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What causes spatial carbon inequality? Evidence from China's Yangtze River economic Belt

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ABSTRACT

Detecting spatial carbon inequality is critical to achieving regional emission reduction targets from the perspectives of ensuring equality and efficiency. While previous studies have measured spatial carbon inequality and identified its drivers, few studies have explored these drivers at a sectorial level. Taking China's Yangtze River Economic Belt (YREB) as a case study example, this study explores the drivers of spatial carbon inequality at the sectoral level and reveals the following key points. (1) The regional heterogeneity in CO_2 emissions driven by economic factors have increased from 2002 to 2012. (2) The wide spatial differences in CO_2 emissions are driven by per capita final demand, production structure, and final demand structure. (3) Driven by emission intensity, the production structure, and the final demand structure effects, the *Electricity and heat production and supply*, *Smelting and pressing of metals*, and *Nonmetal mineral products* have become the most critical sectors aggravating the spatial carbon inequality. (4) Driven by the production structure and final demand structure, most of the middle and lower reaches of the YREB emit more CO_2 in the aforementioned sectors. Our findings support the implementation of coordinated emission reduction plans in the YREB region.

1. Introduction

As the world's top CO_2 emitter (IEA, 2012), China has attached great importance to tackling its CO_2 emissions. In this light, at the 2015 Paris Climate Conference, the country proposed to reduce its 2005 level CO_2 emissions per unit GDP (carbon intensity) by 40–45% and 60–65% by respectively, 2020 and 2030 (UNFCCC, 2015). Due to China's regional administration, these national targets are often decomposed into sub-national targets. However, as there are large discrepancies across China's regions in their natural resources, economic development patterns, and environmental policies, it is challenging to achieve sub-national targets while simultaneously ensuring equality and efficiency (Cao et al., 2019; Wang et al., 2016, 2019, 2020). Constrained by regional target reductions, highly-developed regions tend to quickly reduce CO_2 emissions by importing high-carbon products from less-developed regions or by transferring their high-pollution industries to less-developed regions (Fang et al., 2020). Consequently, to satisfy the needs of their economic development, less-developed regions continue to produce high-carbon products, which lead to more pressure on their emission reduction targets (Miao et al., 2019). Such instances serve as reminders to policymakers that achieving sub-national emission reduction targets should not only produce a sufficient emission reduction performance but also be based on the principle of equal and coordinated development among regions (Bai et al., 2016; Jiang et al., 2019; Li et al., 2020). Toward this end, understanding the spatial inequality of CO_2 emissions among different regions and its underlying social-economic driving forces is a key step to address the above issues (Wang et al., 2020).

Previous studies on carbon emissions inequality have mainly examined the carbon inequalities related to income and household consumption levels. Some common indicators of inequality are applied to measure the degree of inequality, for example, the variation coefficient (Duro, 2012); Gini Index (Heil and Wodon, 1997; Teixidó-Figueras et al., 2016); and the Theil Index (Padilla and Duro, 2013). Using these indicators, researchers have investigated carbon inequality levels among different countries and regions, e.g., the Belt and Road countries (Han

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et al., 2020), developing countries, the E.U., and the USA (Hubacek et al., 2017), and among different sub-regions within a country, e.g., provinces of China (Clarke-Sather et al., 2011; Mi et al., 2020) and 21 cities in the Pearl River Delta (Chen et al., 2019c). These researches have predominantly highlighted the stark disparity of carbon emissions between high- and low-income groups and regional inequalities.

To further reveal the determinants of carbon inequality, researchers have explored the socioeconomic drivers of carbon emissions inequality among global countries (Wang and Zhou, 2018), China's regions (Li et al., 2017; Luo et al., 2020), and Chinese cities (Chen et al., 2019c). Specifically, most of these studies have examined multiple drivers of carbon inequality by using spatial index decomposition analysis (IDA) (Chen et al., 2019a) and spatial structural decomposition analysis (SDA) (Wu et al., 2020; Zhao et al., 2020). Compared with IDA, SDA is based on input-output analysis (IOA) which can provide richer information on the internal structure of economic systems (Román-Collado and Colinet, 2018; Zhou et al., 2020), e.g., production structure and demand structure, and evaluate how the spatial carbon inequalities are driven directly and indirectly by socio-economic drivers (Hoekstra and van den Bergh, 2003; Su and Ang, 2012; Yan and Su, 2020). For example, by using the spatial SDA method, the socio-economic drivers (e.g., production structure) of the carbon emissions of 30 provinces in China have been explored (Wu et al., 2020). These studies have focused on the overall economy; however, they lack a specific sectorial-level analysis of the socio-economic drivers. As the Chinese government continues to propose strategies for regional development, a thorough grasp of the drivers of spatial carbon inequality at the sectorial level can lead to more regionally relevant policies (e.g., technological advancement at the sectoral level) for carbon emission reductions and sustainable economic development. To the best of our knowledge, no study has so far examined the drivers of spatial carbon inequality at the sectorial and subnational levels.

To fill these knowledge gaps, this paper aims to scrutinize the socioeconomic drivers underlying spatial carbon inequality at the sectorial and sub-national level by conducting a case study of the Yangtze River Economic Belt (YREB) region in China. We choose the YREB region for the following reasons. First, the Chinese government issued the "Outline for the Development of the Yangtze River Economic Belt" in October 2016, in which it revealed that the YREB region has the highest potential for development in China (Sun et al., 2018). Second, the YREB region has been, for a very long time, facing problems of an unbalanced regional economic development and high resource consumption and pollution discharge. Third, China places great importance on the future development of this region. For example, the State Council has pointed out that the development of the YREB region has an indispensable practical and far-reaching strategic significance for realizing the nation's sustainable development (State Council, 2014).

In this paper, we have addressed the following questions. First, what are the spatial–temporal dynamics of carbon emissions and carbon inequality in the YREB region? Second, what are the impacts of socioeconomic drivers on the regional and sub-regional carbon inequality and how do these impacts change over time? Third, how do the drivers of spatial carbon inequality perform at the sectoral level? The above question led us to combine the analysis of the drivers of spatial carbon inequality with a regional classification analysis based on per capita GDP and per capita carbon emissions. Based on this combined analaysis, we address as our fourth and final question: what measures can we reach to promote the coordinated carbon emissions reduction of the YREB region? To address these questions, we assessed the spatial carbon inequality in the YREB region using the Gini index. We then investigated the drivers of spatial carbon inequality and detected the sectoral contribution of the drivers to spatial carbon inequality by applying the spatial SDA method.

This study contributes to the literature in the following ways. Firstly, the study measures the carbon inequality of the YREB region and identifies its underlying socio-economic drivers of spatial carbon inequality. Secondly, a precise sectoral level analysis of the drivers of spatial carbon inequality is conducted which provides a thorough knowledge of drivers of spatial carbon inequality. The rest of the paper is organized as follows. Section 2 introduces the inequality measurement, spatial decomposition analysis, attribution analysis, the case description, and the data sources of this research. Section 3 presents the results of spatial Structural Decomposition Analysis. Policy recommendations are discussed in Section 4 and the conclusion follows in Section 5.

2. Methodology and data

2.1. Inequality measurement

The measurement of carbon inequality has been widely conducted by recent studies. Most studies detected carbon inequality in terms of household income by using an inequality indicator. For example, carbon footprint Gini coefficients were calculated to measure carbon inequality for households across China's provinces (Mi et al., 2020). The relationship between U.S. state-level CO_2 emissions and two measures of income inequality: the income share of the top 10% and the Gini coefficient, has also been investigated (Jorgenson et al., 2017). The above studies have concentrated on investigating carbon inequality caused by different income levels in a specific region, while other studies investigated the carbon inequality among regions and proposed some specific indicators and indices. For example, the carbon inequality per capita between different countries and regions has been identified by the Theil index (Han et al., 2020). These previous studies provide references for the measurement of spatial carbon inequality in this study.

This study measures spatial carbon inequality by using the Lorenz curve, which is a distribution curve showing the population percentage from the "poorest to richest" corresponding to the income of each population percentage. The horizontal axis represents the cumulative population percentage (grouped by income from low to high), and the vertical axis represents the cumulative income percentage; the arc is the Lorentz curve (Lorenz, 1905; Teixidó-Figueras et al., 2016). The curvature degree of the Lorenz curve is of great significance. Generally, it reflects inequality in income distribution. The greater the curvature degree, the more unequal is the income distribution, and vice versa. To detect the spatial inequality of carbon emissions in a certain region, this study constructs the Lorenz curve and calculates the Gini index using the carbon emissions and population data. The horizontal and vertical axes represent the cumulative percentages of the population and the corresponding carbon emissions, respectively. We use the following symbols for the inequality measurement of carbon emissions across sub-regions in the YREB region, where the sub-region index is given by the subscript *i*:

C_i = Carbon dioxide emission in sub-region i;

P_i = Population size in sub-region i;

$g_i \equiv \frac{C_i}{\sum_i C_i}$ = Regional carbon dioxide emission share

$p_i \equiv \frac{P_i}{\sum_i P_i}$ = Regional population share

To start with, we sort sub-regions according to their CO_2 emissions (C_i). Let $F(g_i)$ and $F(p_i)$ be the cumulative proportion of regional CO_2 emissions and the cumulative proportion of the region population based on this ranking. The Lorenz curves in Fig. 3b now depicts $F(g_i)$, the cumulative regional share in CO_2 emissions, on the vertical axis, plotted against $F(p_i)$, the cumulative regional population share, on the horizontal axis, for three years, 2002, 2007, and 2012. We choose Smoothing Spline in MATLAB to fit the curve. The diagonal, also called the perfect equality line, with a slope equal to unity, represents the hypothetical situation of equal CO_2 emission per capita across subregions. Finally, we calculate the Gini coefficient, which is defined as the ratio of the area lying between the Lorenz curve and the perfect equality line to the total triangle area below the perfect equality line.

2.2. Spatial SDA

In the SDA method, we assume that the aggregate measure refers to a region, the sub-categories are industry sectors, and the aggregate is presented as the summation of sub-category values. Assuming that every sub-region is divided into n sectors and has k types of final demand, such as urban household consumption and fixed investment, the CO_2 emissions of a sub-region can be expressed as the product of several independent variables representing the decomposition factors:

$$C = e \times L \times Ys \times Yc \times g \times p \tag{1}$$

where the $m \times 1$ vector C represents the amount of CO_2 emissions; the $m \times n$ matrix e indicates the CO_2 emissions intensity; the $n \times n$ matrix L ($L = (I–A)^{-1}$) is the *Leontief Inverse* matrix (Miller and Blair, 2009), where I is the $n \times n$ identity matrix and A is the $n \times n$ direct input coefficient matrix; the $n \times k$ matrix Ys represents the share of each n sector in each of the k categories of final demand; the $k\times 1$ vector Yc stands for the allocation of total final demand of k categories of the final demand; and scalars g and p are respectively the per capita final demand and population.

In the sum notation, Eq. (1) can be written as

$$C = \sum_{j=1}^{n} \sum_{h=1}^{k} e_i \times L_{ij} \times Ys_{jh} \times Yc_h \times g \times p \tag{2}$$

As seen as in Fig. 1, spatial SDA can identify the contribution of socioeconomic drivers underlying the spatial heterogeneity in carbon emissions in the sub-regions in a given year (Su and Ang, 2016). This study employs a multi-regional spatial SDA model to compare the discrepancy in CO_2 emissions in the YREB region and explain why these differences occur. In the group of a region, $R = (R_1, R_2,\cdots,R_u)$, R_u is the given sub-region and R_a is a hypothetical benchmark region constructed. Following most literatures (Yan and Su, 2020), this study uses the arithmetic average carbon emissions of the YREB regions to construct the benchmark R_a. Moreover, there are two different models that can be formulated for spatial SDA: additive spatial SDA and multiplication spatial SDA. The additive spatial SDA is applied to decompose the difference in absolute regional performance such as total CO_2 emissions, while the multiplication spatial SDA is used to decompose the difference in relative regional performance such as the aggregate CO_2 emissions intensity. In this study, we use the additive spatial SDA method, and the difference in CO_2 emissions between R_u and R_a for a given year t can be expressed as

$$\Delta C_{TOT}^{R_u-R_a} = \Delta_e C^{R_u-R_a} + \Delta_L C^{R_u-R_a} + \Delta_{Y_S} C^{R_u-R_a} + \Delta_{Yc} C^{R_u-R_a} + \Delta_g C^{R_u-R_a} + \Delta_p C^{R_u-R_a} \tag{3}$$

where ΔC_{TOT} stands for the total discrepancy in carbon emissions between R_u and R_a in a given year. The variables $\Delta_e C$, $\Delta_L C$, $\Delta_{Ys} C$, $\Delta_{Yc} C$, $\Delta_g C$, and $\Delta_p C$ represent the emission intensity effect (dEPI), production structure effect (dL), final demand structure effect (dys), final demand composition effect (dyc), per capita final demand effect (dpg), and population effect (dpop) between a targeted sub-region and the benchmark sub-region.

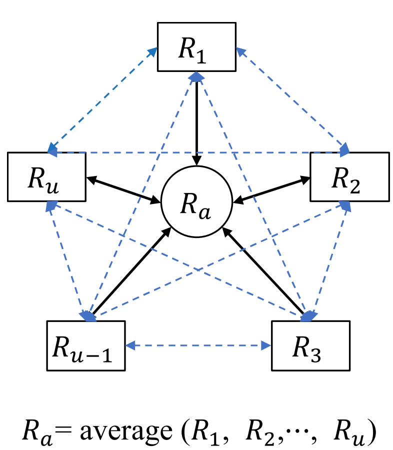

Fig. 1. Multi-region spatial decomposition analysis model.

To identify the critical sectors underlying the aforementioned drivers of carbon emission difference, this study adopts the logarithmic mean Divisia index (LMDI) method for the attribution analysis, which refers to a two-stage decomposition at the sectoral level. Due to its simplicity in application and computation at the sub-aggregate decomposition with no residual, the LMDI method has been widely used in IDA and SDA studies (Ang, 2015). Using the method of LMDI, in Eqs. (4)–(6), $\Delta_e C_i$, $\Delta_L C_i$, and $\Delta_{Ys} C_i$ denote the contribution of respectively, $\Delta_e C$, $\Delta_L C$, and $\Delta_{Ys} C$, to the i-th economic sector in a specific year t. The variables $\Delta_e C_i$, $\Delta_L C_i$, and $\Delta_{Ys} C_i$ are calculated by the following formulas:

$$\Delta_e C_i^{R_u-R_a} = \sum_{i=1}^{n} \sum_{h=1}^{k} w_{ijh} \times ln \frac{e^{R_u}}{e^{R_a}} \tag{4}$$

$$\Delta_L C_i^{R_u-R_a} = \sum_{i=1}^{n} \sum_{h=1}^{k} w_{ijh} \times ln \frac{L^{R_u}}{L^{R_a}} \tag{5}$$

$$\Delta_{Ys} C_i^{R_u-R_a} = \sum_{i=1}^{n} \sum_{h=1}^{k} w_{ijh} \times ln \frac{Ys^{R_u}}{Ys^{R_a}} \tag{6}$$

$$w_{ijh} = \frac{z_{ijh}(R_u) - z_{ijh}(R_a)}{ln(z_{ijh}(R_u) - z_{ijh}(R_a))} \tag{7}$$

$$z_{ijh} = e_i \times L_{ij} \times Ys_{jh} \times Yc_h \times g \times p \tag{8}$$

where w_{ijh} is a weighting coefficient, (R_u) and $\cdot(R_a)$ are respectively the value of a variable for the given sub-region and the benchmark, and $z_{ijh}(R_u)$ and $z_{ijh}(R_a)$ are respectively the value of z_{ijh} for the given sub-region R_u and the benchmark R_a. By summing up $\Delta_e C_i$, $\Delta_L C_i$, and $\Delta_{Ys} C_i$ for all the economic sectors, we obtain the discrepancy of carbon emissions between a given sub-region and the benchmark.

2.3. Data sources

Three types of data are needed for this study: input–output tables (IOTs), CO_2 emissions by sector, the population, and the GDP of the YREB region. IOTs are in a 42-sector format and covering years 2002, 2007, and 2012. The sectorial classifications of IOTs are listed in Table S1 in the Supplementary Information (SI) of this paper. IOTs for years 2002, 2007, and 2012 are collected from the China Multi-regional Input-Output tables (Liu et al., 2012). The population and GDP data are taken from the YREB sub-region Statistical Yearbooks. The CO_2 emissions data are obtained from the China Emission Accounts and Datasets (CEADs) (Shan et al., 2017). To remove the influence of the deflation, we convert all current prices to 2012 constant prices using the double deflation method (UNDESASD, 1999). In line with most of the studies (Yu et al., 2019), we consider the CO_2 emissions from all the industrial sectors in YREB, and not from the household sector. From our calculations, household CO_2 emissions account for only about 10% of the total YREB CO_2 emissions. Thus, excluding the household sector from the system will not have a significant impact on our results.

2.4. Case description

The Yangtze River is the golden waterway carrying the largest freight volume in the world, thus making the channel the most essential east–west axis in China's territory space, playing a strategically indispensable role in the country's regional economic development. The YREB region covers nine provinces, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Sichuan, Yunnan, and Guizhou, and two cities, Shanghai and Chongqing (as shown in Fig. 2). The region covers an area of about 2.05

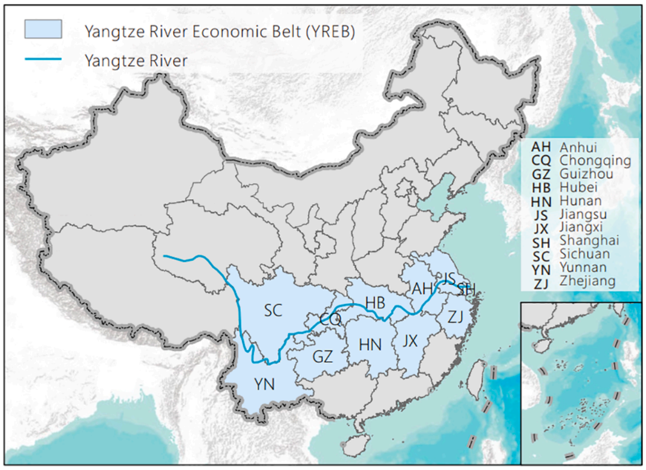

Fig. 2. Location of the YREB region in China.

million square kilometers, accounting for 21% of the country's total area. The total GDP of the YREB region in 2017 was valued approximately at CNY 37.01 trillion, accounting for more than 44% of the national GDP (Tian and Sun, 2018). The decision of the Chinese Party Central Committee to develop the YREB region has become a major strategy related to the overall development of the country (Qiushi, 2019). Meanwhile, the development of the YREB region has been facing several challenges and problems that need to be solved urgently; for example, the severe ecological environment, the bottleneck restriction of the Yangtze River waterways, and the serious problem of unbalanced regional development (NDRC, 2016). The sustainable development of the region faces enormous challenges associated with the reduction of CO_2 emissions (Li and Wei, 2019)

3. Results

3.1. Spatial carbon inequality

Fig. 3 shows the carbon emissions in the YREB region and the Lorenz curves for carbon emissions in 2002, 2007, and 2012. From the figure, the carbon emissions in the YREB region show observable trends differing by sub-region, with some sub-regions showing rapidly increasing trends and others showing relatively slowly growing trends during the 2002–2012 period. Carbon emissions show a rapid growth from 2002 to 2007 (mainly due to the rapid regional economic development during this period), with the Hunan, Yunnan, and Guizhou sub-regions showing the highest rates, accounting for respectively, 146%, 135%, and 124%. Another notable result is that most of the sub-regions could effectively curb the carbon emission growth trends from 2007 to 2012, indicating the actual control of carbon emissions. Nevertheless, the sub-regions show a remarkable difference in carbon emissions. For example, in the YREB region, Jiangsu is ranked at the top in carbon emissions, accounting for 641.3 Mt, which is around three times more than the emissions of Chongqing. Thus, it is worthwhile to measure the spatial inequality of carbon emissions and scrutinize the drivers leading to this inequality.

Furthermore, we draw the Lorenz curve using the carbon emissions and population data and calculate the Gini index based on the Lorenz curve, which was 0.15, 0.11, and 0.10 respectively, in the years 2002, 2007, and 2012. The decreasing Gini coefficient indicates more equally distributed carbon emissions in the YREB sub-regions during this period. This observation is in line with (Chen et al., 2019b), which implies that the inequality in CO_2 emissions at the provincial level was relatively small during 2011–2015. In the following section, the observed patterns of spatial carbon inequality are decomposed in line with the proposed drivers. This could reflect the origin of the spatial carbon inequality and the drivers that are more decisive in determining the variable spatial carbon emissions distribution pattern.

3.2. Drivers of spatial carbon inequality

The total contributions of drivers to the spatial carbon inequality from 2002 to 2012 are illustrated in Fig. 4. In general, the spatial carbon inequality due to efficiency and economic factors has increased during the 2002–2012 period. The per capita final demand (dpg) contributes most to the increases in spatial carbon inequality, followed by population (dpop), production structure (dL), intensity (dEPI), final demand structure (dys), and final demand composition (dyc).

More specifically, the total contribution of the per capita final demand in 2012 was approximately 2119.5 Mt; this is larger than the 2002 contribution by 1466.3 Mt, reflecting the widening inequality in carbon emissions driven by the affluence of the YREB region. The increase in the contribution of per capita final demand implies that the carbon inequality is fundamentally driven by the discrepancy in economic boom and urbanization in the YREB region. Population plays a less important role in spatial carbon inequality, contributing to a carbon inequality of 932.6 Mt in 2012. Another driver is the production structure, representing the total upstream inputs required to produce one unit of the final product, with the total contribution to spatial carbon emissions reaching approximately 889.8 Mt in 2012, or 170.1 Mt larger than the 2002 emissions. Note that the contribution of production structure during 2007–2012 increased significantly, indicating that imbalance in the production structure of the YREB region plays an increasingly important role in carbon inequality. Moreover, emission intensity and

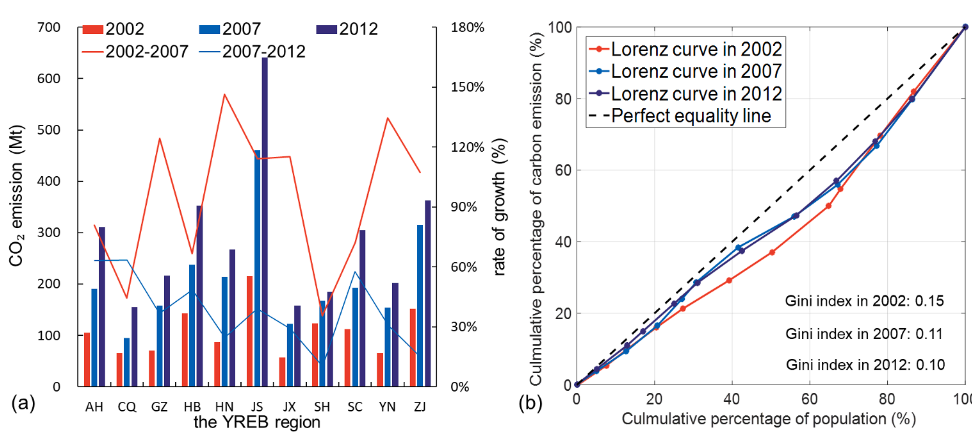

Fig. 3. Carbon emissions in the YREB region and the Lorenz curves of carbon emissions (SH: Shanghai; JS: Jiangsu; ZJ: Zhejiang; AH: Anhui; JX: Jiangxi; HB: Hubei; HN: Hunan; CQ: Chongqing; SC: Sichuan; GZ: Guizhou; YN: Yunnan).

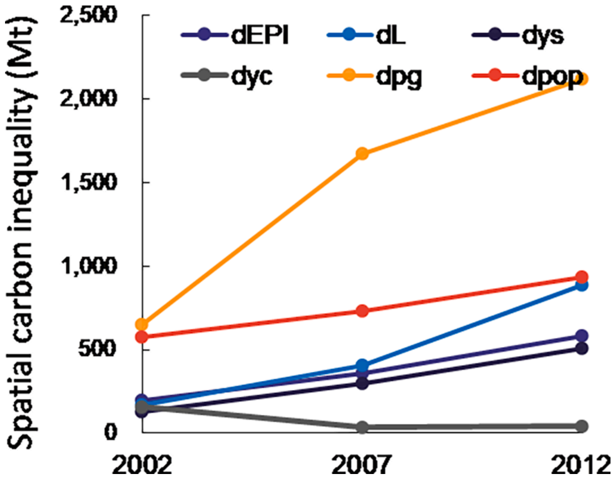

Fig. 4. Total contributions of drivers of spatial carbon inequality (dEPI: emissions intensity; dL: production structure; dys: final demand structure; dyc: final demand composition; dpg: per capital final demand; dpop: population).

final demand structure have obvious effects on spatial carbon inequality. However, the final demand composition does not have a significant effect on the spatial carbon inequality.

After presenting the total contributions of the drivers, we examine in detail the sub-regional results of the drivers, as shown in Fig. 5. Owing to limitations of space in this paper, we discuss the results for the year 2012 only, presenting the results for the other years in Figs. S1 and S2 in SI. Overall, six out of 11 areas, namely, Chongqing, Jiangxi, Shanghai, Yunnan, Guizhou, and Hunan, tend to have lower CO_2 emissions compared to the regional average, mainly due to the per capital final demand, production structure, and population effects.

Specifically, three sub-regions, Shanghai (207.4 Mt), Jiangsu (78.9 Mt), and Zhejiang (23.4 Mt), show more CO_2 emissions than the average level driven by per capital final demand effects, an indicator of affluence. On the contrary, other sub-regions, especially Guizhou, Yunnan, and Sichuan, have more CO_2 emissions due to this effect. These results are largely due to a wide gap in the economic development level and the average consumption level, i.e., the former sub-regions show a more prosperous economy and higher consumption levels. According to (Zhou et al., 2020), the consumption activities of developed provinces are the major sources of China's emissions, suggesting that demand-side solutions targeting rich regions could motivate towards more reduction of national emissions. Jiangsu (209 Mt), Sichuan (146.8 Mt), and Hunan (104.4 Mt) show more CO_2 emissions driven by population effects than the average level. This indicates that due to their growing populations, these sub-regions face more emission pressure than others. Population growth will create immense demand in housing and infrastructure which in turn is accompanied by significant carbon emissions. Thus, carbon reduction measures in these sub-regions may include a transition to a low-carbon economy lead by optimizing the region's energy consumption structure and vigorously developing high-tech industries.

The spatial carbon inequality induced by the carbon intensity effect differed significantly between highly-developed and less-developed regions. Five sub-regions, namely, Zhejiang (−125.2 Mt), Jiangxi (−120.3 Mt), Shanghai (−55.2 Mt), Sichuan (−43.8 Mt), and Hunan (−21.4 Mt) show better performance in intensity effect than the regional average level. This suggests that sub-regions adopt more advanced emission reduction technologies or corresponding policies. On the contrary, Guizhou (86.1 Mt), Yunnan (51.7 Mt), and Hubei (34.2 Mt) show a lower performance in the intensity effect. This indicates that these sub-regions do not simultaneously achieve economic development and carbon emission reduction and this can be caused by the region's high economic dependence on heavy manufacturing industries. Sub-regions performing well in emissions intensity do not perform well in production structure. Only Shanghai shows better efficiency in production (−74.5 Mt) and final demand (−17.9 Mt) structure than the average regional level. As regards the drivers of production structure, Jiangxi (138 Mt), Sichuan (128.5 Mt), and Zhejiang (117.5 Mt) are the three worst-performing sub-regions. This indicates that the sub-regions with more heavy industries have more serious carbon emissions and can mitigate carbon emissions by adjusting the industrial structures and promoting the development of their tertiary industries.

The final demand structure describes the share of each sectoral production in various final demands, including household consumptions, fixed capital formation, inventory changes, and exports. The final demand structure effect indicates the emission reduction performance influenced by the sectoral production which is driven by the final demand. Lower carbon emissions driven by final demand structure indicate that the final demand structure is becoming much "greener", in other words, the sectoral production driven by final demand leads to fewer carbon emissions. As is demonstrated in Fig. 5, the carbon inequality driven by the final demand structure differed between highly-developed regions and less-developed regions. Highly-developed regions, such as Shanghai (−17.9 Mt), Jiangsu (3.2Mt), and Zhejiang (4.1Mt), have much "greener" final demand structures. In contrast, Guizhou (84.2 Mt), Anhui (80 Mt), and Yunnan (67.3 Mt) are the three sub-regions with the worst performance of final demand structure, implying that these sub-regions use products consuming relatively higher energy in their final usage. This observation differs from previous studies, such as by Cao et al. (2019), which concluded that that four provinces maintaining the highest final demand efficiency where Shanghai, Sichuan, Hunan, and Guizhou. This is mainly due to the different benchmarking and also because the object of their study was focused on carbon intensity. The observations in this study are however confirmed by Wu et al. (2020), which examine the spatio-temporal variation of CO_2 emissions at the provincial level from 1997 to 2012. In this study, the final demand composition has a negligible effect on spatial carbon inequality, which demonstrates the impact of the

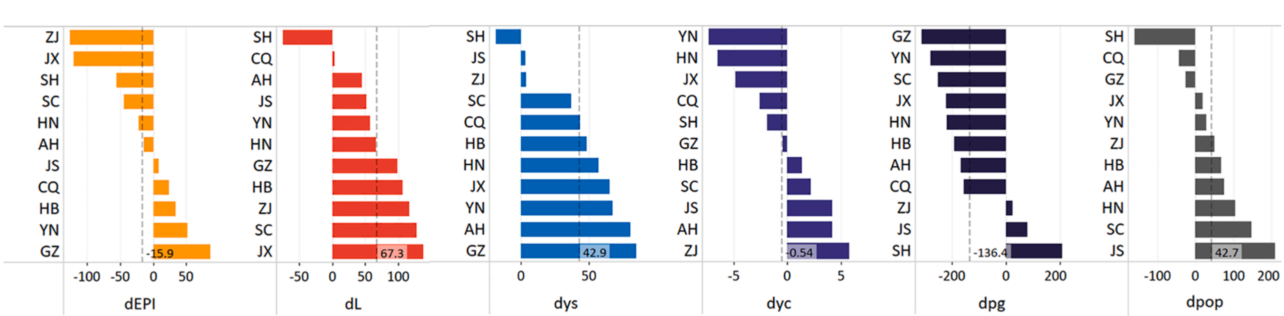

Fig. 5. Sub-regional spatial carbon inequality drivers in 2012 (SH: Shanghai; JS: Jiangsu; ZJ: Zhejiang; AH: Anhui; JX: Jiangxi; HB: Hubei; HN: Hunan; CQ: Chongqing; SC: Sichuan; GZ: Guizhou; YN: Yunnan) (dEPI: emissions intensity; dL: production structure; dys: final demand structure; dyc: final demand composition; dpg: per capital final demand; dpop: population).

proportion of various final demand categories on spatial carbon inequality. Zhejiang (5.8 Mt), Anhui (4.2 Mt), and Jiangsu (4.2 Mt) are the top three sub-regions with higher CO_2 emissions driven by final demand composition, implying that the allocation patterns of various final demands in these regions contribute to more CO_2 emissions.

3.3. *Sectoral contribution of the drivers to spatial carbon inequality.*

To explore the sectoral emission mitigation policies at the regional level, we use attribution analysis to reflect the sectoral contribution of the drivers underlying the spatial differences in CO_2 emissions (Fig. 6). Owing to limitations of space in this paper, we discuss the results for the year 2012 only, with the results for the other years presented in Tables S2–S10 in SI. Here, we show the main effects of the three drivers, carbon emission intensity, production structure, and final demand structure, by sector. For a better presentation of our results, we mainly give the decomposition results of each driver in the top eight sectors. The sub-regions are ranked according to the total emission reduction contribution of each driver.

As Fig. 6a shows, the spatial carbon inequality induced by intensity effect is mainly embodied in S25 (*Electricity and heat production and supply*), S14 (*Smelting and pressing of metals*), S13 (*Nonmetal mineral products*), S12 (*Chemical products*), S2 (*Coal mining and dressing*), S29 (*Transportation*), S11 (*Petroleum processing and coking*), and S31 (*Wholesale and retail trade*). From the results of the previous section, six out of 11 sub-regions, including Shanghai, Zhejiang, Jiangxi, Hunan,

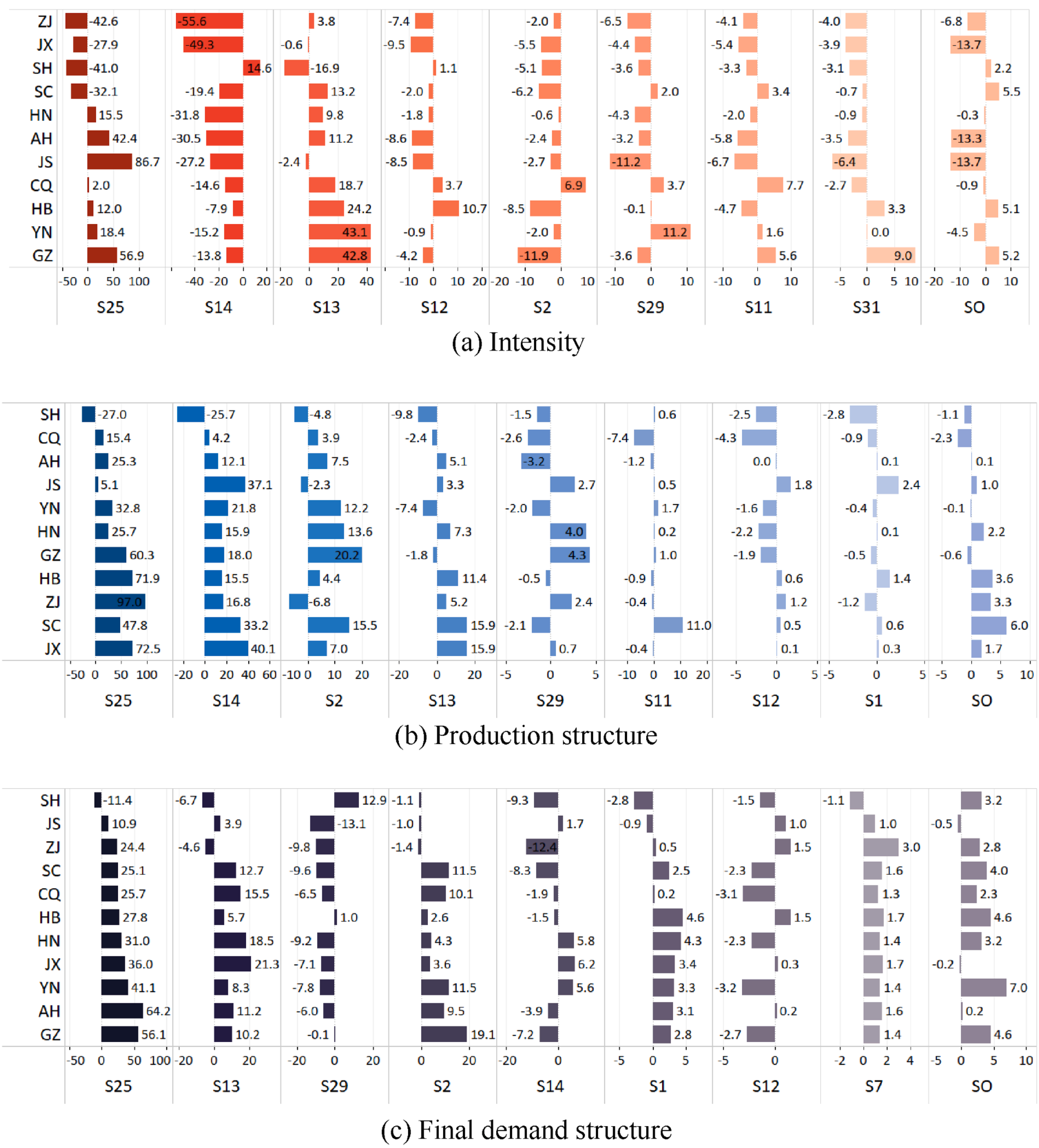

Fig. 6. Contributions of drivers to spatial carbon inequality in 2012 by sector (S1: *Agriculture*; S2: *Coal mining and dressing*; S7: *Textile Industry*; S11: *Petroleum processing and coking*; S12: *Chemical Industry*; S13: *Nonmetal minerals products*; S14: *Smelting and Pressing of Metals*; S25: *Electricity and heat production and supply*; S29: *Transportation*; SO: *Other sectors*).

and Sichuan, show higher intensity effect efficiency than the average. Conversely, the sub-regions in S25 and S14, such as Zhejiang, Jiangxi, and Sichuan, show higher intensity effect efficiency, the sub-regions in S13, and S25, such as Jiangsu, Hubei, Guizhou, and Yunnan, show lower intensity affect efficiency. Specifically, S25 shows lower intensity effect efficiency in Jiangsu (86.7Mt), Guizhou (57Mt), and Anhui (42.4Mt), and higher efficiency in Zhejiang (−42.6Mt), Shanghai (−41Mt), and Sichuan (−32Mt). Conversely, S14 shows a higher intensity effect efficiency level in most sub-regions compared to other sectors, such as Zhejiang (−55.6Mt) and Jiangxi (−49.3Mt), except for Shanghai (14.6Mt), S13 exhibits lower intensity effect efficiency in most of the sub-regions, such as Yunnan (43.1Mt) and Guizhou (42.8Mt), except for Shanghai (−17Mt). Moreover, emission intensity induces more carbon emissions in Hubei in S12, Chongqing in S2, Yunnan in S29, Jiangsu and Guizhou in S11, and Guizhou in S31.

The production structure represents the total upstream inputs required for the production of one unit of the final product and indicates the production efficiency of each sector. As illustrated in Fig. 6b, the spatial carbon inequality induced by the production structure effect is mainly found in S25, S14, S2, S13, S29, S11, S12, and S1 (*Agriculture*). Shanghai is the only sub-region with higher production structure efficiency; this can be attributed to S14 and S25. Sectors S25 and S14 indicate a lower efficiency in production structure in most sub-regions compared to other sectors. For example, this driver causes Jiangsu (97 Mt), Jiangxi (72.5Mt), and Hubei (71.9Mt) to emit more carbon emissions in S25. The S2 sector also exhibits lower efficiency in the production structure in Guizhou (20.3Mt) and Sichuan (15.5Mt). Moreover, the production structure effect induces more carbon emissions in Jiangxi and Sichuan in S13, Sichuan in S11, and Hunan and Guizhou in S29.

The spatial carbon inequality induced by the final demand structure effect differed significantly between highly-developed regions and less-developed regions. The final demand structure effect is mainly found in S25, S13, S29, S2, S14, S1, S12, and S7 (*Textile industry*). From Fig. 6c, Shanghai shows more efficiency in most sectors, especially S25 and S14, and less efficiency in S29. Sector S25 shows lower final demand structural efficiency in more sub-regions compared to other sectors, such as Anhui (64.2Mt), Guizhou (56.1Mt), and Yunnan (41.1Mt). Sector S13 exhibits lower final demand structural efficiency in most sub-regions [e.g., Jiangxi (21.3Mt) and Hunan (18.5Mt)], while sector S29 indicates higher final demand structural efficiency in more sub-regions compared to other sectors. Another notable finding is that the final demand structural effect on carbon emissions increased in S2 in most sub-regions, such as, Guizhou, Yunnan, Sichuan, and Chongqing.

4. Discussion

To meet its national carbon emission control targets, China has made several profound decisions on reducing its carbon emissions in recent years. Given the spatial carbon inequality, the task of emission reduction should preferably be decentralized to the regional level. This study examines the carbon inequality in the YREB region, to find carbon emissions more equally distributed among the sub-regions from the perspective of population distribution. To identify the socio-economic drivers underlying the spatial carbon inequality in the YREB region, we decompose the inequality by six drivers, emissions intensity, production structure, final demand structure, final demand composition, per capita final demand, and the population at the sectoral level. The results indicate that emission intensity plays a significant role in spatial carbon emissions. Zhejiang, Jiangxi, and Shanghai are more efficient, while Guizhou, Yunnan, and Hubei are less efficient due to intensity effect. Production structure refers to the total upstream inputs required to produce one unit of final product, i.e., it indicates the production efficiency of each sector. The various production structures differ in the type and structure of their energy consumption, thus affecting regional carbon emissions. Our results indicate that production structure is another crucial driver for the large disparity in CO_2 emissions in the YREB regions. The final demand structure effect indicates how the final demand influences the regional carbon emissions heterogeneity and plays an important role in enlarging the CO_2 emissions gap in the YREB regions. From the perspective of the drivers, our findings show the need to narrow down the spatial carbon inequality and undertake experience sharing to reduce the regional emissions in the YREB region.

4.1. Regional classification based on per capita GDP and CO_2 emissions

From our results, per capita final demand is the major driver for spatial carbon inequality in the YREB region, implying that unbalanced economic development and inconsistent urbanization results in spatial carbon inequality. To show the relationship between regional affluence and carbon emissions clearly, we group the sub-regions by the relationship between their per capita CO_2 emissions and per capita GDP in 2012 – the four quadrants obtained are illustrated in Fig. 7a. This regional classification can help in formulating policies for sub-regions sharing similar development trajectories to reduce their carbon emissions and narrow regional carbon inequality from the perspective of the key drivers and sectors.

Quadrant I includes the regions with low per capita GDP and high per capita carbon emissions, such as Guizhou and Hubei. Quadrant II includes Jiangsu, Shanghai, and Zhejiang, with characteristics of both high per capita GDP and carbon emissions. Quadrant III includes Chongqing, Anhui, Yunnan, Hunan, Sichuan, and Jiangxi, and is characterized by low per capita GDP and carbon emissions. Quadrant IV includes none of the sub-regions. This classification reflects the economic development levels and carbon emissions, both varying in the YREB regions. Regions in the same quadrant commonly possess a similar relationship between economic development and carbon emissions, which implies that these regions can benefit from one another's experience in on the reduction of emissions. Thus, it is crucial to make comparisons among the driving forces of carbon emissions in the similar regions (as demonstrated in Fig. 7b) and forward policy implications on regional emission reductions.

4.2. Policy implications for regional emissions reduction

First, Guizhou and Hubei (in Quadrant I), with high per capita carbon emissions and low per capita GDP, both have high carbon emissions induced by carbon intensity, production structure, and final demand structure. Reducing carbon emissions induced by the production structure is of primary importance for these two sub-regions. Combined with the sectoral attribution analysis in Section 4, we conclude that optimizing the production structure in the *Electricity and heat production and supply* and *Smelting and pressing of metals* sectors is needed for both Guizhou and Hubei. Moreover, Guizhou should adjust the production structure of the *Coal mining and dressing* sector, which can be achieved by drawing lessons from this sector in Hubei. This can be achieved, for example, by strengthening the efficient utilization of coal and enlarging the exploitation and application of clean coal technology. Reducing the sectoral carbon emissions intensity is also important for achieving a reduction in carbon inequality. The corresponding measures may include a reduction in the proportion of fossil energy in energy consumption, boosting the utilization of renewable energy, the development of more energy-efficient technologies, and the diffusion of low-carbon technologies. These measures should be implemented in the crucial sectors leading in CO_2 emissions, such as *Electricity and heat production and supply, Nonmetal mineral products* sectors for Guizhou, and *Chemical products* sector for Hubei.

The final demand structure contributes to differences in sectoral carbon emissions inequality. From this perspective, it is suggested that emission mitigating measures reducing the use of high energy-consumption products as intermediate input should be adopted in the *Coal mining and dressing* sector in Guizhou and the *Electricity and heat production and supply* and *Nonmetal mineral products* in Hubei, as these

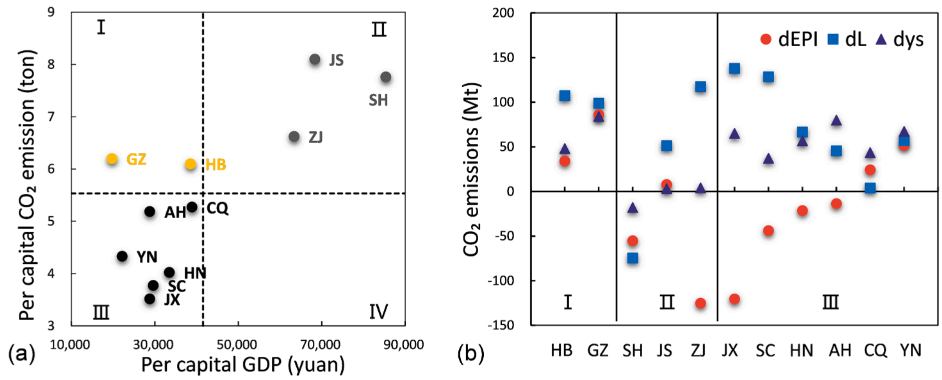

Fig. 7. a: Regional classification based on the per capita GDP and per capita carbon emissions in the YREB region. b: Contributions of emissions intensity (dEPI), production structure (dL), and final demand structure (dys) to the spatial carbon emissions.

sectors produce more CO_2 emissions due to influence of the final demand structure. Specifically, the *Coal mining and dressing* sector in Guizhou can reduce emissions by promoting the structural reform of this sector from the supply side and improving its capacity utilization. The *Electricity and heat production and supply* and *Nonmetal mineral products* sectors in Hubei should cooperate with upstream enterprises with low carbon emission and low energy consumption and decrease the final usage of high energy-consumption products.

Second, Shanghai, Jiangsu, and Zhejiang are characterized by high per capita GDP and high per capita carbon emissions. Zhejiang and Shanghai have restrained their CO_2 emissions by improving their technology by leaps and bounds. However, the production structure effect contributes to more CO_2 emissions in Jiangsu. Thus, Jiangsu should pay more attention to improving its technological efficiency, updating its equipment, developing more energy-efficient technologies for the *Smelting and pressing of metals* sector, and may also look adopt more advanced green technologies as found in Shanghai and Zhejiang. The production structure effect leads to more CO_2 emissions in Zhejiang than in Jiangsu and Shanghai, mainly due to emissions of the *Electricity and heat production and supply* sector. Thus, Zhejiang should immediately reduce the use of high energy products, promote the energy-saving transformation of local coal-fired thermal power industries, and vigorously develop distributed generation technologies based on renewable clean energy. Moreover, for these sub-regions which have high per capita GDP, we also need to highlight some demand-side emission mitigation efforts to restrain the sharp increases in carbon inequality from household consumption. This could be achieved by optimizing green consumption awareness and encouraging consumers to use fewer CO_2 intensive products.

Third, as for the sub-regions with low per capita GDP and per capita carbon emissions, that is, Jiangxi, Sichuan, Hunan, Anhui, Chongqing, and Yunnan, the amount of CO_2 emissions associated with the effects of intensity and production structure vary significantly among these sub-regions. Furthermore, the critical sectors with higher CO_2 emissions differ in their distinct industrial structures and economic development levels. Since Yunnan and Chongqing are less efficient due to intensity effect, critical measures for the reduction in emissions intensity should be adopted for Yunnan in *Nonmetal mineral products* and *Transportation* sectors, and for Chongqing in *Nonmetal mineral products*, *Coal mining and dressing*, and *Petroleum processing and coking* sectors. The production structure effect causes more CO_2 emissions in Jiangxi and Sichuan than in other sub-regions. Specifically, Jiangxi should improve its production structure efficiency in *Nonmetal mineral products* and *Smelting and pressing of metals* sectors. Sichuan should focus on improving its production structure efficiency in *Coal mining and dressing*, *Petroleum processing and coking*, and *Nonmetal mineral products* sectors by referring to the production structure mode of Chongqing, where the production structure effect greatly promotes carbon emissions mitigation.

The final demand structure effects show insignificant differences in the spatial carbon inequality of the sub-regions. However, driven by the final demand structure, the sectoral contributions show unequal carbon emissions. Specifically, reduction measures by adjusting the final demand structure should be implied in *Electricity and heat production and supply* for Anhui, *Nonmetal mineral products* for Jiangxi, *Agriculture,* and *Nonmetal mineral products* for Hunan, and *Coal mining and dressing* and *Smelting and pressing of metals* for Yunnan. To Promote economic prosperitiy, not only should these critical sectors reduce the use of high energy consumption in the final demand of products and spur the formation of a low-carbon consumption structure, but the sub-regions should also manage the trade-off between economic prosperity and carbon emissions and avoid a sharp increase in carbon emissions. These viewpoints are consistent with those of (Zhou et al., 2020), which recommended that structural adjustments should be directed to the northeast, central, and western provinces of China.

The analysis of the driving forces of spatial carbon inequality at the sectoral level provide novel and specific information on the sources of regional differences. This in turn informs the formulation of regional emissions reduction policies. Initial achievements in the reduction of regional carbon emissions have been made by exploring the historical changes of carbon emissions and analyzing the production- and demand-side reduction measures. However, given the wide regional disparities in economic structures, sectoral-technological levels, and emissions reduction targets, detecting the driving forces of spatial carbon inequality, from the socio-economic perspective, should be emphasized more. In the coming decades, the YREB region should formulate specific sub-regional emission reduction measures at the sectoral level and narrow the carbon inequality by reducing the carbon intensity and adjust the production structure and final demand structure to achieve a more harmonious development of the YREB region.

5. Conclusions

This study explores the drivers underlying the spatial carbon inequality of the YREB region at the sectoral level. Our results reveal large spatial carbon inequalities driven by several vital socio-economic drivers, namely, per capita final demand, production structure, and final demand structure. Various drivers have different impacts on regional carbon emissions. For example, Zhejiang, Jiangxi, and Shanghai are more efficient due to intensity effect, while Guizhou, Yunnan, and Hubei are less efficient. Further attribution analysis identifies critical sectors widening the gap among different areas of the YREB region, such as the *Electricity and heat production and supply*, *Smelting and pressing of metals*, and *Nonmetal mineral products* sectors. To promote a more regionally coordinated development, the formulation of regional emission mitigating measures should attach more importance to the divergence of regional economic development and carbon emissions at the sectoral level. Moreover, the method used in this study can also be used to explore the sectoral level socio-economic drivers of the spatial differences between various environmental indicators. For example, the socio-economic drivers of CO_2 emissions, energy consumption, and water consumption levels for other megaregions, for example, the Jing-Jin-Ji (Beijing city, Tianjin city, and Hebei province) region and the Guangdong-Hong Kong-Macao Greater Bay Area.

This study is not without limitations: Limitations in the availability of relevant data in the I-O table databases restricted the period of the present study to only three years. The study of regional disparities in more recent years may provide more useful information for practical application. This calls for more frequent and timely work on updating the regional I-O tables in the statistical department of the Chinese local government. Moreover, some uncertainty analysis should also be conducted in future research, for example, uncertainties caused by the quality of I-O data (Fournier Gabela, 2020), deviations of carbon emissions inventories, which is mainly caused by emission factors (Mi et al., 2017, 2019), and by sectoral aggregation (Zhang et al., 2019).

CRediT authorship contribution statement

Shuo Zhang: Writing - original draft, Visualization. **Ali Kharrazi:** Investigation, Validation. **Yadong Yu:** Conceptualization, Methodology, Software, Supervision, Project administration, Funding acquisition. **Hongtao Ren:** Methodology, Software. **Liyun Hong:** Investigation. **Tieju Ma:** Conceptualization, Supervision, Project administration, Funding acquisition.

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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