI with an annual contribution of 0.28, but the contributions of industrial emission

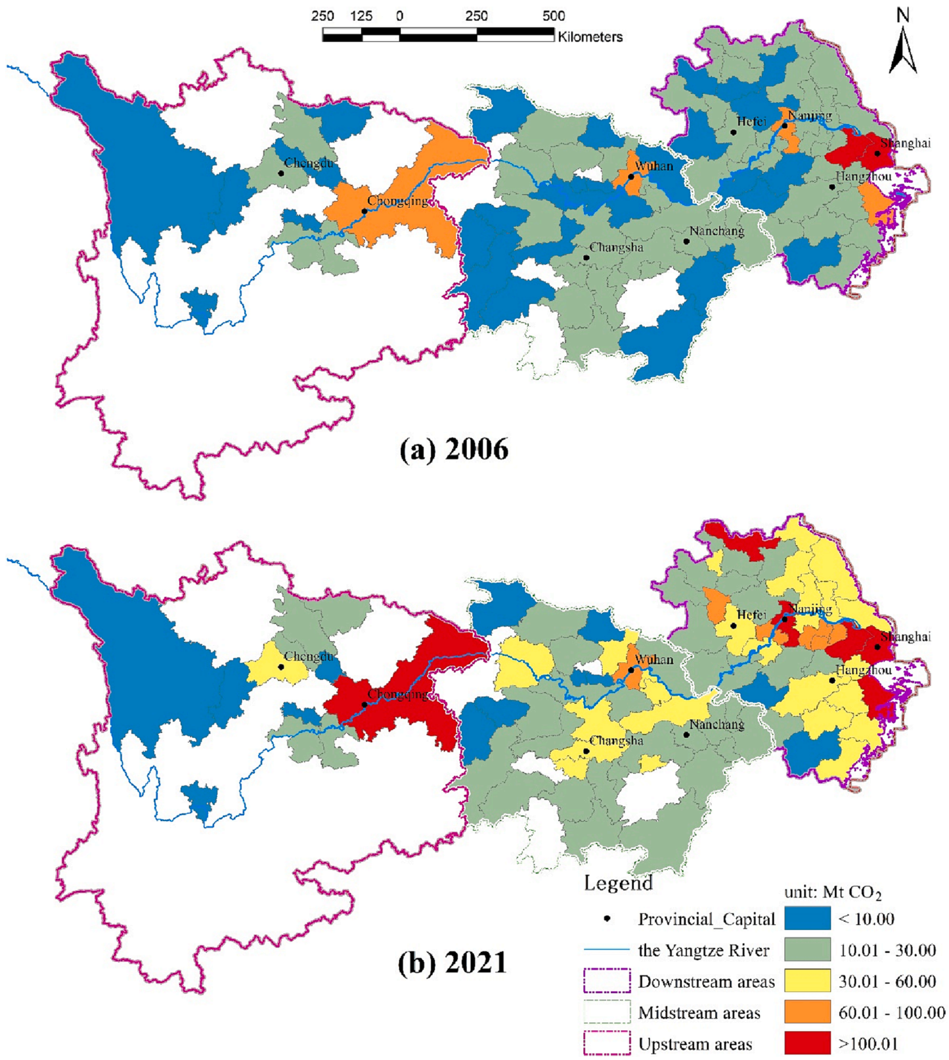


Fig. 2. Carbon emissions of cities in China's YREB (unit: Million tons).

structure and energy intensity to promoting CEI are quite smaller. The economic development level is highly coupled with carbon emissions. Production and living activities are concentrated in developed areas, leading to greater carbon emissions accumulation.

As shown in Fig. 5, industrial energy mix, energy emission intensity and industrial structure are important factors that mitigate carbon inequality. Specifically, the contributions of the industrial energy mix are negative throughout 2006–2021, showing that the regional disparities of industrial energy mix help mitigate carbon inequality. In addition, energy emission intensity also contributes to mitigating carbon inequality in the YREB during the study period, but its impact is very small. By contrast, the impact of industrial structure is negative in most periods since 2011 but its contribution is small.

Based on Eqs. (15)-(16), we attempt to explain the changes in CEI of the YREB from 2006 to 2021. To reveal the dynamic variation characteristics of CEI, this paper sets 2006 as the base period and studies the variation in CEI from 2006 to the target year. The decomposition results of CEI changes in the YREB are given in Fig. 6. The CEI index shows a decrease except for 2008–2010, indicating China's regional carbon inequality has decreased in most sub-periods compared with the 2006 level. Especially, CEI reached its valley point in 2020.

From Fig. 6, it is found that the contributions of energy intensity and energy emission intensity are positive in most periods. The change in energy intensity disparity is the main factor accounting for the increasing CEI in the YREB, while the negative impact of energy emission intensity is much smaller. In addition, Fig. 6 shows that the contribution of industrial structure is negative in all years, indicating industrial structure disparity change results in a decrease in CEI. This may be due to China's regional industrial transfer and the resulting technology spillover effects. We find that the change in economic development disparity also plays a role in reducing CEI. Its contribution is negative in all periods except the period 2006–2017. On the whole, the energy intensity effect is the main factor causing CEI to increase, followed by the energy emission intensity effect. By contrast, the effects of industrial structure and economic development are important in mitigating CEI. However, the impact of industrial emission structure is minor.

4.2. Between-urban agglomeration inequality decomposition analysis

The decomposition results for the CEI between the three urban agglomerations in the YREB are shown in Fig. 7. It can be seen that the between-region CEI was the largest in 2015, while the lowest was recorded in 2006. It is found that economic development disparity plays a major role in explaining the between-urban agglomeration CEI, and its annual average contribution amounts to 0.05. China's economic development shows remarkable regional differences. Especially, the per capita GDP of the eastern coastal regions, such as Guangdong, Jiangsu, and Zhejiang, is significantly larger than inland areas such as Xinjiang, Qinghai, and Gansu. In addition, the energy intensity disparity also

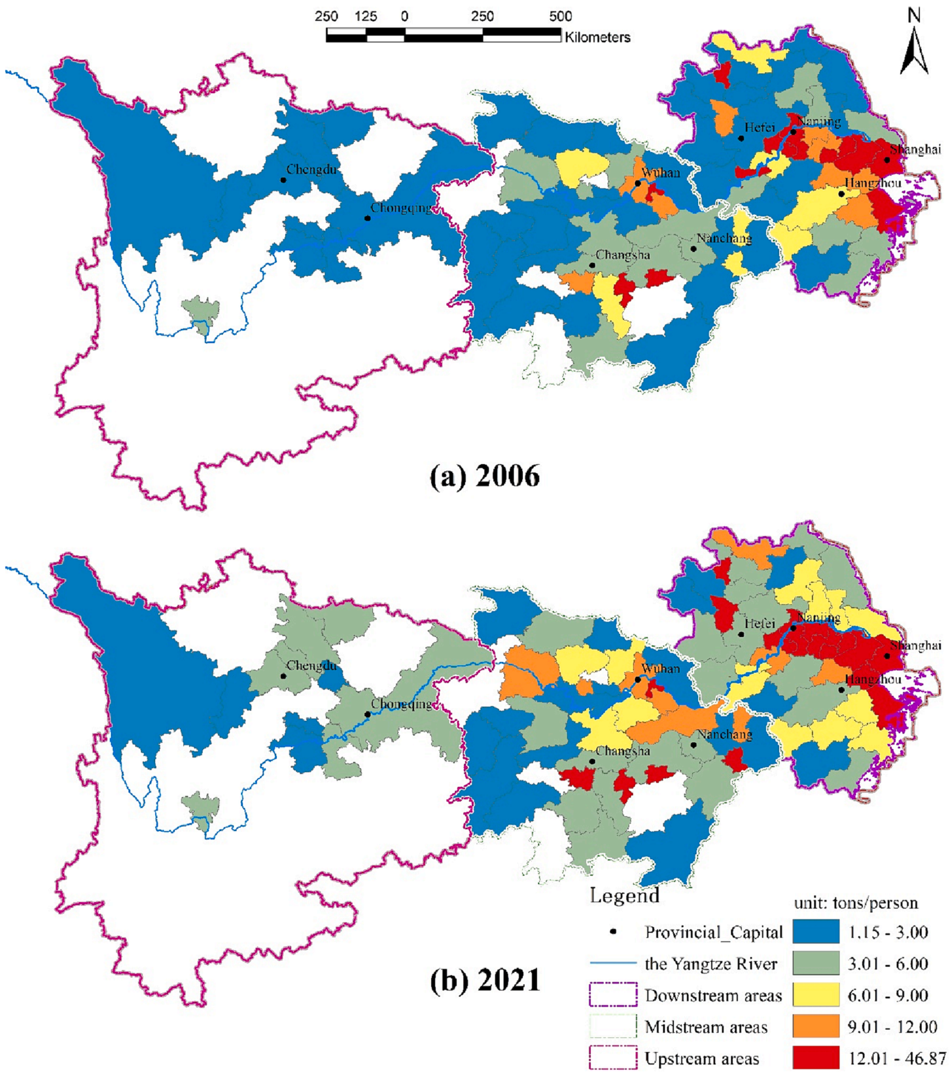


Fig. 3. Carbon emissions per capita of cities in China's YREB (unit: tons/person).

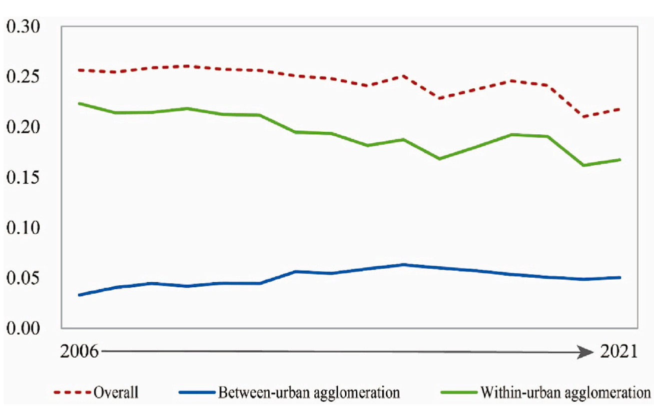


Fig. 4. Tread of carbon inequalities in the YREB during 2006–2021.

contributes to generating CEI, its contribution is positive in most periods, changing from negative during 2006–2010 to positive during 2011–2021. However, the influence direction of industrial structure varies greatly over time, decreasing from positive to negative and then to positive.

As shown in Fig. 7, industrial energy mix disparity negatively influences the between-urban agglomeration CEI, implying that the spatial disparities of industrial energy mix have mitigated the carbon inequality among the three urban agglomerations. We can see energy emission intensity also has some effect on mitigating between-urban agglomeration inequality in most periods, but its contribution is small. On the whole, the between-urban agglomeration CEI can be partly attributed to the disparities of economic development and energy intensity, while the disparity of industrial energy mix plays a vital role in mitigating CEI.

We then look at the evolution of the between-urban agglomeration CEI over time, The decomposition results of the changes in between-urban agglomeration CEI from 2006 to the target year are shown in Fig. 8. It can be seen that the between-urban agglomeration CEI has risen in 2007–2021 relative to the 2006 level, and the biggest increment of 0.03 was recorded in the period 2006–2015, indicating the CEI between the three urban agglomerations reached the peak in 2015. From Fig. 8, we can find that energy intensity is the major positive driver of the between-urban agglomeration CEI throughout the research period. The growing regional disparity of energy intensity, represented by energy use per unit of GDP, has exacerbated the carbon inequality between urban agglomerations. We also find that economic development and industrial structure make a significant contribution to decreasing between-urban agglomeration CEI. It indicates that the low-carbon transformation of economic structure is important in mitigating the

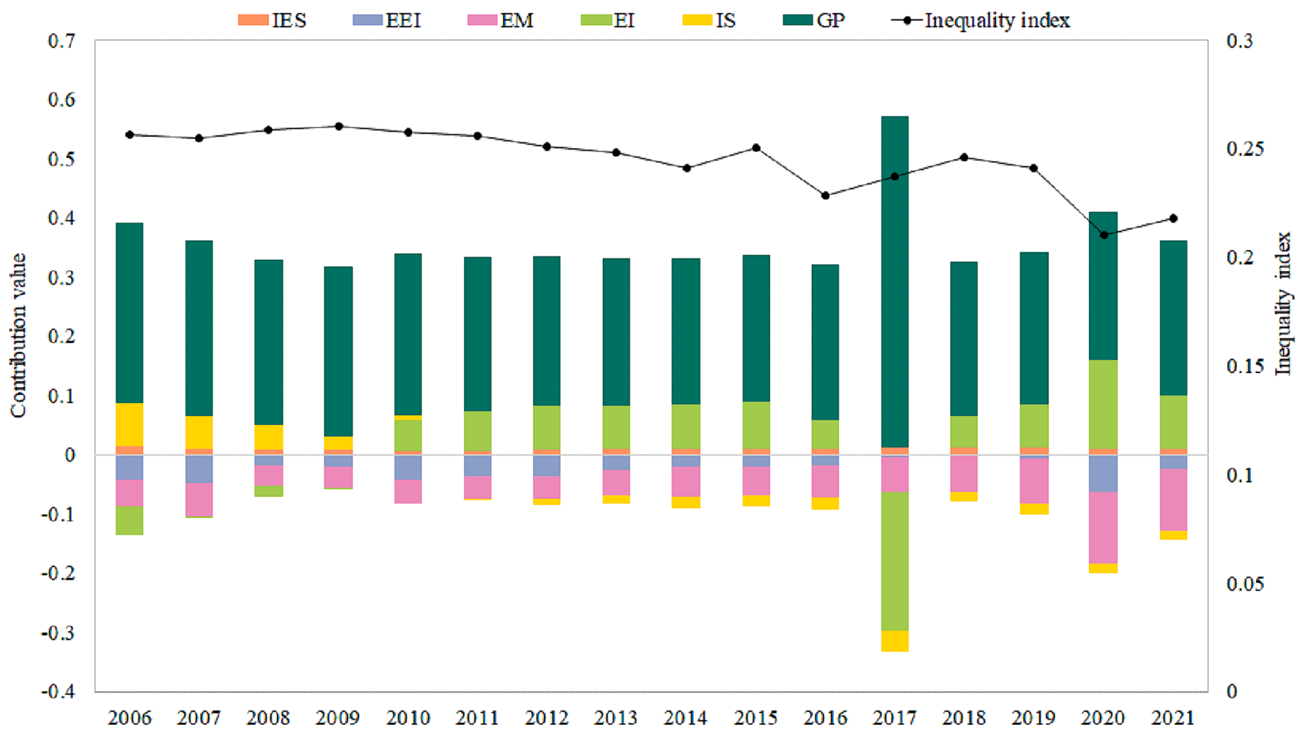


Fig. 5. Influencing factors of city-level carbon inequality in the YREB. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

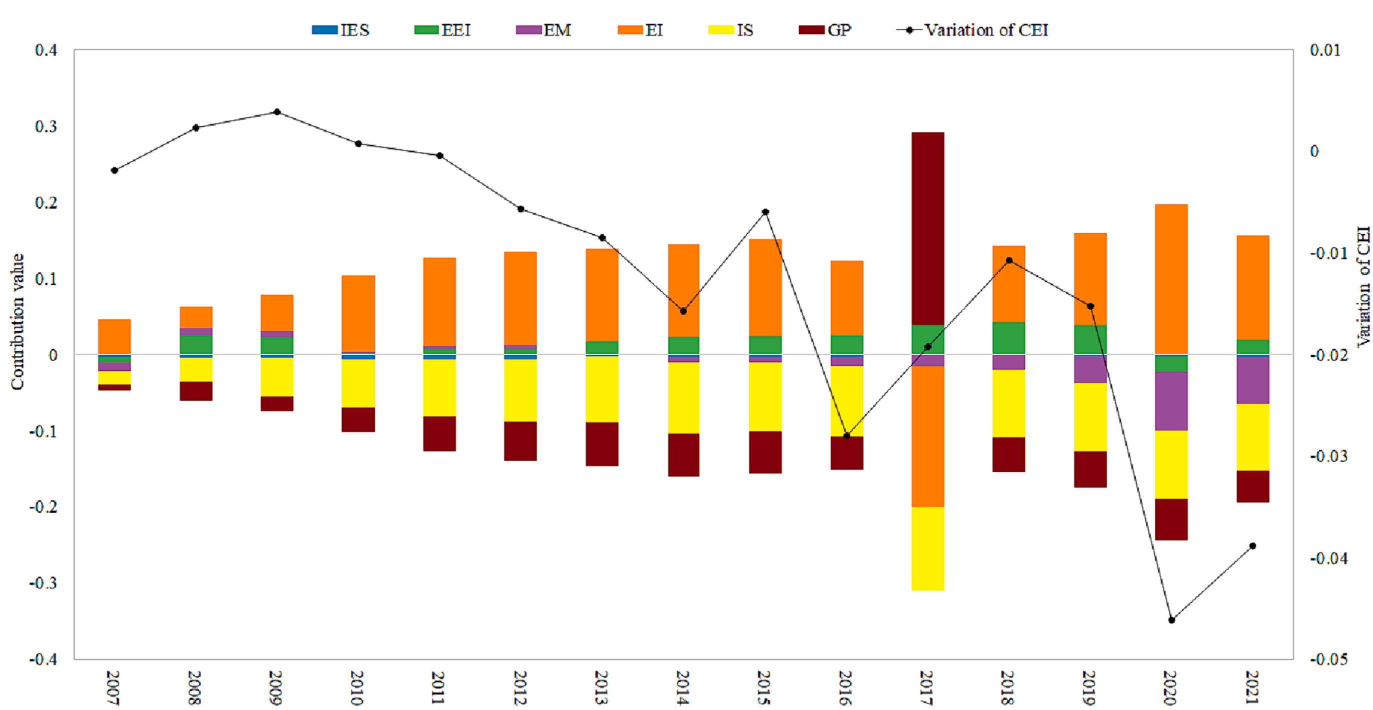


Fig. 6. Decomposition results of change in carbon inequality relative to the 2006 level. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

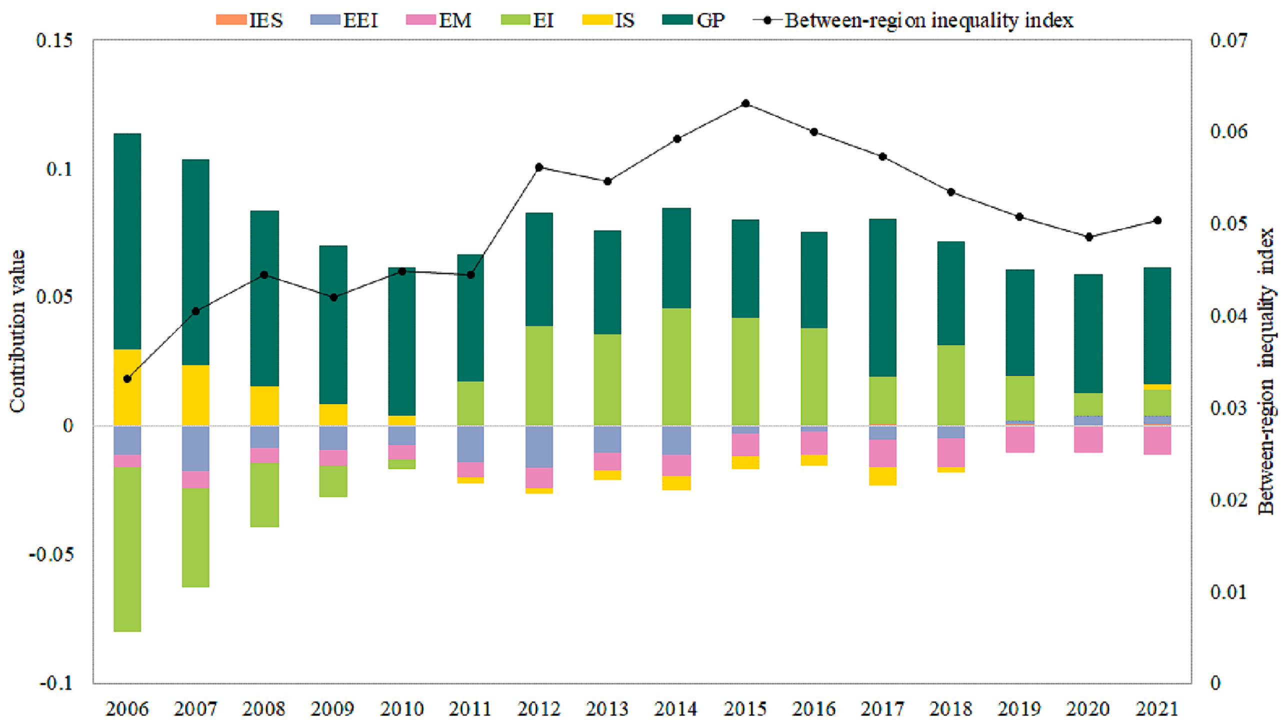


Fig. 7. Influencing factors of between-urban agglomeration carbon inequality. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

carbon inequality among urban agglomerations. Although the contribution of industrial energy mix is negative in all periods, it has a only limited impact on decreasing between-urban agglomeration CEI.

4.3. Within-urban agglomeration inequality decomposition analysis

The YREB's carbon inequality mainly comes from the within-urban agglomeration differences. Revealing the influence mechanism of the within-urban agglomeration CEI index is essential for developing regional carbon mitigation policies. The decomposition results for the driving factors of the within-urban agglomeration CEI are presented in Fig. 9. We find that the results in Fig. 9 are quite similar to the results for the overall CEI in Fig. 5. The main positive driver of within-urban agglomeration CEI is the disparity of economic development with an annual contribution of 0.23. This is because compared with low-emissions cities, some high-emissions cities usually have higher economic development levels, leading to shaping within-urban agglomeration CEI. In addition, the energy intensity disparity also plays an important role in generating the within-region CEI in most periods, but its impact is significantly lower than that of economic development. Although the contributions of industrial emission structure are positive in all years, the impact is negligible.

It is found that industrial energy mix is the major negative driver, showing that the disparities in industrial energy mix contribute largely to mitigating within-urban agglomeration CEI. Fig. 9 shows that industrial structure also has a small impact on mitigating within-urban agglomeration CEI in most periods, specifically, the contribution of industrial structure effect changes from positive during 2006–2010 to negative during 2011–2021. In addition, the disparity of energy emission intensity makes a small contribution to decreasing within-urban agglomeration CEI. The reason is that the differences in energy consumption structure within individual urban agglomerations are minor.

Fig. 10 presents the decomposition results for within-urban agglomeration CEI changes in various periods. We can see that the within-urban agglomeration CEI shows a decrease in all sub-periods. The largest decrement of within-urban agglomeration CEI was observed for the period 2006–2020, indicating the within-urban agglomeration CEI reached its lowest value of 0.16 in 2020. The results show the decline in within-urban agglomeration CEI is mainly attributable to the change in industrial structure disparity, whose contribution is negative through the research period. In addition, industrial energy mix has a significant effect on mitigating within-urban agglomeration CEI in individual periods. However, the contribution of energy intensity is positive in most periods. On the whole, during 2006–2021, industrial structure and industrial energy mix are crucial factors decreasing the within-urban agglomeration CEI, while the energy intensity effect hinders the decline of within-urban agglomeration CEI. In contrast, other factors have little on mitigating within-urban agglomeration CEI.

5. Results and discussion of carbon emission inequality at the urban agglomeration level

Carbon emissions per capita displays significant differences within and between different urban agglomerations (see Fig. 3). The within-urban agglomeration CEI plays a dominant role in influencing the overall CEI in the YREB, the analysis of CEI at the urban agglomeration level is of great significance to mitigating carbon inequality. An important question naturally arises. What are the reasons for the differences in the carbon emission patterns among these urban agglomerations? We further conduct a comparative analysis to examine the determinants of CEIs in upper reaches, middle reaches, and lower reaches urban agglomerations of the YREB, and look at what contributes to the changes in CEIs within different urban agglomerations.

5.1. Driving factors of CEIs in the three urban agglomerations

Fig. 11 shows the influencing factor of CEIs in individual urban agglomerations. Comparing Fig. 11 (a)-(c) shows that the main determinants of CEIs in different regions show significant differences.

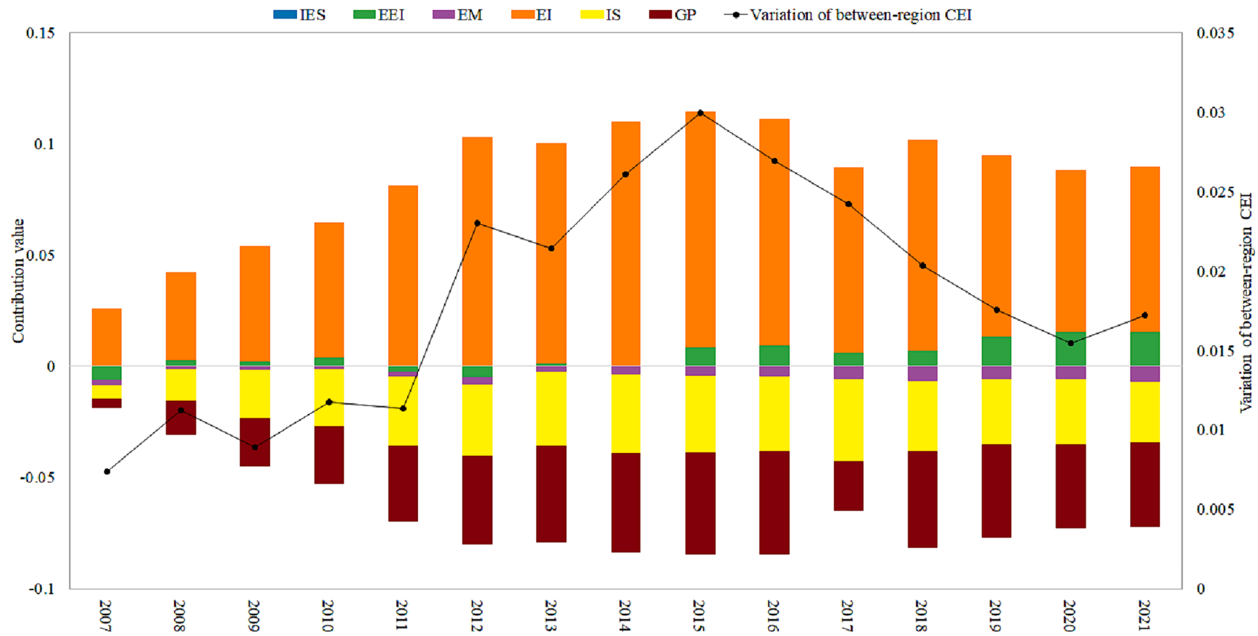


Fig. 8. Decomposition results of change in between-urban agglomeration carbon inequality relative to the 2006 level. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

Although the effects of individual factors vary over time, the major positive or negative drivers of CEI generally remain the same in different years.

It is found from Fig. 11 (a) that carbon inequality in upper reaches shows a remarkable increase from 0.06 in 2006 to 0.25 in 2021. The impact of economic development dominates the upper reaches' CEI and its contribution remains constant over time, with an average contribution of 0.26. In contrast, energy intensity is another significant factor influencing CEI in the upper reaches, with an average contribution of 0.02, surpassing that of industrial emission structure. It is recognized that the industrial energy mix plays a predominant role in mitigating carbon inequality, while the impact of other negative contributors remains relatively minor.

As shown in Fig. 11 (b), CEI in the middle reaches urban agglomeration displays a distinct drop from 0.15 in 2006 to 0.06 in 2021. The results show that the contribution of economic development disparity is

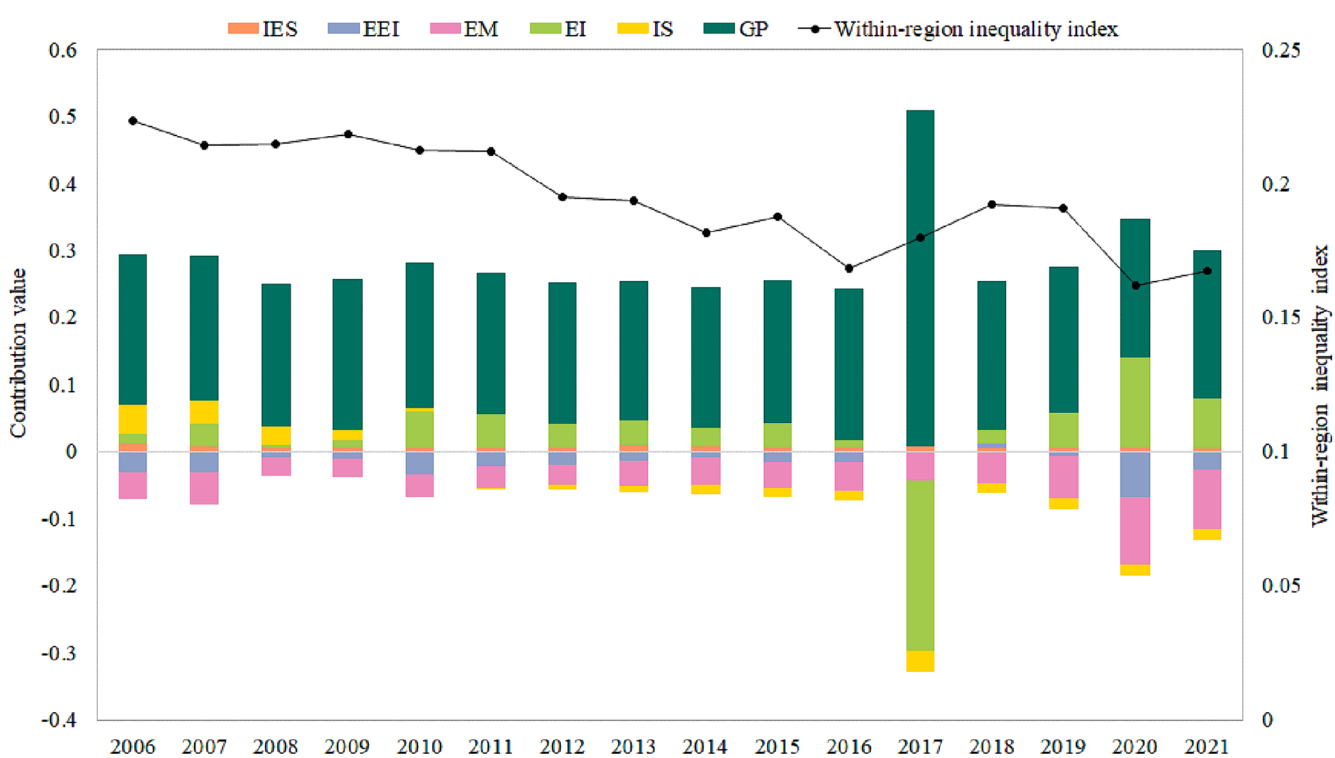


Fig. 9. Influencing factors of within-urban agglomeration carbon inequality. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

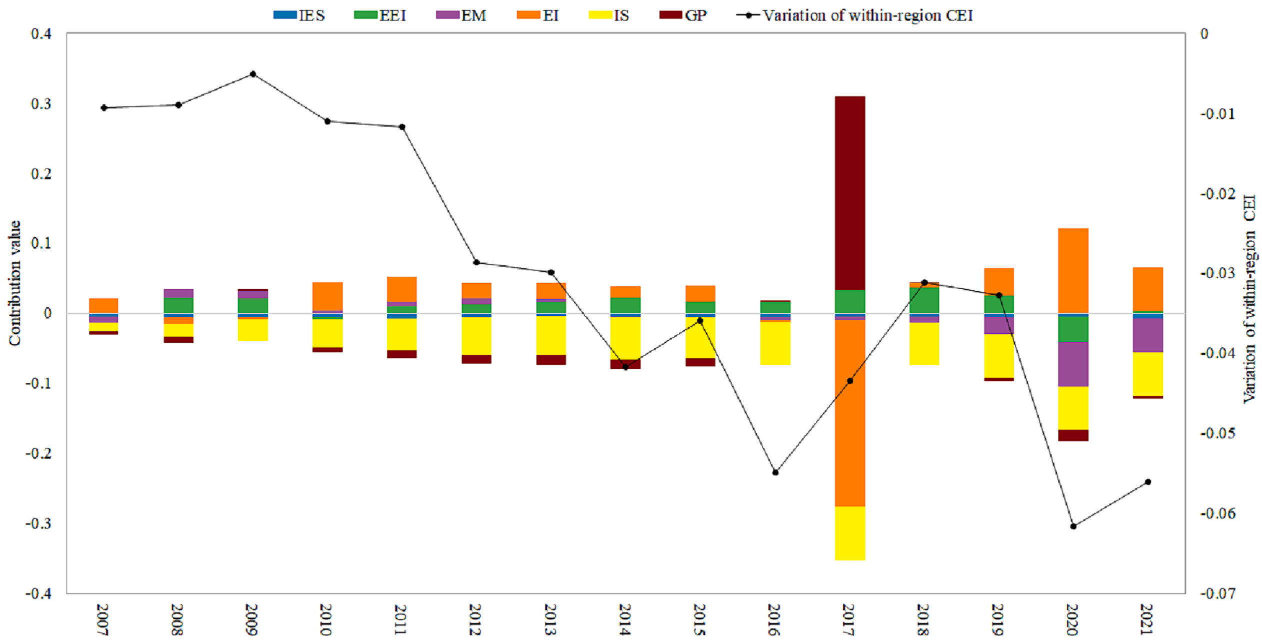


Fig. 10. Decomposition results of change in within-urban agglomeration haze inequality relative to the 2006 level. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

the most important effect causing CEI in the middle reaches. It is found that the industrial energy mix makes an important contribution to mitigating CEI in the middle reaches, and its effect is constant over time. Nevertheless, the contributions of other factors are comparatively modest, and their influence direction fluctuates between positive and negative.

As for the lower reaches urban agglomeration, Fig. 11 (c) shows that the CEI presents a significant declining trend from 0.34 in 2006 to 0.23 in 2021, with an annual average of 0.28, which is much higher than the upper and middle reaches. The decomposition results indicate the major driver of CEI in lower reaches urban agglomeration is the disparity of economic development with an average contribution of 0.32, followed by the energy intensity effect. We also find that the contributions of energy emission intensity, industrial energy mix, and industrial structure are negative in most years, and they are key determinants mitigating CEI in lower reaches. However, the impact of the industrial emission structure is negligible.

On the whole, during 2006–2021, the contributions of economic development and energy intensity in Fig. 11 (a)-(c) are positive and much bigger than other positive drivers, which suggests economic development and energy intensity disparities are the leading determinants shaping CEI in the YREB's three major urban agglomerations. However, the main negative drivers show some differences among the three regions. Industrial energy mix has a significant contribution to mitigating CEI in the upper, middle, and lower reaches, while in lower reaches energy emission intensity and industrial structure are also the major negative contributors.

5.2. *Decomposition of the changes in carbon inequalities of the three urban agglomerations*

To account for the variations of CEIs in various urban agglomerations, this paper decomposes the changes in CEIs at the urban agglomeration level based on Eqs. (15)-(16). The decomposition results are given in Fig. 12, in which 2006 is treated as the benchmark year. The results show that the determinants of changes in CEIs in different urban agglomerations present significant differences in terms of influence direction and contribution magnitudes.

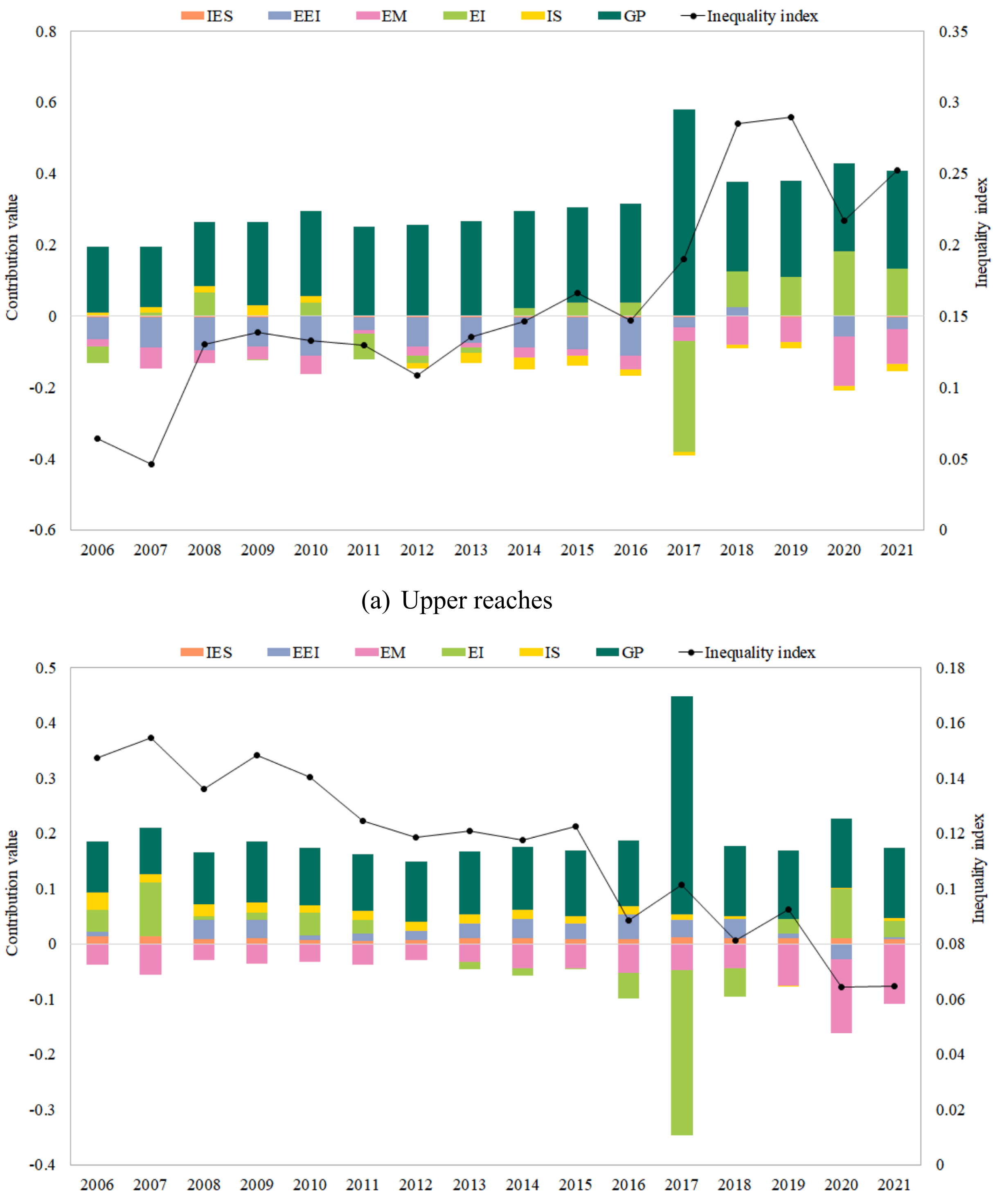
It can be seen from Fig. 12 (a) that economic development and energy intensity contribute to increasing CEI in most periods. The results show the rise of CEI in upper reaches urban agglomeration is mainly explained by the change in economic development and energy intensity disparities during 2006–2021, followed by the effect of energy emission intensity. In contrast, the contributions of industrial energy mix and industrial structure are negative in most periods, showing the changes in the disparities of industrial energy mix and industrial structure contribute to decreasing the upper reaches' CEI. Especially, the negative contribution of industrial energy mix is significantly greater than industrial structure.

Fig. 12 (b) shows that the middle reaches urban agglomeration's CEI shows a significant decrease relative to the 2006 level, with the largest decrement recorded in the period 2006–2019. We also find that industrial emission structure contributes significantly to rising CEI in the middle reaches; In addition, the influence directions of energy emission intensity and energy intensity switched between positive and negative, and on the whole they have a small effect on decreasing CEI over 2006–2021. The contribution of industrial structure is positive throughout the study period, and it also makes a significant contribution to decreasing CEI. However, economic development's contribution is positive in most periods, and it contributes to increasing CEI by 0.03 during 2006–2021. Compared with other determinants, the effect of industrial emission structure is quite minor.

It can be seen from Fig. 12 (c) that CEI in the lower reaches urban agglomeration also shows significant drops in all sub-periods with 2006 as the base year. It is found that the decline in CEI is mainly attributed to changes in industrial structure and economic development disparities, contributing to decreasing CEI by 0.1 and 0.06 respectively. In addition, industrial energy mix and industrial emissions structure also play a role in mitigating CEI in the lower reaches urban agglomeration, but their contributions are very small. However, the energy intensity effect is the main determinant leading to increasing CEI, followed by energy emissions intensity with a small contribution.

6. Comparative analysis of carbon emissions at the city level

The previous sections have explored the spatial–temporal



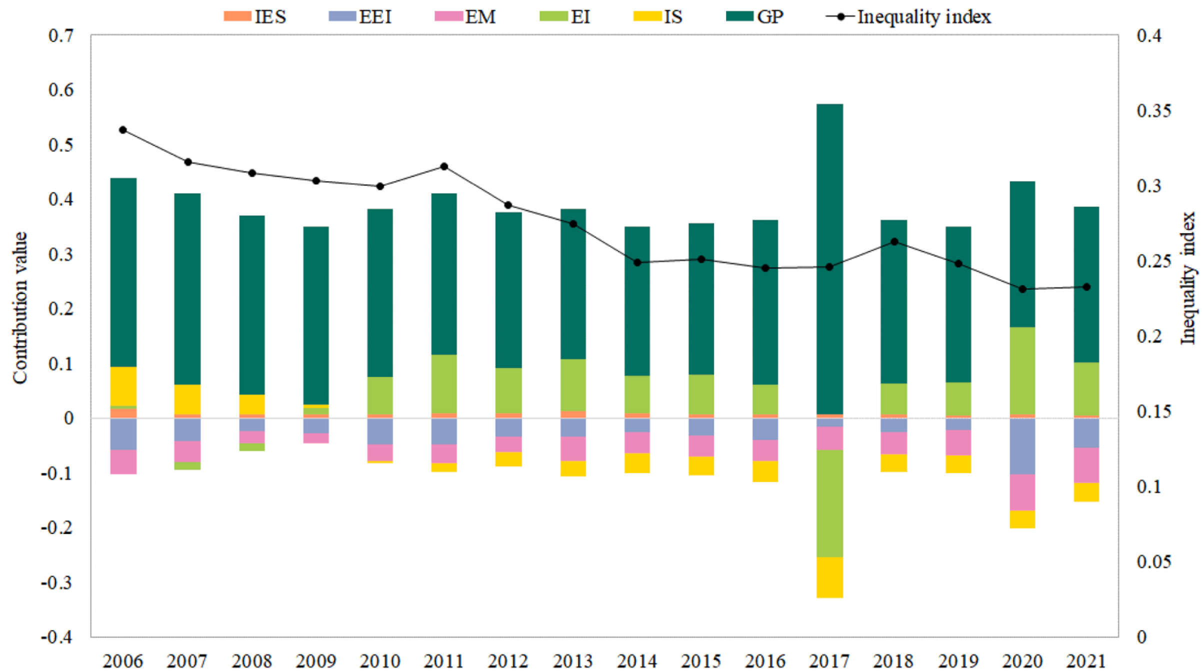
(a) Upper reaches

(b) Middle reaches

Fig. 11. Carbon inequalities and their drivers within urban agglomerations of the upper, middle, and lower reaches. Note: IES denotes industrial emission structure. EEI denotes energy emission intensity. EM denotes industrial energy mix. EI denotes energy intensity. IS denotes industrial structure. GP denotes economic development.

heterogeneity of CEIs and associated drivers in the YREB, from both regional and urban agglomeration perspectives. To reveal more refined city-level heterogeneity features, this paper adopts the spatial decomposition approach to conduct a comparative analysis of city-level carbon emissions. Based on the multiplicative decomposition in Eq. (7), the gap of carbon emissions per capita between each city and the benchmark is decomposed into six factors. The spatial index decomposition analysis utilizes the same benchmark (represented by the YREB-wise average indexes during 2006–2021) in cross-city comparison.

To account for the carbon spatial heterogeneity across cities in the



(c) Lower reaches

Fig. 11. (*continued*).

YREB, Fig. 13 depicts the decomposition results of the disparities of carbon emissions per capita between various cities and the benchmark level. The index in Fig. 13g represents the gap of carbon emissions per capita between each city and the benchmark: the higher the index, the lower the city's emissions relative to the benchmark. It is found that 56 cities have lower carbon emissions per capita than the benchmark level, while the remaining 33 cities, mainly located downstream, have larger carbon emissions per capita, such as Suzhou, Ningbo, Nanjing, Wuxi, and Shanghai. The decomposition results are classified in terms of individual influencing factors (Fig. 13a-f) to emphasize the prioritized emission reduction direction for each city.

As shown in Fig. 13a, the index D_{IES} in 56 cities is larger than 1, indicating that these cities have less carbon-intensive industrial emission structure than the benchmark. However, in the rest 33 cities with an index D_{IES} lower than 1, industrial emission structure is more carbon-intensive compared with the benchmark level. This is highly consistent with the results in Fig. 13g. That is to say, high-emission cities typically have high carbon-intensive emission structures among the primary, secondary, and tertiary industries. It should be noted that all the D_{IES} indexes in the 89 cities are very close to 1, indicating the limited impact of industrial emission structure. The above results provide important policy insights for carbon mitigation at the sectoral level.

Fig. 13b presents the contribution of energy emission intensity to the emission disparity between each city and the benchmark. It can be seen that 46 cities have an index D_{EEI} larger than 1, such as Shanghai, Chongqing, Chengdu, Changsha, Wuhan, Nanjing, etc. That means energy emission intensity in these cities is below the average level. Among them, 12 cities such as Shanghai, Wuhan, Nanjing, Hangzhou, etc., have higher emissions than the benchmark, so the lower energy emission intensity (i.e., low-carbon energy consumption structure) effect mitigates the gap of carbon emissions. By contrast, the other 43 cities have a greater energy emission intensity than the benchmark. In particular, 21 cities, such as Xuzhou, Wuhu, Wuxi, etc., have higher emissions than the benchmark, indicating the energy emission intensity effect plays a role in causing the high emissions in these cities, and it is necessary to improve energy structure in those cities.

As presented in Fig. 13c, 36 cities have an index D_{EM} larger than 1 but quite close to 1, showing that the differences in industrial energy mix between these cities and the benchmark are inconspicuous, though industrial energy mix may contribute to lowering their carbon emissions compared with the benchmark level. By contrast, 53 cities have the D_{EM} index smaller than 1. That means the industrial energy mix effect contributes to increasing carbon emissions, especially in some cities such as Huangshan, Huaihua, Suizhou, and Xiangxi where the industrial energy mix should be noticed and optimized.

The contribution of energy intensity is presented in Fig. 13d. It is found that the number of cities with an index D_{EI} larger than 1 is as high as 51, showing energy intensity in these regions is smaller than the reference level. That contributes to lowering carbon emissions in these cities especially Huangshan, Changsha, Chengdu, and Hefei relative to the benchmark. However, energy intensity in the rest 38 cities is above the average level. Among them, 23 cities such as Nanjing, Xuzhou, Suzhou, and Zhenjiang, have larger emissions than the benchmark, so the energy intensity effect can explain part of the carbon emissions disparity, and there is a need to improve energy efficiency in those cities.

From Fig. 13e, we find that 38 cities have an index D_{IS} larger than 1, indicating that industrial structure in these areas helps decrease carbon emissions per capita. It is worth noting that in six cities including Shanghai, Hangzhou, Nanjing, Zhoushan, Wuhan, and Xuzhou with higher emissions, the industrial structure effect helps mitigate their carbon emissions per capita. In contrast, the remaining 51 cities have a D_{IS} lower than the average level. Among them 27 cities, such as Panzhihua, Tongling, Maanshan, and Yingtan, have higher emissions than the benchmark, the industrial structure effect can account for the high carbon emissions to a certain extent, and it is indispensable to optimizing industrial structure in these areas.

As for the economic development effect, Fig. 13f shows that as many as 60 cities have the D_{GP} index bigger than 1, indicating most cities have a lower economic development than the reference. That can partly account for the lower emissions in most low-emissions cities. Especially, the economic development in Fuyang, Bozhou, Lu'an, and Shaoyang significantly lags, the corresponding indices are 4.37, 3.69, 3.61, and

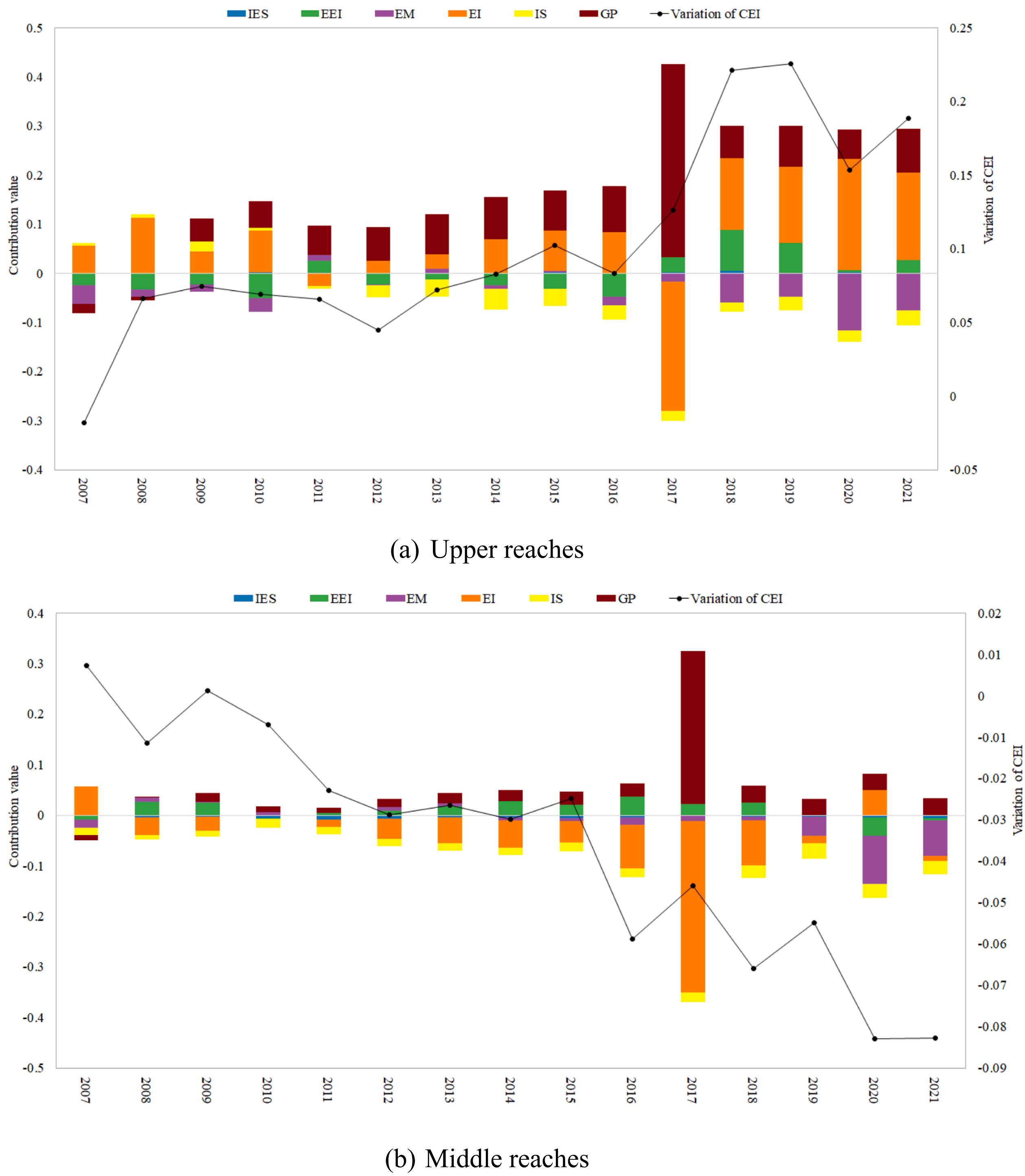


Fig. 12. Decomposition results of change in carbon inequality within urban agglomerations of the upper, middle, and lower reaches.

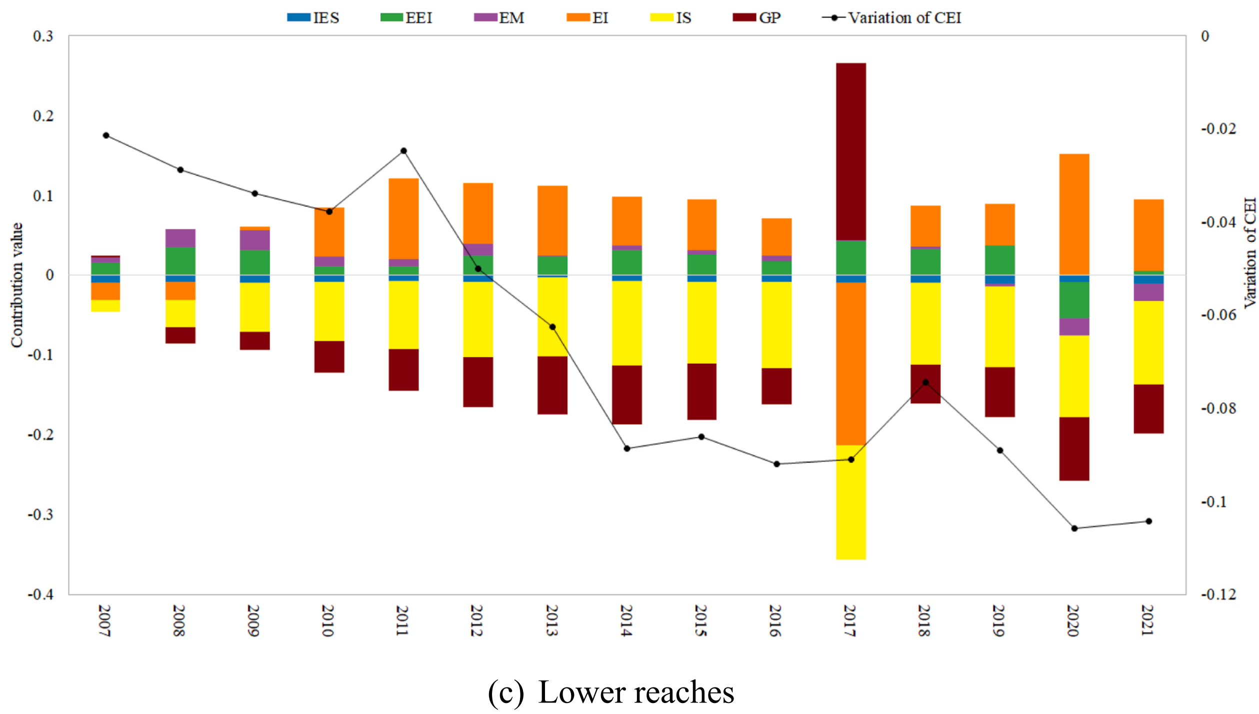


Fig. 12. (*continued*).

3.54, respectively. The results show that the rest 29 cities, mainly located in the lower reaches of the YREB, have relatively higher economic development levels than the benchmark. Economic development and emissions per capita are both stratified into five categories. It is found that the strata of economic development in Fig. 13f are highly consistent with that of emissions per capita in Fig. 13g, indicating that carbon emissions are highly coupled with economic development.

7. Conclusions and policy implications

7.1. Main conclusions

The discussion on climate justice issues has been persistent and controversial. Carbon neutrality, as a strategy to combat climate change, should uphold the ideals of climate justice and be achieved without exacerbating carbon inequalities. Using data from 89 cities in China's YREB, this paper analyzes the dynamic evolution of city-level carbon emissions inequality (CEI) and associated drivers through an integrated framework that combines mean logarithmic deviation with LMDI decomposition. The CEIs at different scales are attributed to six influencing factors, with decomposition analysis performed at the regional, urban agglomeration, and city levels.

The main findings include. (1) The within-urban agglomerations emissions inequality dominates the overall CEI in the YREB. Economic development and energy intensity are the major determinants accounting for CEIs at different scales, while industrial energy mix disparity mitigates multi-CEI. (2) The declining CEI in YREB from 2006 to 2021 primarily results from changes in disparities of industrial structure and economic development, while the energy intensity effect partially offsets the decreased CEI. However, industrial emission structure has little effect on CEIs. (3) The increase in CEI of the upper reaches is primarily associated with the energy intensity effect. By contrast, the effects of industrial energy mix and industrial structure dominate the decreased CEIs in middle reaches and lower reaches, respectively. (4) Spatial decomposition emphasizes the prioritized emission reduction direction for each city. Notably, the strata of industrial emission structure and economic development highly align with the distribution of emissions across the YREB, indicating a strong coupling relationship with carbon emissions.

7.2. Policy implications

This paper offers valuable policy implications for city-level coordinated carbon mitigation.

(1) Based on the economic development level and carbon emission status of different regions, policymakers should establish specific emission reduction targets that are suitable for each region; meanwhile, sufficient financial support should be provided to regions with higher CEI to facilitate the transition towards a low-carbon economy. Besides, policies should encourage sustainable and environmentally responsible economic growth models. This can be achieved through incentives for clean production processes and technologies, such as implementing environmental standards, offering tax incentives, and strengthening investments in research and development for green technology innovations.

(2) Energy intensity is identified as a major determinant of CEIs, highlighting the improvement of energy efficiency. This could include establishing energy efficiency standards, providing incentives for industries to reduce energy consumption, offering technological support, and encouraging the adoption of energy-saving technologies. Especially, cities with high emissions and energy intensity, such as Nanjing, Xuzhou, Suzhou, and Zhenjiang, should prioritize improving industrial energy efficiency. Promote energy technology innovation and transfer. Developed regions can cooperate with underdeveloped regions in energy technology innovation and transfer, sharing advanced energy technologies and experiences to improve energy efficiency and reduce carbon emissions.

(3) Governments should develop tailored strategies or policy priorities for each city, urban agglomeration, or region based on their unique characteristics and challenges. The upper reaches urban

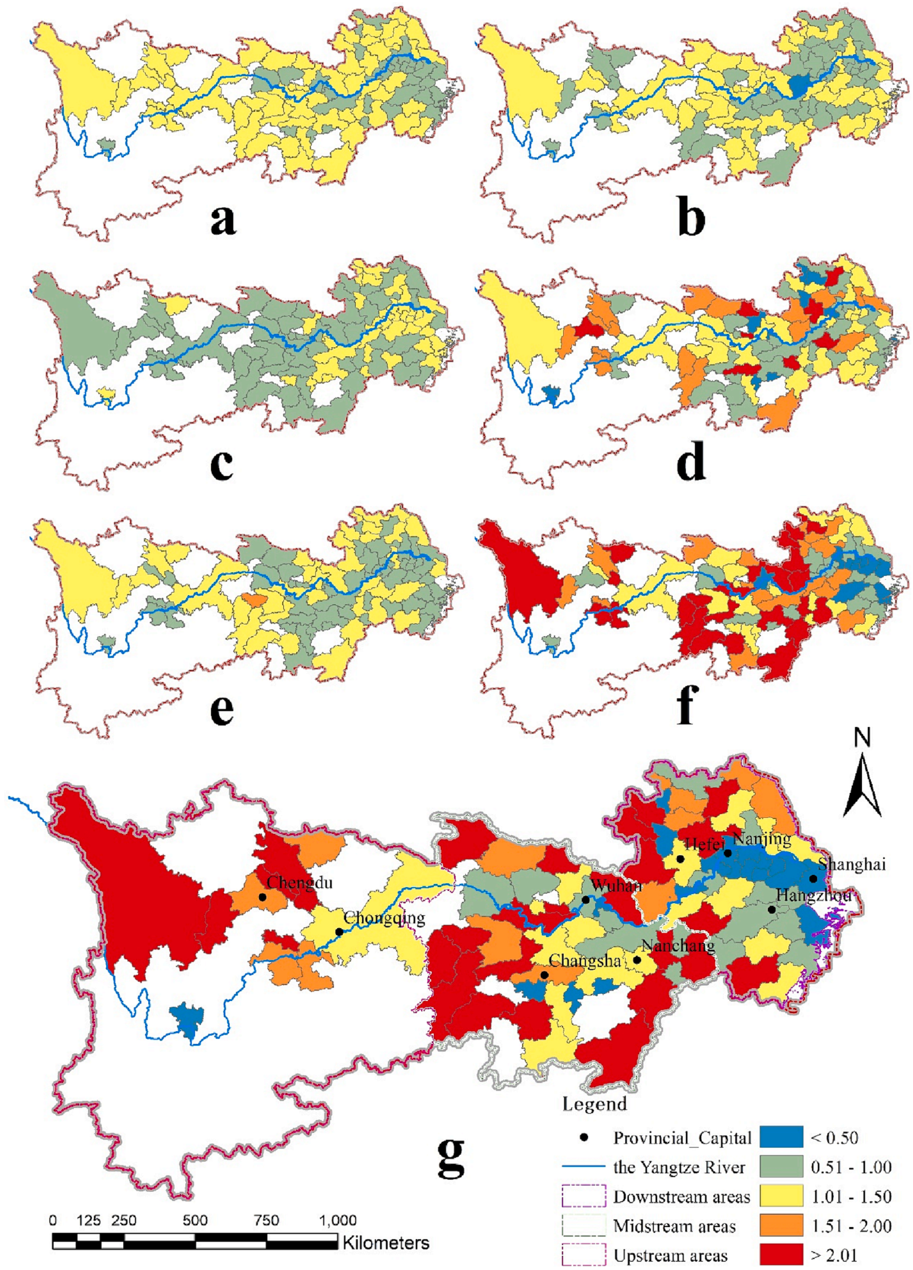


Fig. 13. Decomposition results of the disparities of carbon emissions per capita between individual cities and the benchmark, 2006–2021. Note: a. Contribution of IES (D_{IES}). b. Contribution of EEI (D_{EEI}). c. Contribution of EM (D_{EM}). d. Contribution of EI (D_{EI}). e. Contribution of IS (D_{IS}). f. Contribution of GP (D_{GP}). g. Gap of emissions per capita.

agglomeration should focus on decreasing energy intensity across sectors, the middle reaches urban agglomeration should prioritize the optimization of their industrial energy mix, and the lower reaches urban agglomeration should actively promote the low-carbon transformation of industrial structure. Since the intra-urban agglomeration inequalities are even more prominent than the between-urban agglomeration inequalities, it is more urgent to develop differentiated emission reduction strategies for individual cities.

(4) Areas with low-carbon industrial structure can provide technical support and training to areas with high-carbon industrial structure to help them improve the greening level of their industrial structures. This includes technology transfer, technical training and knowledge sharing to promote the transformation of industrial structures and the reduction of carbon emissions. In addition, various regions can strengthen cooperation and achieve resource sharing and complementary advantages through industrial cooperation and industrial chain extension. It is crucial to promote low-carbon industrial development and encourage the transformation of high-carbon emission industries, such as supporting the growth of green and clean industries including renewable energy, clean technologies, waste recycling, and sustainable agriculture.

(5) There is a need to promote a shift towards a cleaner energy consumption structure across regions to optimize the industrial energy mix. Additionally, enhancing energy production and combustion efficiency, along with implementing end-of-pipe treatment, holds substantial practical significance. For regions with relatively backward energy consumption structures, the government can provide support and funding to assist them in

energy transformation. This can include funding for energy transformation projects, providing energy technology training, and knowledge transfer to achieve coordinated emission reductions.

Future research can further utilize the methodological framework in this paper for carbon inequalities in urban agglomerations of other regions and countries. Furthermore, the role of urbanization in influencing carbon emission inequality in urban agglomerations needs to be explored. The emissions differences in cities at different urbanization development stages should be discussed for achieving coordinated urbanization development and carbon emission reduction. Moreover, it is necessary to further explore the multiple couplings of carbon emissions in adjacent or distant urban agglomerations, such as transboundary energy and resource complementarity to improve energy efficiency and promote carbon reduction. Besides, future studies should also explore the policy framework, regulatory system and implementation mechanism for collaborative emission reduction in urban agglomerations. For example, the collaborative emissions reduction potential of industrial agglomeration in urban agglomeration deserves future discussion.

CRediT authorship contribution statement

Bolin Yu: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Zhenci Xu:** Writing – review & editing, Validation, Supervision, Formal analysis. **Congcong Du:** Validation, Software, Methodology, Data curation. **Jinghang Xu:** Writing – review & editing, Visualization, Investigation, Data curation. **Yuling Pan:** Writing – review & editing, Visualization, Validation, Formal analysis. **Junfang Zhou:** Visualization, Formal analysis. **Yuli Shan:** Writing – review & editing, Visualization, Validation, Supervision, Methodology.

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.

Data availability

Data will be made available on request.

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References

Alajmi, R.G., 2021. Factors that impact greenhouse gas emissions in Saudi Arabia: Decomposition analysis using LMDI. Energy Policy 156, 112454.
Arneth, A., Sitch, S., Pongratz, J., Stocker, B.D., Ciais, P., Poulter, B., Bayer, A.D., Bondeau, A., Calle, L., Chini, L., 2017. Historical carbon dioxide emissions caused by land-use changes are possibly larger than assumed. Nat. Geosci. 10, 79–84.
Arto, I., Dietzenbacher, E., 2014. Drivers of the growth in global greenhouse gas emissions. Environmental Science Technology 48, 5388–5394.
Bianco, V., Proskuryakova, L., Starodubtseva, A., 2021. Energy inequality in the eurasian economic union. Renew. Sustain. Energy Rev. 146, 111155.
Bindzar, P., Saderova, J., Sofranko, M., Kacmary, P., Brodny, J., Tutak, M., 2021. A case study: Simulation traffic model as a tool to assess one-way vs. two-way traffic on urban roads around the city center. Appl. Sci. 11, 5018.
Boyce, J.K., Zwickl, K., Ash, M., 2016. Measuring environmental inequality. Ecol. Econ. 124, 114–123.
Bruckner, B., Hubacek, K., Shan, Y., Zhong, H., Feng, K., 2022. Impacts of poverty alleviation on national and global carbon emissions. Nat. Sustainability 5, 311–320.
Chancel, L., 2022. Global carbon inequality over 1990–2019. Nat. Sustainability 5, 931–938.
Chen, L., Xu, L., Yang, Z., 2019. Inequality of industrial carbon emissions of the urban agglomeration and its peripheral cities: A case in the Pearl River Delta, China. Renew. Sustain. Energy Rev. 109, 438–447.
Clarke-Sather, A., Qu, J., Wang, Q., Zeng, J., Li, Y., 2011. Carbon inequality at the sub-national scale: A case study of provincial-level inequality in CO_2 emissions in China 1997–2007. Energy Policy 39, 5420–5428.
Crost, B., Duquennois, C., Felter, J.H., Rees, D.I., 2018. Climate change, agricultural production and civil conflict: Evidence from the Philippines. Journal of Environmental Economics Management 88, 379–395.
Dong, F., Yu, B., Hua, Y., Zhang, S., Wang, Y., 2018. A Comparative Analysis of Residential Energy Consumption in Urban and Rural China: Determinants and Regional Disparities. Int J Environ Res Public Health 15, 2507.
Dong, F., Yu, B., Pan, Y., Hua, Y., 2020. What contributes to the regional inequality of haze pollution in China? Evidence from quantile regression and Shapley value decomposition. Environ. Sci. Pollut. Res. 27, 17093–17108.
Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., Pan, Y., 2022. How does digital economy affect carbon emissions? Evidence from global 60 countries. Sci. Total Environ. 852, 158401.
Downey, L., Hawkins, B., 2008. Race, Income, and Environmental Inequality in the United States. Sociol Perspect 51, 759–781.
Duro, J.A., Padilla, E., 2006. International inequalities in per capita CO_2 emissions: A decomposition methodology by Kaya factors. Energy Econ. 28, 170–187.
Fan, W., Li, L., Wang, F., Li, D., 2020. Driving factors of CO_2 emission inequality in China: The role of government expenditure. China Econ. Rev. 64, 101545.
Guan, Y., Shan, Y., Huang, Q., Chen, H., Wang, D., Hubacek, K., 2021. Assessment to China's recent emission pattern shifts. Earth's. Future 9, e2021EF002241.
Hassan, T., Khan, Y., He, C., Chen, J., Alsagr, N., Song, H., Naveed, K., 2022. Environmental regulations, political risk and consumption-based carbon emissions: Evidence from OECD economies. J Environ Manage 320, 115893.
Hou, J., Wan, M., Song, M., 2024. Carbon emission inequality and fairness from energy consumption by prefecture-level cities in China. Ecol. Ind. 158, 111364.
Huang, Y., Matsumoto, K.I., 2021. Drivers of the change in carbon dioxide emissions under the progress of urbanization in 30 provinces in China: A decomposition analysis. J. Clean. Prod. 322, 129000.
Kaya, Y., 1989. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. Intergovernmental Panel on Climate Change/response Strategies Working Group, May.
Khattak, S.I., Ahmad, M., ul Haq, Z., Shaofu, G., Hang, J., 2022. On the goals of sustainable production and the conditions of environmental sustainability: Does cyclical innovation in green and sustainable technologies determine carbon dioxide emissions in G-7 economies. Sustainable Production and Consumption 29, 406–420.
Li, R., Wang, Q., Liu, Y., Jiang, R., 2021. Per-capita carbon emissions in 147 countries: the effect of economic, energy, social, and trade structural changes. Sustainable Production and Consumption 27, 1149–1164.
Li, N., Yuan, R., Wang, J., 2022. Analysis of current and future energy inequality by energy categories in China. Sustainable Production and Consumption 32, 393–406.
Liddle, B., 2010. Revisiting world energy intensity convergence for regional differences. Appl. Energy 87, 3218–3225.
Liu, J., Li, S., Ji, Q., 2021. Regional differences and driving factors analysis of carbon emission intensity from transport sector in China. Energy 224, 120178.
Lu, W., Wu, H., Yang, S., Tu, Y.P., 2022. Effect of environmental regulation policy synergy on carbon emissions in China under consideration of the mediating role of industrial structure. J Environ Manage 322, 116053.
Luo, M., Zhao, T., Zhao, L., Wang, J., 2020a. Understanding regional inequality in per capita CO 2 emissions in China during 1997–2016: Sources and driving factors. Environ. Sci. Pollut. Res. 27, 32100–32115.
Luo, Q., Zhou, J., Li, Z., Yu, B., 2020b. Spatial differences of ecosystem services and their driving factors: a comparation analysis among three urban agglomerations in China's Yangtze River Economic Belt. Sci. Total Environ. 725, 138452.
Luo, Q., Zhou, J., Zhang, Y., Yu, B., Zhu, Z., 2022. What is the spatiotemporal relationship between urbanization and ecosystem services? A case from 110 cities in the Yangtze River Economic Belt. China. Journal of Environmental Management 321, 115709.
Milindi, C.B., Inglesi-Lotz, R., 2023. Impact of technological progress on carbon emissions in different country income groups. Energy Environ. 34, 1348–1382.
NDRC, 2016. National Development and Reform Commission (NDRC), 2016. Outline of Yangtze River Economic Belt Development Plan.
Newell, P., 2005. Race, class and the global politics of environmental inequality. Global Environmental Politics 5, 70–94.
Pan, Y., Dong, F., 2023. The impacts of energy finance policies and renewable energy subsidy on energy vulnerability under carbon peaking scenarios. Energy 273, 127228.
Pan, X., Wang, Y., Tian, M., Feng, S., Ai, B., 2023. Spatio-temporal impulse effect of foreign direct investment on intra-and inter-regional carbon emissions. Energy 262, 125438.
Pecl, G.T., Araujo, M.B., Bell, J.D., et al., 2017. Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. Science 355, eaai9214.
Quan, C., Cheng, X., Yu, S., Ye, X., 2020. Analysis on the influencing factors of carbon emission in China's logistics industry based on LMDI method. Sci. Total Environ. 734, 138473.

Rehman, E., Rehman, S., 2022. Modeling the nexus between carbon emissions, urbanization, population growth, energy consumption, and economic development in Asia: Evidence from grey relational analysis. Energy Rep. 8, 5430–5442.
Remuzgo, L., Sarabia, J.M., 2015. International inequality in CO_2 emissions: A new factorial decomposition based on Kaya factors. Environ Sci Policy 54, 15–24.
Ribeiro, K., Pacheco, F.S., Ferreira, J.W., de Sousa-Neto, E.R., Hastie, A., Krieger Filho, G. C., Alvalá, P.C., Forti, M.C., Ometto, J.P., 2021. Tropical peatlands and their contribution to the global carbon cycle and climate change. Glob. Chang. Biol. 27, 489–505.
Rosa, E.A., Dietz, T., 2012. Human drivers of national greenhouse-gas emissions. Nat. Clim. Chang. 2, 581–586.
Scholze, M., Knorr, W., Arnell, N.W., Prentice, I.C., 2006. A climate-change risk analysis for world ecosystems. Proc. Natl. Acad. Sci. 103, 13116–13120.
Sepehri, A., Sarrafzadeh, M.-H., Avateffazeli, M., 2020. Interaction between Chlorella vulgaris and nitrifying-enriched activated sludge in the treatment of wastewater with low C/N ratio. J. Clean. Prod. 247, 119164.
Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., Mi, Z., Liu, Z., Zhang, Q., 2018. China CO_2 emission accounts 1997–2015. Sci. Data 5, 1–14.
Shan, Y., Huang, Q., Guan, D., Hubacek, K., 2020. China CO_2 emission accounts 2016–2017. Sci. Data 7, 1–9.
Shan, Y., Guan, Y., Hang, Y., Zheng, H., Li, Y., Guan, D., Li, J., Zhou, Y., Li, L., Hubacek, K., 2022. City-level emission peak and drivers in China. Science Bulletin 67, 1910–1920.
Shorrocks, A.F., 1980. The class of additively decomposable inequality measures. Econometrica 613–625.
Steinberger, J.K., Roberts, J.T., Peters, G.P., Baiocchi, G., 2012. Pathways of human development and carbon emissions embodied in trade. Nat. Clim. Chang. 2, 81–85.
Tian, Q., Zhao, T., Yuan, R., 2021. An overview of the inequality in China's carbon intensity 1997–2016: a Theil index decomposition analysis. Clean Techn. Environ. Policy 23, 1581–1601.
Wang, Z., Cui, C., Peng, S., 2019. How do urbanization and consumption patterns affect carbon emissions in China? A decomposition analysis. J. Clean. Prod. 211, 1201–1208.
Wang, F., Harindintwali, J.D., Wei, K., Shan, Y., Mi, Z., Costello, M.J., Grunwald, S., Feng, Z., Wang, F., Guo, Y., 2023. Climate change: Strategies for mitigation and adaptation. The Innovation Geoscience 1, 100015–100061.
Wang, H., Zhang, R., 2022. Effects of environmental regulation on CO_2 emissions: An empirical analysis of 282 cities in China. Sustainable Production and Consumption 29, 259–272.
Xiao, K., Yu, B., Cheng, L., Li, F., Fang, D., 2022. The effects of CCUS combined with renewable energy penetration under the carbon peak by an SD-CGE model: Evidence from China. Appl. Energy 321, 119396.
Xu, L., Fan, M., Yang, L., Shao, S., 2021. Heterogeneous green innovations and carbon emission performance: evidence at China's city level. Energy Econ. 99, 105269.
Xu, C., Wang, B., Chen, J., Shen, Z., Song, M., An, J., 2022. Carbon inequality in China: Novel drivers and policy driven scenario analysis. Energy Policy 170, 113259.
Yu, B., Fang, D., Kleit, A.N., Xiao, K., 2022. Exploring the driving mechanism and the evolution of the low-carbon economy transition: Lessons from OECD developed countries. The World Economy 45, 2766–2795.
Yu, B., Fang, D., Pan, Y., Jia, Y., 2023a. Countries' green total-factor productivity towards a low-carbon world: The role of energy trilemma. Energy 278, 127894.
Yu, B., Fang, D., Xiao, K., Pan, Y., 2023b. Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak. Renewable Sustainable Energy Reviews 178, 113247.
Yue, X.-L., Gao, Q.-X., 2018. Contributions of natural systems and human activity to greenhouse gas emissions. Adv. Clim. Chang. Res. 9, 243–252.
Zhang, F., Deng, X., Phillips, F., Fang, C., Wang, C., 2020. Impacts of industrial structure and technical progress on carbon emission intensity: Evidence from 281 cities in China. Technological Forecasting Social Change 154, 119949.
Zhang, Q., Su, S., 2016. Determinants of urban expansion and their relative importance: A comparative analysis of 30 major metropolitans in China. Habitat Int. 58, 89–107.
Zhao, M., Tan, L., Zhang, W., Ji, M., Liu, Y., Yu, L., 2010. Decomposing the influencing factors of industrial carbon emissions in Shanghai using the LMDI method. Energy 35, 2505–2510.