



Research article

Regional disparities and dynamic evolution of carbon emission distribution in China

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Abstract: This study is centered on the measurement of carbon emissions at the provincial level in China and the analysis of their spatial distribution. We address the quantification of regional disparities and the dynamic evolution of emission patterns, which are critical for informing climate governance. Moreover, we aim to systematically measure carbon emissions across Chinese provinces and to investigate the regional disparities and the dynamic evolution in their distribution. Our goal is to provide an empirical basis for formulating differentiated and well-targeted emission reduction policies. The modified carbon emission factor method was employed for accounting. The Theil index and its decomposition were used to quantify regional disparities, while kernel density estimation was applied to characterize the dynamic evolution trends of the emission distribution. The results revealed significant regional imbalances in China's carbon emission distribution, with inter-regional differences identified as the primary source of overall disparity. Kernel density curves further showed distinct heterogeneity in distribution shapes and dynamic evolution across regions, reflecting deep-seated differences in emission structures and development stages. Our findings provide critical data for designing differentiated regional carbon reduction strategies and can directly support policy-making for coordinated emission reduction. They offer practical insights for industrial green transition planning at national and provincial levels, aiding in the alignment of economic development with climate targets.

Keywords: modified carbon emission factor method; regional disparities; Theil index; Kernel density estimation

1. Introduction and literature review

With the changes in lifestyle and the rapid economic growth in China, the carbon emissions resulting from the burning of fossil fuels have increased rapidly. As the largest developing country, China has fulfilled its commitments, showing the role of a responsible and major country, and is an important contributor and leader in constructing a global ecological civilization while facing increasingly severe environmental issues. At the historic Paris Agreement on 12 December 2015, the Chinese government promised that its carbon emissions will peak by 2030 [1] and there will be a 60%-65% decrease in carbon emission intensity (carbon emissions per unit of GDP) by 2030 in comparison to its 2005 level [2]. In September 2020, China announced the strategic target of 'carbon peaking by 2030 and carbon neutrality by 2060'. Centered around the 'dual carbon' goal, the construction of ecological civilization during the '14th Five-Year plan' period concentrates on achieving carbon reduction and green expansion. An accurate accounting of China's carbon emissions is the first step in achieving emissions reduction, considering that China has a vast territory, and different regions in China have their own characteristics in economic development level, resource endowment, ecological environment, industrial structure and so on. Thus, accurately identifying the carbon emission characteristics of regions in China has become a key issue in achieving China's carbon emissions reduction goals.

Carbon emission accounting primarily follows the methodology established by the Intergovernmental Panel on Climate Change (IPCC), specifically the 2006 IPCC Guidelines for National Greenhouse Gas Inventories [3]. These guidelines form the international basis for accounting and endorse key methods such as the emission factor method, input-output method, and factor decomposition method [4]. The most widely applied is the emission factor method (Emissions = Activity Data × Emission Factor), which underpins national and sub-national inventories, including China's provincial compilation guidelines [5]. Scholars have extensively used this IPCC-based methodology. For instance, Sun et al. [6] constructed an accounting framework for China, while Liu et al. [7] compiled a national CO₂ inventory, with their data supporting official government reports. Researchers have also applied the method to analyze trends in Oman [8] and, combined with models like STIRPAT and PLSR, to examine driving forces in Chinese provinces [9,10]

As a convenient estimation method, the input-output method is employed to study the interdependent economic quantity relationships between each part of the economic system in terms of output and input. Due to its intuitive and concise nature, it is widely applied for estimating carbon emissions in industries. Yu et al. [11] embedded regional input-output tables into global ones and constructed corresponding carbon emission accounts. Using input-output models, they explained the carbon emission transfer effects brought about by the added value of domestic and foreign trade in regions of China. This shows that the input-output model has a very wide range of application fields. For more details about the input-output model, please refer to [12–14] and the references therein.

It is widely recognized that the two most common methods based on factor decomposition for accounting carbon emissions are Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA). SDA is a type of static analysis method that concentrates on decomposing the variation of a dependent variable in an independent variation of different forms and sums up into an economic system to determine the degree of influence of different independent variables on the variation of the dependent variable. The SDA method is widely used in various fields. For example [15], Zhang et al. utilized the IPAT model to measure the future carbon emissions and carbon intensity of Anhui Province in view of energy consumption data from 1995 to 2010 in planning scenarios, inertia scenarios, and

low-carbon scenarios.

Additionally, relying on an improved STIRPAT model, the relationship between industrial carbon emissions and economic growth in China was empirically studied [16], as well as its major influencing factors, using Chinese industrial panel data grouped by carbon emission characteristics from 1995 to 2010 as samples. IDA mainly includes the LMDI method. Based on the basic identity of carbon emissions, Xu et al. [17] established a factor decomposition model of China's per capita carbon emissions using the LMDI method and quantitatively analyzed the impact of changes in energy structure, energy efficiency, economic development, and other factors on China's per capita carbon emissions from 1995 to 2004. Guo [18] constructed a carbon emission identity based on economic aggregate, economic structure, energy utilization efficiency, energy consumption structure, and carbon emission coefficient, and used the LMDI decomposition method to decompose China's carbon emissions from 1995 to 2007 at the industrial and regional levels. Hu et al. [19] established implicit carbon productivity indicators based on input-output data and energy carbon emission data from 2002 to 2020. Using the LMDI-PDA comprehensive decomposition method, they systematically sorted out the impact of various effects and sub sectors on the overall implicit carbon productivity changes of industrial sectors.

According to the formula of carbon emission factors method, it can be seen that the accuracy of carbon emission accounting for a region or country depends on the precision of activity data and carbon emission factors. Activity data usually comes from Statistical Yearbooks, and scholars often encounter such these when doing carbon emission accounting: The selection of energy varieties is incomplete or the selection range is too narrow. For example, only a wide range of coal, oil, and gas are selected. Carbon emission factor data is related to regions, energy varieties, and industries. That is to say, different regions, energy varieties, or industries have different carbon emission factors. Due to the difficulty in obtaining actual carbon emission factors, many researchers directly use the default values in IPCC Guidelines. To some extent, the carbon emissions calculated through this method will be overestimated. Moreover, when accounting for carbon emissions at the national or regional level, many researchers adopt the default values from the IPCC as carbon emission factors, which may lead to less accurate calculations. Therefore, we calculate carbon emission factors that align with China's actual conditions based on the *General Rules for Calculation of Comprehensive Energy Consumption* (GB/T 2589-2020) and the *Guidelines for Provincial Greenhouse Gas Inventory Compilation* (2011), and then apply the revised carbon emission factors to estimate China's carbon emissions.

On the other hand, scholars mainly apply the Theil index for measuring income inequality to measure regional disparities in carbon emissions [20–24]. For example, Wang et al. [21] calculated the Theil index to measure regional disparities of per capita carbon emissions within China and concluded that the overall level in per capita carbon emissions in the eastern region has decreased, while there has been no significant change in per capita carbon emissions in the central and western regions. Wang et al. [22] used the Theil index to assess the regional disparities in the carbon emission intensity of the tourism industry from 1993 to 2012. Their study suggested that these disparities were primarily driven by inter-regional disparities. Han et al. [23] calculated the Theil index to measure the provincial disparities in economic development and carbon emissions in China. They found that while economic development disparities between provinces are narrowing, carbon emission disparities are widening. It should be pointed out that in terms of spatial differences and distribution dynamics, most of the research is conducted from the perspective of the traditional regional division. Chen et al. [24] calculated the Economic High Quality Development Index of China from 2004 to 2017 and analyzed the spatiotemporal characteristics, regional disparities, and evolutionary trends of high-quality economic development in various regions and provinces. They used the Dagum Gini coefficient to

reveal regional disparities and sources of high-quality economic development and used the kernel density estimation method to characterize the distribution dynamics and evolutionary trends of high-quality economic development.

Although the Theil index can be used to characterize regional disparities in carbon emission intensity, it has some shortcomings, such as the inability to describe the spatial distribution patterns and evolutionary trends of carbon emissions. In contrast, the kernel density estimation method can effectively overcome these limitations of the Theil index. Furthermore, the kernel density estimation method has been widely used in the study of spatial regional disparities and distribution dynamics [25–29]. Chen et al. [26] constructed a MinDS model to measure the ecological efficiency level of the Yellow River Basin from 2004 to 2017 and used the kernel density estimation method to explore the spatial disparities and dynamic evolution of the region. Furthermore, the driving factors of the spatiotemporal evolution of ecological efficiency in the region were studied. Based on county-level data from 2014 to 2018, Zhang et al. [27] used the kernel density estimation method to explore the distribution dynamics and regional disparities of rural digital inclusive finance development. Lei [28] measured the new quality productive forces of 30 provinces in China from 2012 to 2022 using the entropy TOPSIS method and analyzed their regional disparities and dynamic evolution using the kernel density estimation method. Liu et al. [29] explored the change of China's per capita disposable income from three aspects, namely dynamic evolution, regional disparities, and spatial agglomeration, by the kernel density estimation method.

The regional disparities on carbon emission generally depend on the division of regions, and most researchers classify regions based on traditional administrative divisions. For example, the country is divided into three regions [30–33], four regions [34], or eight regions [35].

In this study, we adopt the modified carbon emission factor method, with the aim of accounting for carbon emissions in China's 30 provinces while analyzing regional disparities. The innovation and marginal contributions are primarily reflected in the following three aspects: First, methodological refinement is when the scope of carbon emission estimation is broader, and the modified carbon emission factors are more suited to China's context. For example, when conducting carbon emissions accounting, we have added a variety of energy sources, including liquefied petroleum gas (LPG) and refinery dry gas. The modified carbon emission factors are calculated based on the 'General rules for calculation of comprehensive energy consumption' (GB/T 2589-2020) and the 'Guidelines for Compilation of Provincial Greenhouse Gas Inventories (Trial) (2011)', which agree better with the situation of China than directly using the default emission factor values in the IPCC Guidelines. Second, in terms of regional division, the 30 provinces in China are divided into four regions based on the dual perspectives of energy consumption and energy intensity, rather than the traditional three, four, or eight regions. This is beneficial for future discussions on carbon reduction, carbon efficiency, and other related issues. Third, in-depth disparity analysis, the regional disparities and dynamic evolution of China's carbon emissions spatial distribution are analyzed using the Theil index and kernel density estimation method, which illustrate the characteristics and disparities among the regions.

The structure of this paper is organized as follows: In Section 2, we show the research methods and data. The results are presented in Section 3. In Section 4, we discuss the regional disparities and sources of regional disparities. Dynamic evolution of the carbon emission distribution is revealed in Section 5. In Section 6, we provide the conclusion.

2. Research methodology and data

2.1. Regional division

The regional classification is conducted using a two-dimensional matrix analysis. Scale and efficiency are the two most direct and clear key aspects for measuring regional disparities. Therefore, we comprehensively consider both dimensions, energy consumption (scale) and energy intensity (efficiency), for regional classification, with the threshold determined based on the median values of these two dimensions.

Initially, we calculate the average annual energy consumption and energy intensity of each province from 2005 to 2021 for the 30 provinces, and then calculate the median of the average annual energy consumption and the average annual energy intensity, respectively. If the average annual energy consumption is greater than the median of the average annual energy consumption of 30 provinces, it is considered that the province has high energy consumption; otherwise, it is considered to have low energy consumption. Similarly, if the average annual energy intensity is greater than the median average annual energy intensity of 30 provinces, it is considered that the energy intensity of that province is high; otherwise, it is considered that the energy intensity of that province is low. Based on this criterion, China's 30 provinces are divided into four regions: High energy consumption-High energy intensity region (Region I), which includes 7 provinces: Shandong, Hebei, Liaoning, Inner Mongolia, Heilongjiang, Shanxi, and Xinjiang. High energy consumption-Low energy intensity region (Region II), including 8 provinces: Jiangsu, Guangdong, Zhejiang, Henan, Hubei, Hunan, Anhui, and Sichuan. Low energy consumption-High energy intensity region (Region III), including 8 provinces: Tianjin, Jilin, Shaanxi, Guizhou, Gansu, Yunnan, Qinghai, and Ningxia. Low energy consumption-Low energy intensity region (Region IV), including 7 provinces: Beijing, Shanghai, Fujian, Jiangxi, Guangxi, Hainan, and Chongqing.

2.2. Research methodology and data sources

2.2.1. Carbon emission accounting method and data sources

According to the 'IPCC Guidelines', the carbon emissions from fossil energy consumption in each province of China are calculated by the carbon emission factor method, with the following formula:

$$C_{it} = \sum_k E_{ikt} * \theta_k * \frac{44}{12} \quad (i = 1, 2, \dots, 30; k = 1, 2, \dots, 10) \quad (1)$$

where C_{it} represents the carbon emissions of province i in the t -th year; E_{ikt} represents the consumption of the k -th type of energy in province i in the t -th year; and θ_k is the carbon emission coefficient for the k -th type of energy. Subscript i denotes the 30 provinces of China (excluding Tibet, Hong Kong, Macau, and Taiwan); subscript k denotes the 10 types of fossil energy sources in this study, which are raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, liquefied petroleum gas, and refinery gas; and subscript t denotes the temporal range of this study, from 2005 to 2021.

The energy types used in this study are identified based on the 'General rules for calculation of comprehensive energy consumption' (GB/T 2589-2020), the 'Guidelines for Compilation of Provincial

Greenhouse Gas Inventories (Trial) (2011)', and the China Energy Statistical Yearbook. The energy types are raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, liquefied petroleum gas, and refinery gas, totaling 10 types. The data for E_{ikt} are consolidated and calculated based on the physical quantity energy balance tables of each province in the *China Energy Statistical Yearbook* (2006–2022), while the values for θ_k are determined based on GB/T 2589-2020 and the 'Guidelines for Compilation of Provincial Greenhouse Gas Inventories (Trial) (2011)'. According to the IPCC carbon emission methodology, researchers commonly calculate carbon emissions by directly applying the default emission factors recommended by the IPCC, which may lead to less accurate results. In this study, based on the IPCC methodology and in accordance with the General Rules for Calculation of Comprehensive Energy Consumption (GB/T 2589-2020) and the Guidelines for Provincial Greenhouse Gas Inventory Compilation (2011), we calculate carbon emission factors that better reflect China's actual conditions for each type of energy source, denoted here as factor θ_k . These revised emission factors are then applied to estimate China's carbon emissions. Table 1 shows the standard coal coefficients and carbon emission factors for each energy type.

Table 1. Standard coal coefficients and carbon emission factors for various energy sources.

Energy type	Standard coal coefficients (kgce/kg, kgce/m ³)	Carbon emission factors(kg/kg, kg/m ³)
Raw coal	0.7143	0.5189
Coke	0.9714	0.7811
Crude oil	1.4286	0.8247
Fuel oil	1.4286	0.8657
Gasoline	1.4714	0.7987
Kerosene	1.4714	0.8241
Diesel oil	1.4571	0.8454
Liquefied petroleum gas	1.7143	0.8681
Refinery gas	1.5714	0.8214
Natural gas	1.3300	0.5904

Sum up the carbon emissions of 30 provinces to obtain the total national carbon emissions, which is:

$$C_t = \sum_i C_{it} \quad (i = 1, 2, \dots, 30) \quad (2)$$

where C_t represents the national carbon emissions in the t -th year. Due to the availability of data, we take the carbon emission data of 30 provinces (cities and regions) in China from 2005 to 2021 as the research sample, excluding Tibet, Hong Kong, Macao, and Taiwan.

According to the definition of carbon emission intensity, regional gross domestic product data are required when calculating carbon emission intensity. To eliminate the influence of prices, adjustments are made based on 2005 as the base year.

2.2.2. Theil index

In 1967, Theil [20] first proposed the concept of the Theil index, which can be used to measure economic disparities between regions. The advantage of the Theil index is that it can decompose

regional differences into two parts: Intra-region and inter-region, which helps further evaluate the contribution of intra-region and inter-region disparities to the overall regional disparities.

In this paper, we use the Theil index to measure the regional disparities in carbon emissions intensity. By calculating the Theil index, we measure the overall disparity in carbon emission intensity across China's 30 provinces and decompose the index to yield intra-regional and inter-regional disparities. Therefore, the changing trends of intra-regional and inter-regional disparities can be obtained. The Theil index ranges from 0 to 1, where smaller values indicate smaller disparities in regional carbon emission intensity, and vice versa. The general expression of the Theil index and its decomposition are as follows:

$$\begin{aligned} Theil &= \sum_i \frac{C_i}{C} \ln\left(\frac{C_i/C}{Y_i/Y}\right) = \sum_j \frac{C_j}{C} T_{wj} + \sum_j \frac{C_j}{C} \ln\left(\frac{C_j/C}{Y_j/Y}\right) \\ &= \sum_j \sum_i \frac{C_j C_{ji}}{C C_j} \ln\left(\frac{C_{ji}/C_j}{Y_{ji}/Y_j}\right) + \sum_j \frac{C_j}{C} \ln\left(\frac{C_j/C}{Y_j/Y}\right) = T_{wr} + T_{br} \end{aligned} \quad (3)$$

$$T_{wr} = \sum_j \frac{C_j}{C} T_{wj} = \sum_j \sum_i \frac{C_j C_{ji}}{C C_j} \ln\left(\frac{C_{ji}/C_j}{Y_{ji}/Y_j}\right) \quad (4)$$

where *Theil* represents the overall Theil index, T_{wr} is the intra-regional Theil index, and T_{br} is the inter-regional Theil index. T_{wj} represents the Theil index for region j ; C_i is the carbon emission of province i ; Y_i is the GDP of province i ; C_j and Y_j are the carbon emissions and GDP of region j , respectively; C and Y represent the national carbon emissions and GDP, respectively; C_{ji} is the carbon emissions of province i in region j ; and Y_{ji} is the GDP of province i in region j .

2.2.3. Kernel density estimation

Kernel Density Estimation (KDE) is a non-parametric estimation method that can be applied to complex data distributions. Its function is to reflect the distribution of random variables through continuous density curves, and it has the advantages of strong robustness and low model dependence. The kernel density estimation can be obtained according to the empirical distribution function, which is depicted as follows [25]:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{X_i - x}{h}\right) \quad (5)$$

where N is the number of observations, X_i represents the independently and identically distributed observations, x represents the average of observations, and bandwidth h determines the smoothness and accuracy of the kernel density curve, a larger bandwidth results in a smoother curve but lower estimation accuracy, while a smaller bandwidth leads to a less smooth curve but higher estimation accuracy. Considering that the KDE result is sensitive to bandwidth, we typically choose a smaller bandwidth. $K(\cdot)$ is the kernel density function. In this paper, we use the Gaussian kernel density function to evaluate the dynamic distribution of carbon emission intensity across the nation and in the four regions, which is represented as:

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \quad (6)$$

Besides, the kernel density function serves as a weighted or smooth function and generally satisfies conditions (7) to (9):

$$\lim_{x \rightarrow \infty} K(x) \cdot x = 0 \quad (7)$$

$$K(x) \geq 0, \int_{-\infty}^{+\infty} K(x) dx = 1 \quad (8)$$

$$\sup K(x) < +\infty, \int_{-\infty}^{+\infty} K^2(x) dx < +\infty \quad (9)$$

The results of kernel density estimation reflect information such as the location, shape, and distribution extensibility. The distribution location indicates the level of carbon emission intensity, the distribution shape is used to analyze the size of regional disparities and degree of polarization in carbon emission intensity, where the height and width of the peaks reflect disparity size, while the number of peaks indicates the degree of polarization, and the distribution extensibility illustrates the regional disparity between the highest carbon emission intensity provinces and other provinces. The longer the tail, the greater the disparities.

Here, we integrate a modified carbon emission factor method, the Theil index, and kernel density estimation to address research gaps and enhance analytical rigor. The modified carbon emission factor improves provincial accounting accuracy by incorporating China-specific energy data, moving beyond international defaults. The Theil index decomposes regional disparities in emission intensity, distinguishing intra- and inter-regional heterogeneity to inform targeted policies. Kernel density estimation visually tracks dynamic distribution patterns, such as polarization or convergence, often missed by conventional methods. Together, these approaches form a comprehensive toolkit that quantifies disparities, reveals their spatiotemporal evolution, and strengthens the robustness of findings. This integrated methodology provides deeper insights into the drivers of carbon emission disparities in China, supporting evidence-based policy and regional coordination strategies.

3. Results

Based on the previous research data, we conducted a study and analysis of the national carbon emissions from two aspects: Carbon emissions and carbon emission intensity, and obtained the following results.

3.1. Characteristics of national carbon emission and carbon emission intensity

By calculate the carbon emissions of the country using formulas (1)-(2), we found that the total

carbon emissions generated by China's fossil energy consumption have showed an upward trend from 2005 to 2021. In 2005, the carbon emissions were 5,425.39 million tons, rising to 10,237.37 million tons in 2021, with an average annual increase of 300.75 million tons and an annual growth rate of 4.05%. Due to changes in statistical criteria in 2013, there was a temporary decline with an annual growth rate of -2.09%, as shown in Figure 1. The trend of carbon emissions aligns with the findings in the literature [7], which is characterized by initial rapid growth, followed by a slowing rate of increase. Furthermore, the carbon emission factors used in this study are the modified carbon emission factors based on 'General rules for calculation of comprehensive energy consumption' (GB/T 2589-2020) and the 'Guidelines for Compilation of Provincial Greenhouse Gas Inventories (Trial) (2011)', rather than the IPCC default values, which cause the calculated carbon emissions to be more accurate and in line with China's actual situation. It should be pointed out that if we use the IPCC default values, the carbon emissions will be overestimated by 7%.

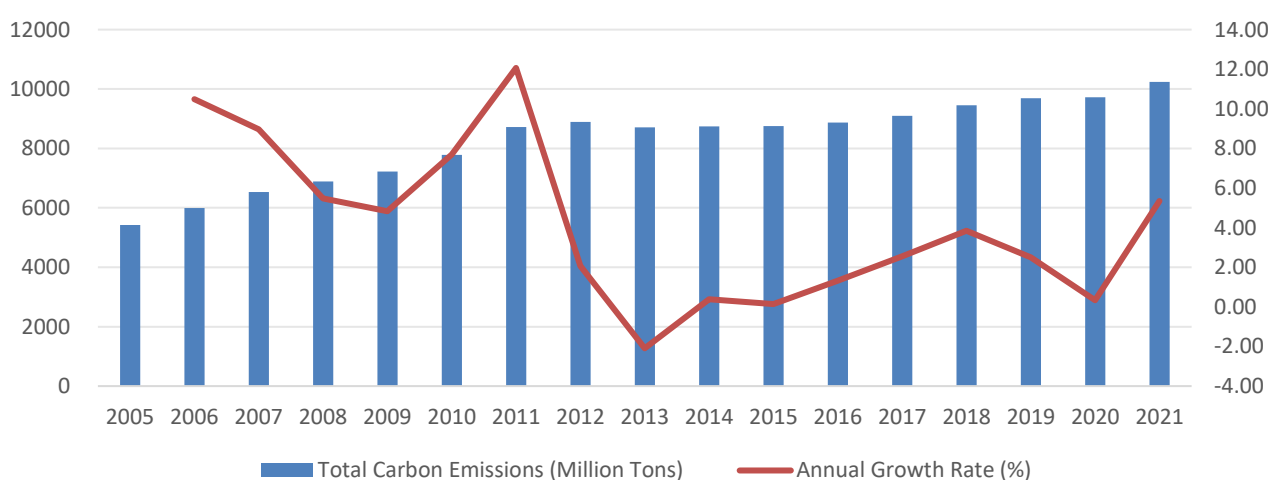


Figure 1. Carbon emission and annual growth rate (2005–2021).

From the perspective of energy consumption structure, the structure was further optimized from 2005 to 2021, and the proportion of carbon emissions from raw coal consumption continued to decrease, while the proportion of carbon emissions from natural gas consumption continued to increase yearly, which can be seen in Table 2.

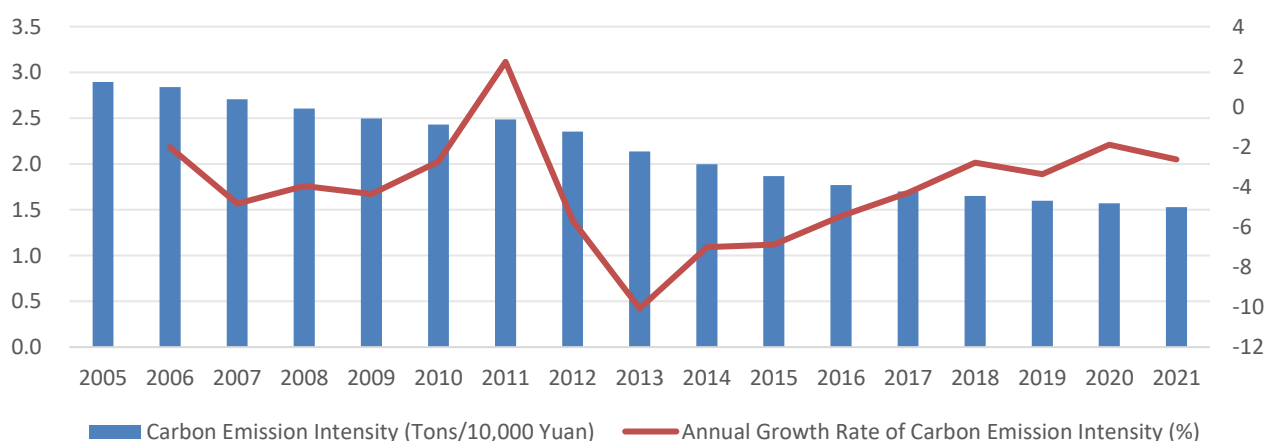
In 2005, the proportion of carbon emissions from raw coal consumption was as high as 72.06%, but it decreased to 67.43% by 2021. This aligns with the conclusions of the literature [7]. Conversely, natural gas emissions accounted for only 1.79% in 2005 but rose to 6.62% by 2021.

Many researchers exclude the carbon emissions from liquefied petroleum gas and refinery gas in their studies. In this study, we take into account energy varieties, making the scope of carbon emission accounting more extensive and complete. In fact, liquefied petroleum gas and refinery gas account for approximately 2% of total carbon emissions together.

Table 2. Proportion of carbon emissions from each type of energy consumption (%).

Year	Raw coal	Coke	Crude oil	Gasoline	Kerosene	Diesel oil	Fuel oil	LPG	Refinery gas	Natural gas
2005	72.06	11.20	0.57	3.38	0.60	6.10	2.53	1.27	0.51	1.79
2006	71.62	11.72	0.60	3.37	0.64	6.08	2.24	1.17	0.50	2.06
2007	71.00	12.25	0.56	3.43	0.65	6.20	1.96	1.14	0.48	2.32
2008	70.88	12.51	0.41	3.32	0.67	6.29	1.78	1.11	0.49	2.54
2009	70.22	12.87	0.44	3.40	0.68	6.38	1.60	1.09	0.50	2.82
2010	69.50	13.28	0.44	3.61	0.71	6.52	1.33	1.04	0.53	3.03
2011	70.38	12.93	0.43	3.58	0.69	6.23	1.16	1.01	0.52	3.08
2012	69.45	13.21	0.31	3.81	0.75	6.41	1.07	0.98	0.52	3.48
2013	69.04	13.37	0.35	3.82	0.82	6.27	1.01	0.98	0.53	3.82
2014	68.00	13.53	0.46	3.99	0.89	6.32	1.01	0.99	0.57	4.24
2015	67.49	13.08	0.38	4.42	0.99	6.42	1.01	1.03	0.60	4.58
2016	67.13	13.10	0.33	4.70	1.11	6.26	0.98	1.02	0.61	4.76
2017	67.43	12.54	0.21	4.81	1.19	6.15	0.87	1.02	0.61	5.17
2018	67.48	12.57	0.18	4.71	1.20	5.73	0.77	0.97	0.63	5.76
2019	66.95	12.93	0.14	4.70	1.23	5.68	0.72	0.93	0.66	6.06
2020	66.66	13.61	0.14	4.58	0.91	5.35	0.76	1.08	0.67	6.25
2021	67.43	12.43	0.08	4.58	0.94	5.35	0.75	1.16	0.66	6.62

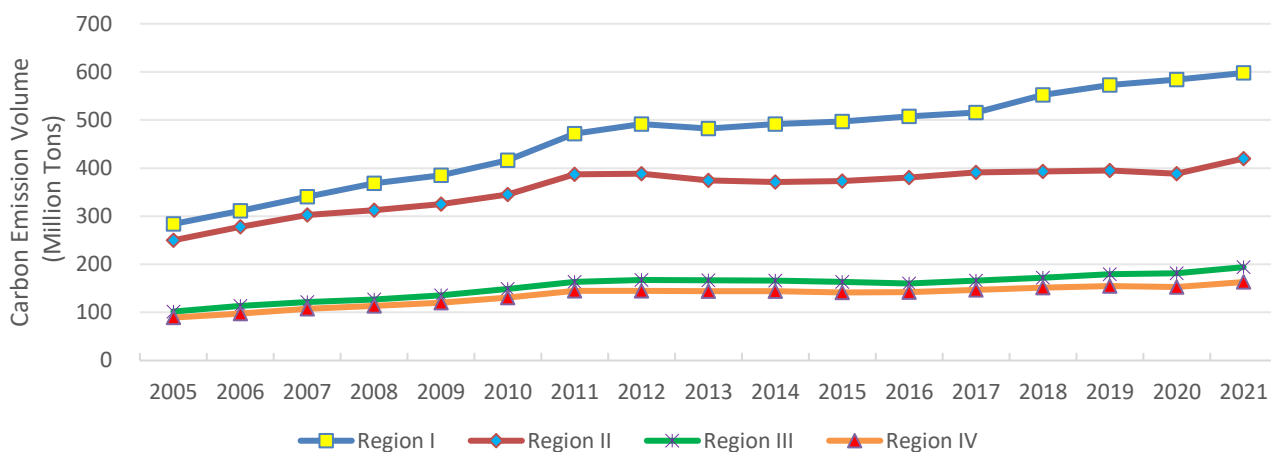
From 2005 to 2021, carbon emission intensity continued to decline, as shown in Figure 2. In 2005, carbon emission intensity was 2.8963 tons per 10,000 yuan, dropping to 1.5289 tons per 10,000 yuan in 2021, with an average annual decrease of 3.91%. In general, the carbon emission intensity in 2021 decreased by 45.83% compared to that in 2005.

**Figure 2.** Carbon emission intensity and annual growth rate (2005–2021).

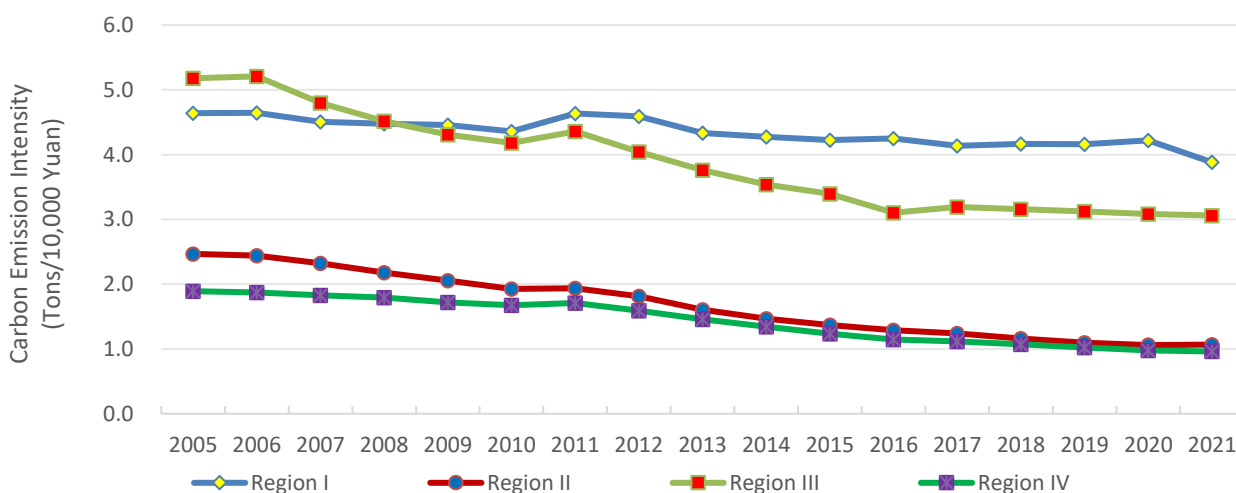
3.2. Regional disparities in carbon emission and intensity distribution among the four regions

China's 30 provinces are divided into four regions (Region I, Region II, Region III, and Region

IV) based on energy consumption and energy intensity. To accurately analyze the current distribution of carbon emissions, we use two indicators: Carbon emissions and carbon emission intensity in each region for analysis. The trends in carbon emission and carbon emission intensity for the four regions are shown in Figure 3.



(a) Carbon emission in the four regions.



(b) Carbon emission intensity in the four regions.

Figure 3. Trends in carbon emission and carbon emission intensity among the four regions.

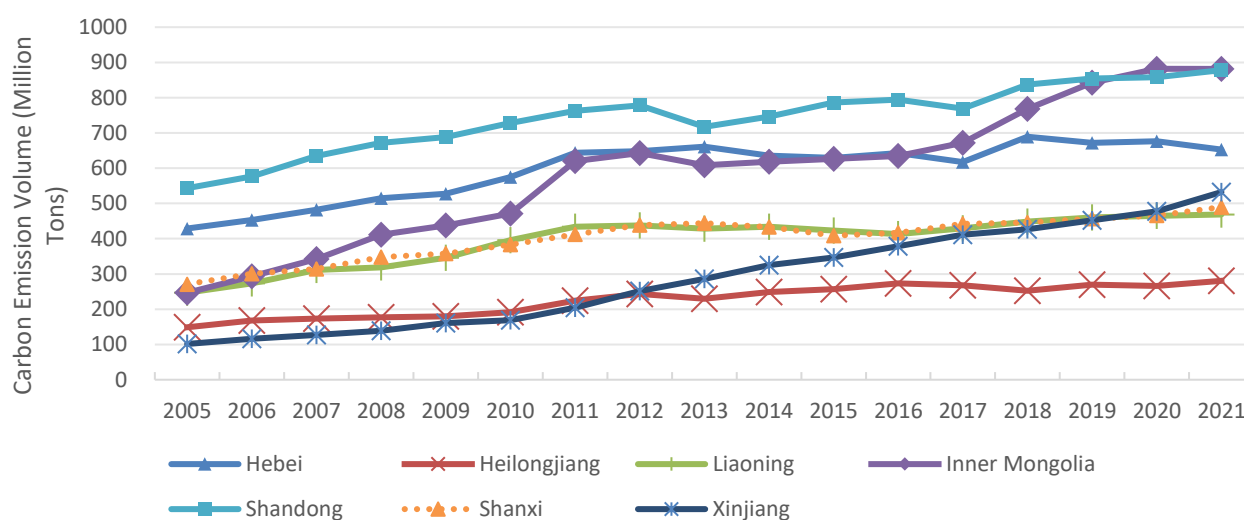
From the carbon emissions of the four regions shown in Figure 3(a), the carbon emissions of Region I and Region II from 2005 to 2021 were significantly higher than those of Region III and Region IV. In Region I, carbon emissions showed a rapid and sustained upward trend from 2005 to 2012, followed by a slight decline in 2013, and then resumed a continuous upward trend from 2013 to 2021, reaching a maximum value in 2021. The carbon emissions of Region II also experienced a rapid increase in carbon emissions from 2005 to 2012, followed by fluctuating growth from 2013 to 2021, with a peak in 2021. Generally, the carbon emissions of Region I were higher than those of Region II, and the gap showed a gradually widening trend from 2005 to 2021. For Regions III and IV, carbon emissions steadily increased from 2005 to 2012, then showed a fluctuating upward trend after 2013, also reaching peak levels in 2021. Overall, the carbon emissions of Region IV have always been lower

than those of Region III. In terms of absolute increases in carbon emissions, the annual average increases for Regions I, II, III, and IV from 2005 to 2021 were 19.62 million tons, 10.62 million tons, 5.77 million tons, and 4.61 million tons, respectively. The average annual growth rates of carbon emissions in Region I, Region II, Region III, and Region IV from 2005 to 2021 were 4.76%, 3.30%, 4.12%, and 3.84%, respectively.

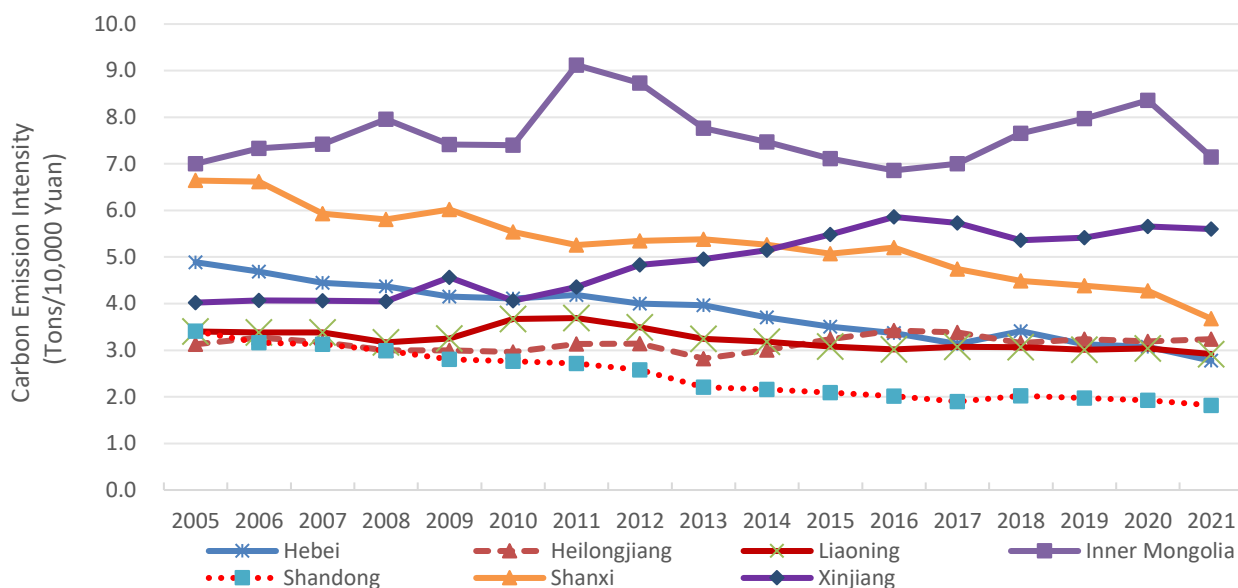
Figure 3(b) shows that the carbon emission intensity of Region I and Region III were significantly higher than that of Region II and Region IV, and all four regions showed a fluctuating downward trend in carbon emission intensity. Regions I and III reached their peak carbon emission intensities in 2006, at 4.6457 tons/10,000 yuan and 5.2089 tons/10,000 yuan, respectively, while Regions II and IV reached their peak intensities in 2005, at 2.4678 tons/10,000 yuan and 1.8913 tons/10,000 yuan, respectively. The lowest carbon emission intensities for Regions I, III, and IV were recorded in 2021, at 3.8823 tons/10,000 yuan, 3.0607 tons/10,000 yuan, and 0.9610 tons/10,000 yuan, respectively, while Region II's lowest intensity was in 2020, at 1.0596 tons/10,000 yuan. From 2005 to 2021, the carbon emission intensities for Regions I, II, III, and IV all showed a decline, i.e., negative growth, with average annual growth rates of -1.11%, -5.12%, -3.24%, and -4.14%, respectively.

3.3. Intra-regional disparities in carbon emission and carbon emission intensity among the four regions

To explore the disparities in carbon emissions among provinces within a region, we take Region I as an example for intra-regional analysis. The trends in carbon emission and carbon emission intensity for each province within Region I are shown in Figure 4.



(a) Carbon emission for each province within region I.



(b) Carbon emission intensity for each province within Region I.

Figure 4. Trends in carbon emission and carbon emission intensity for each province within Region I.

From the trend of carbon emissions in each province within Region I shown in Figure 4(a), all provinces exhibit a fluctuating upward trend in carbon emissions. Shandong's carbon emissions experienced a continuous rapid increase from 2005 to 2012, a slight decrease in 2013, and then a fluctuating upward trend from 2013 to 2021, reaching a maximum in 2021. Hebei's carbon emissions showed a sustained and rapid increase from 2005 to 2013, a slight decline from 2014 to 2017, reaching a peak in 2018, followed by a slight decline in the subsequent years. Liaoning's carbon emissions displayed a continuous rapid increase from 2005 to 2012, with slight decreases in 2013 and 2015 compared to the previous year, followed by a continuous rise from 2016 to 2021, reaching a maximum in 2021. The carbon emissions in Inner Mongolia showed a sustained and rapid upward trend from 2005 to 2012, with a slight decrease in 2013, from 2013 to 2020, the carbon emissions continued to rise and reached their maximum value in 2020, in 2021, the carbon emissions slightly decreased. The carbon emissions in Shanxi showed a sustained and rapid upward trend from 2005 to 2013, with a slight decrease in 2014, and from 2015 to 2021, the carbon emissions continued to rise and reached their maximum value in 2021. Heilongjiang's carbon emissions displayed a continuous rapid increase from 2005 to 2012, a slight decrease in 2013, and a fluctuating upward trend from 2013 to 2021, reaching a maximum in 2021. Xinjiang experienced a continuous rapid increase in carbon emissions from 2005 to 2021.

In terms of the average annual increase in carbon emissions of each province within Region I, Inner Mongolia had the highest average annual growth rate from 2005 to 2021, reaching 39.69 million tons, followed by Xinjiang with an average annual growth rate of 26.93 million tons from 2005 to 2021. Heilongjiang had the smallest average annual increase, at 8.23 million tons. Regarding the average annual growth rate of carbon emissions in various provinces within Region I, Xinjiang had the highest average annual growth rate from 2005 to 2021, at 10.92%, followed by Inner Mongolia with an average annual growth rate of 8.29%, while Hebei had the smallest average annual growth rate, at 2.66%.

As shown in Figure 4(b), the carbon emission intensity within Region I had an overall fluctuating trend, with inconsistent trends across provinces. The carbon emission intensity of Inner Mongolia

exhibited a pattern of rise–fall–rise–fall–rise–fall trend, reaching a maximum in 2011 and a minimum in 2016. Hebei's carbon emission intensity displayed a fluctuating downward trend from 2005 to 2021, with the highest value in 2005 and the lowest in 2021. The carbon emission intensity in Shanxi was the same as that in Hebei. Liaoning's carbon emission intensity showed a fall–rise–fall trend, reaching the highest value in 2011 and the lowest in 2021. Xinjiang's carbon emission intensity showed a fluctuating increase followed by a fluctuating decrease, with the lowest value in 2005 and the highest in 2016. Heilongjiang's carbon emission intensity exhibited a trend of first fluctuating and then increasing, and then fluctuating and decreasing again, reaching the lowest value in 2013 and the highest in 2016. Shandong's carbon emission intensity showed a fluctuating downward trend, with the highest value in 2005 and the lowest in 2021.

The highest carbon emission intensity within Region I in 2005 was in Inner Mongolia, at 7 tons per 10,000 yuan, followed by Shanxi with 6.642 tons per 10,000 yuan, while the lowest was in Heilongjiang at 3.1284 tons per 10,000 yuan. In 2021, the highest carbon emission intensity within Region I remained in Inner Mongolia, at 7.15 tons per 10,000 yuan, followed by Xinjiang at 5.6003 tons per 10,000 yuan, while the lowest was in Shandong at 1.8185 tons per 10,000 yuan.

From 2005 to 2021, the carbon emission intensity of Xinjiang, Inner Mongolia, and Heilongjiang in Region I showed an upward trend, with an average annual growth rate of 2.09%, 0.13%, and 0.22%, respectively. The average annual growth rate of carbon emission intensity in other provinces was negative, indicating a downward trend. Among them, Shandong had the largest average annual decline rate of 3.85%, followed by Shanxi with an average annual decline rate of 3.63%. Additionally, if we analyze only the carbon emission intensity of 2021 and 2005, we see that Shandong's carbon emission intensity in 2021 decreased the most compared to that in 2005, by 46.63%, while Xinjiang's carbon emission intensity increased by 39.23% over the same period.

4. Regional disparities of carbon emission distribution

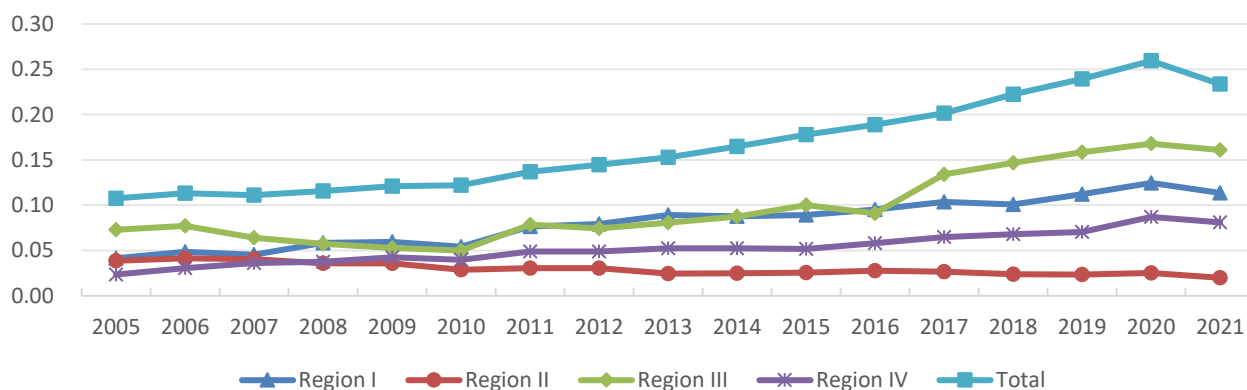
The results intuitively reflect the regional disparities in the distribution of carbon emissions and carbon intensity in China. To further analyze and explain the total and regional distribution disparities of carbon emissions in China, as well as the major sources of these disparities, we use the Theil index and its decomposition method to study them. Based on formulas (3) and (4), the corresponding results were obtained through programming in STATA.

4.1. Total regional disparities in carbon emission distribution

First, we calculate the Theil index for China's carbon emission intensity using formulas (3) and (4), as shown in Table 3. Then, we decompose the total disparities in carbon emission intensity into intra-regional disparities and inter-regional disparities, where the intra-regional disparities refer to the disparities within Regions I, II, III, and IV, and inter-regional disparities refer to the disparities between these regions. The trends of total and intra-regional disparities in carbon emission intensity are shown in Figure 5.

Table 3. Theil index of China's carbon emission intensity (2005–2021).

Year	Region I	Region II	Region III	Region IV	Intra-regional	Inter-regional	Total
2005	0.0415	0.0386	0.0729	0.0235	0.0431	0.0645	0.1076
2006	0.0485	0.0414	0.0772	0.0306	0.0482	0.0650	0.1131
2007	0.0453	0.0405	0.0641	0.0361	0.0453	0.0659	0.1111
2008	0.0584	0.0358	0.0575	0.0375	0.0476	0.0679	0.1156
2009	0.0596	0.0358	0.0529	0.0427	0.0480	0.0730	0.1210
2010	0.0543	0.0288	0.0501	0.0396	0.0429	0.0793	0.1222
2011	0.0763	0.0304	0.0785	0.0489	0.0571	0.0798	0.1370
2012	0.0795	0.0305	0.0743	0.0489	0.0581	0.0864	0.1445
2013	0.0892	0.0244	0.0805	0.0526	0.0613	0.0914	0.1528
2014	0.0877	0.0249	0.0872	0.0524	0.0622	0.1024	0.1647
2015	0.0892	0.0255	0.1001	0.0519	0.0649	0.1129	0.1778
2016	0.0953	0.0275	0.0909	0.0580	0.0672	0.1218	0.1890
2017	0.1036	0.0267	0.1341	0.0648	0.0772	0.1242	0.2014
2018	0.1008	0.0240	0.1469	0.0679	0.0783	0.1440	0.2223
2019	0.1122	0.0235	0.1583	0.0704	0.0854	0.1538	0.2392
2020	0.1246	0.0253	0.1679	0.0871	0.0952	0.1642	0.2594
2021	0.1137	0.0199	0.1610	0.0811	0.0865	0.1472	0.2337
Average	0.0811	0.0296	0.0973	0.0526	0.0629	0.1026	0.1654

**Figure 5.** Trends in total and intra-regional disparities of carbon emission intensity.

As shown in Table 3 and Figure 5, the average total Theil index of national carbon emission intensity was 0.1654, ranging from 0.1076 to 0.2594. The total Theil index of national carbon emission intensity initially increased and then decreased, reaching the minimum value in 2005 and the maximum in 2020, with a decline in 2021. The average annual growth rate of the total Theil index of national carbon emission intensity from 2005 to 2021 was 4.97%.

4.2. Intra-regional disparities

Table 3 and Figure 5 further reveal the trend of intra-regional disparities in carbon emission intensity among the four regions. From 2005 to 2021, the intra-regional Theil index of carbon emission intensity showed a trend of first fluctuating and decreasing, then continuously increasing, and

decreasing again. In 2005, intra-regional Theil index of carbon emission intensity was 0.0431, with a fluctuating decline reaching a minimum of 0.0429 in 2010, followed by a rapid increase from 2010 to 2020, peaking at 0.0952 in 2020, and then decreasing to 0.0865 in 2021. The average intra-regional Theil index of carbon emission intensity from 2005 to 2021 was 0.0629.

The Theil index of carbon emission intensity in Region III showed an overall trend of first fluctuating and decreasing, then fluctuating and increasing, and decreasing again, with the minimum in 2010 and the maximum in 2020. For Region I, the Theil index of carbon emission intensity generally showed an overall upward trend followed by a decline, with the minimum in 2005 and the maximum in 2020. Coincidentally, the Theil index of carbon emission intensity of Region IV showed the same trend as that in Region I. In Region II, the Theil index of carbon emission intensity exhibited a trend of initial increase followed by a fluctuating decline, peaking in 2006 and reaching a minimum in 2021.

4.3. Inter-regional disparities

As shown in Table 3, the average Theil index of inter-regional carbon emission intensity in China was 0.1026, with a minimum value of 0.0645 in 2005 and a maximum of 0.1642 in 2020. From 2005 to 2021, the average annual growth rate of the inter-regional Theil index of carbon emission intensity was 5.29%. The inter-regional Theil index of carbon emission intensity showed a trend of continuous increase followed by a decrease, reaching a minimum of 0.0645 in 2005, continuously rising to the maximum of 0.1642 in 2020, and then decreasing to 0.1472 in 2021, as shown in Figure 6.

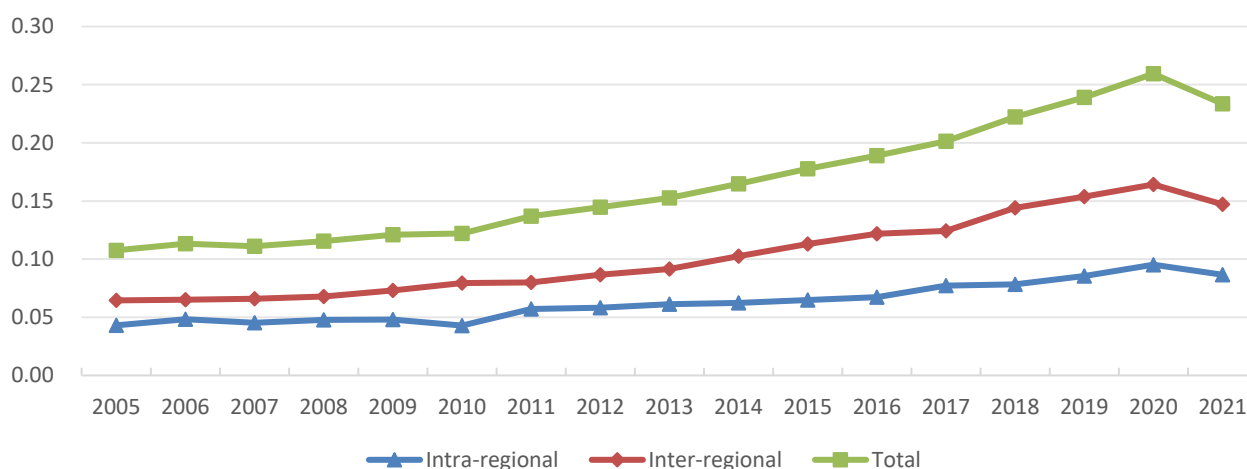


Figure 6. Disparities of national carbon emission intensity.

4.4. Sources of disparities and contribution rates

By decomposing the Theil index of China's overall carbon emission intensity, we calculate the contribution rates of each regional disparities and inter-regional disparities to the total Theil index, as shown in Table 4. From 2005 to 2021, the contribution rate of inter-regional disparities among the four regions to the overall carbon emission intensity ranged between 57.42% and 64.92%, with an average of 61.52%. The contribution rate of intra-regional disparities within the four regions to the overall carbon emission intensity ranged between 35.08% and 42.58%, with an average of 38.48%. This finding aligns with those in the literature [23]. This indicates that the total disparities in China's carbon emission intensity is mainly caused by inter-regional disparities among the four regions. Regarding

intra-regional disparities, Region I has the highest contribution rate, exceeding 14%, reaching as high as 22.61% in 2013, while Region IV has the lowest contribution rate for intra-regional disparities.

In this sense, the contribution rate of inter-regional disparities among the four regions in China showed a trend of first decreasing, then fluctuating upward, decreasing again, and finally fluctuating upward. The contribution rate of intra-regional disparities within the four regions of China showed a trend of first increasing, then fluctuating downward, increasing again, and finally fluctuating downward once again. The contribution rate of intra-regional disparities within Region I to the overall carbon emission intensity showed a trend of fluctuating increases followed by fluctuating decreases.

Table 4. Contribution rates of the Theil index for China's carbon emission intensity (%).

Year	Region I	Region II	Region III	Region IV	Intra-regional	Inter-regional
2005	14.12	13.21	10.17	2.52	40.02	59.98
2006	15.58	13.56	10.36	3.08	42.58	57.42
2007	14.88	13.51	8.60	3.74	40.73	59.27
2008	18.92	11.23	7.33	3.74	41.22	58.78
2009	18.37	10.65	6.56	4.10	39.69	60.31
2010	16.65	8.36	6.26	3.82	35.08	64.92
2011	21.10	7.87	8.59	4.16	41.72	58.28
2012	21.25	7.35	7.74	3.85	40.19	59.81
2013	22.61	5.48	8.08	3.98	40.15	59.85
2014	20.94	5.13	8.05	3.67	37.79	62.21
2015	19.92	4.89	8.41	3.29	36.52	63.48
2016	20.20	4.99	6.93	3.45	35.57	64.43
2017	20.41	4.55	9.74	3.63	38.33	61.67
2018	18.56	3.59	9.64	3.42	35.21	64.79
2019	19.42	3.20	9.81	3.29	35.72	64.28
2020	20.22	3.12	9.68	3.69	36.70	63.30
2021	19.89	2.80	10.45	3.87	37.00	63.00
Average	19.00	7.26	8.61	3.61	38.48	61.52

5. Dynamic evolution of carbon emission distribution

Although the Theil index reflects regional disparities in carbon emission intensity, it cannot capture the spatial distribution patterns and evolution trends. In contrast, the kernel density estimation method effectively addresses the issue of spatial distribution imbalances in carbon emission intensity. Therefore, we use the kernel density estimation method to study the spatial distribution imbalance of carbon emission intensity, which will reveal the dynamic evolution process of absolute disparities in carbon emission intensity at the national level and in the four regions. Next, we use the kernel density estimation method to explore the location, distribution trend, distribution extension, and polarization trend of carbon emission intensity distribution at the national level and in the four regions.

5.1. Dynamic distribution of national carbon emission intensity

Using MATLAB, we generate a three-dimensional distribution curve of national carbon emission intensity, as shown in Figure 7. It can be seen that from 2005 to 2021, the distribution of national carbon emission intensity underwent an evolutionary process of first shifting to the right and then to the left, but overall showed a trend of leftward shift, indicating a general decline in national carbon

emission intensity. The distribution exhibited a trend toward multi-polarization, with multiple peaks appearing on the right side, though the side peaks were relatively low. This suggested that the national carbon emission intensity distribution has a certain gradient effect, displaying a weak trend of multi-polarization. The magnitude of its main peak showed an overall increasing trend from 2005 to 2021. Moreover, the main peak of the national carbon emission intensity kernel density estimation curve showed a trend of increasing height, increasing slope, and narrowing width with a right tail phenomenon, indicating significant disparities in national carbon emission intensity. However, the absolute disparities in national carbon emission intensity decreased.

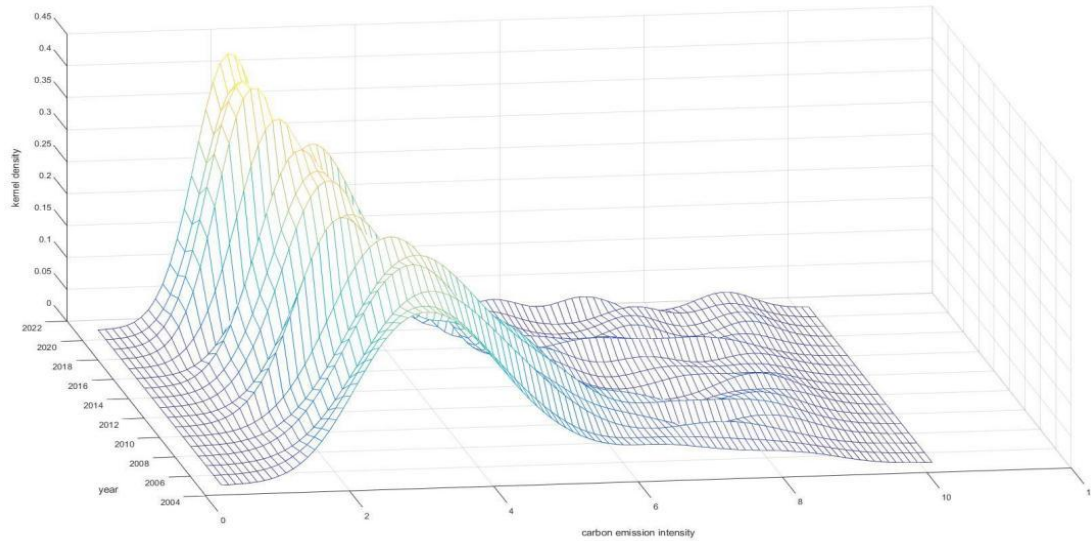
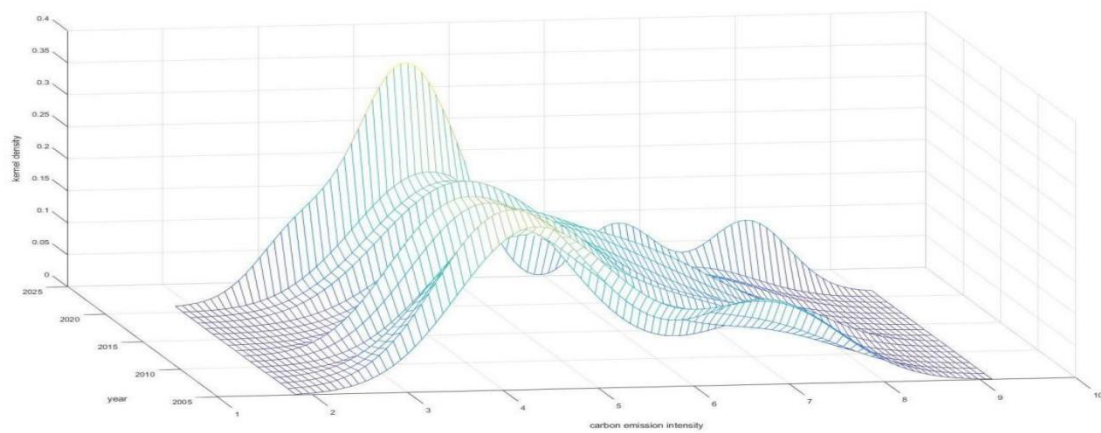


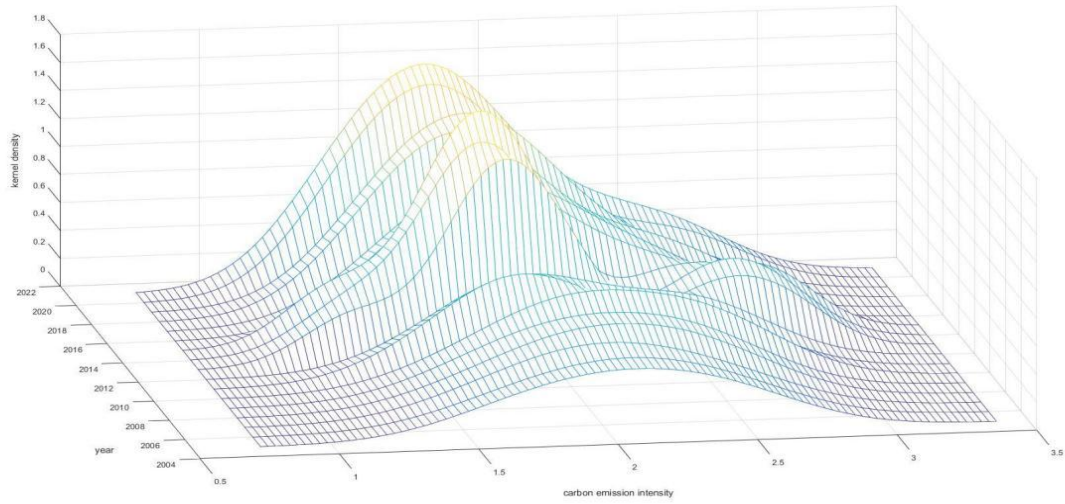
Figure 7. Dynamic distribution of national carbon emission intensity.

5.2. Dynamic distribution of carbon emission intensity among the four regions

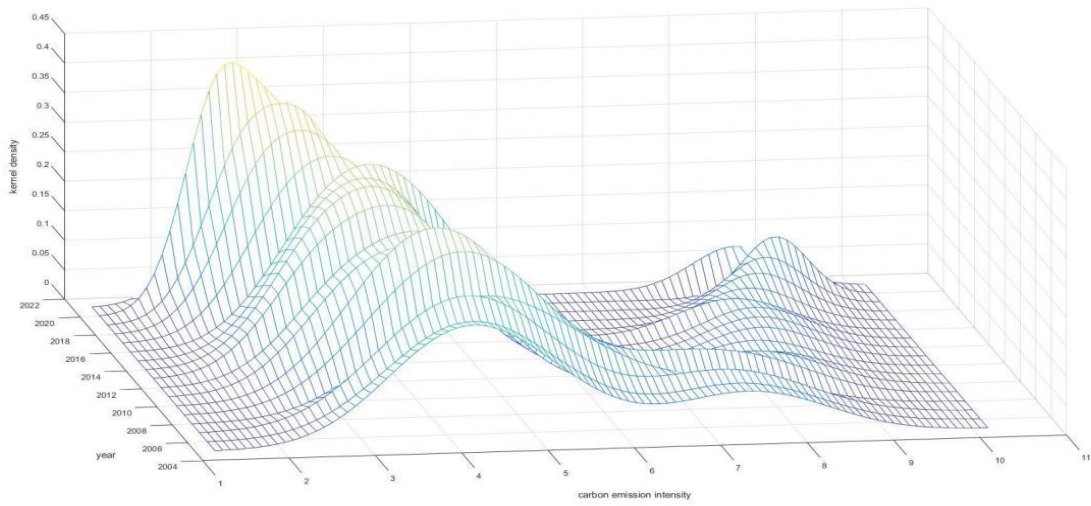
We continue to use MATLAB to draw three-dimensional distribution curves of carbon emission intensity in the four regions, as shown in Figure 8.



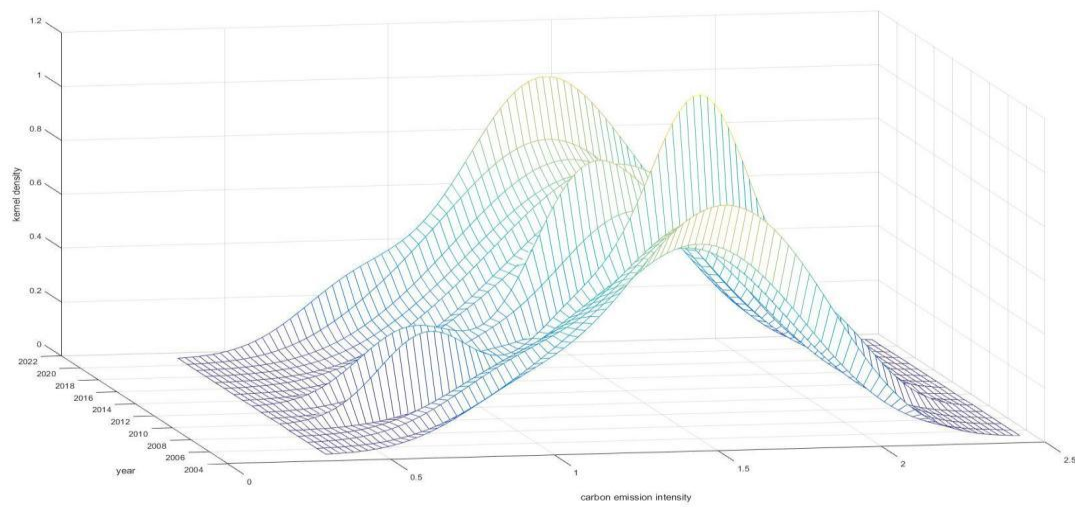
(a) Region I



(b) Region II



(c) Region III



(d) Region IV

Figure 8. Dynamic distribution of carbon emission intensity in the four regions.

According to Figure 8(a), from 2005 to 2021, the distribution of carbon emission intensity in Region I underwent an evolutionary process of first shifting to the right and then to the left, but overall showed a trend of leftward shift, indicating an overall downward trend in carbon emission intensity. The distribution of carbon emission intensity in Region I displayed a multi-polarization trend and underwent an evolution from ‘multi-peak–single peak–multi-peak’. When multiple peaks appeared, the side peak was on the right and relatively low, suggesting a gradient effect and a weak multi-polarization trend in Region I. The magnitude of its main peak remained relatively stable from 2005 to 2020 but increased sharply in 2021. The main peak in the kernel density estimation curves showed a complex change, with a trend of decreasing peak value first and then increasing, and increasing width first and then narrowing, indicating that the absolute disparities in carbon emission intensity in Region I initially increased and then decreased.

Figure 8(b) shows that from 2005 to 2021, the distribution of carbon emission intensity in Region II also underwent a rightward and then leftward shift, overall showing a leftward trend, indicating an overall decline in carbon emission intensity. The distribution in Region II displayed a multi-polarization trend, evolving from ‘single peak–multi-peak–single peak’. The side peak was on the left and relatively high, indicating a gradient effect and a stronger multi-polarization trend in Region II. The magnitude of its main peak remained largely unchanged from 2005 to 2012, increased sharply in 2013, and remained relatively stable during the period from 2013 to 2021. The main peak of the kernel density estimation curves for carbon emission intensity in Region II increased in height before decreasing, with a narrowing width, indicating decreasing absolute disparities in carbon emission intensity in Region II.

Figure 8(c) shows that from 2005 to 2021, the distribution of carbon emission intensity in Region III underwent a leftward shift, indicating an overall downward trend in the carbon emission intensity of Region III. The distribution in Region III displayed a multi-polarization trend, with side peaks on the right of the main peak, which were relatively prominent, suggesting a gradient effect and a strong multi-polarization trend in Region III. The magnitude of its main peak showed an overall increasing trend from 2005 to 2021. The main peak in the kernel density estimation curves showed an increase in peak height, a steeper slope, and a narrowing width, indicating a decreasing trend in absolute disparities in carbon emission intensity in Region III.

As seen in Figure 8(d), the distribution of carbon emission intensity in Region IV followed the same trend as that in Regions I and II, undergoing an evolutionary process of first shifting to the right and then to the left during the period from 2005 to 2021. The distribution in Region IV displayed a multi-polarization trend, evolving from ‘single peak–multi-peak–single peak’. When multiple peaks appeared, the side peak was on the left of the main peak and relatively low, suggesting a gradient effect and a weak multi-polarization trend in Region IV. The magnitude of its main peak showed a trend of initially increasing, subsequently decreasing and stabilizing, and then increasing again. The main peak in the kernel density estimation curves showed a complex pattern with irregular fluctuations in peak height and a narrowing width, indicating a decreasing trend in absolute disparities in carbon emission intensity in Region IV.

6. Conclusion and policy recommendations

In this paper, we use the modified carbon emission factor method to calculate the carbon emissions and carbon emissions intensity of 30 provinces in China from 2005 to 2021, on the basis of energy consumption data. Then, the Theil index and kernel density estimation method are used to characterize the regional disparities and dynamic evolution. The major conclusions as follows:

First, there are significant regional disparities in both the carbon emission and carbon emissions intensity in China. Specifically, the carbon emissions of Region I and Region II are significantly higher than those of Region III and Region IV. The carbon emissions of Region I showed a rapid and continuous upward trend from 2005 to 2012, with a slight decrease in 2013, followed by a continuous upward trend from 2013 to 2021, reaching the highest level in 2021. Region II experienced a rapid increase in carbon emissions from 2005 to 2012, followed by a generally fluctuating upward trend from 2013 to 2021, with the highest level reached in 2021. Regions III and IV exhibited continuous increases in carbon emissions from 2005 to 2012, followed by fluctuating upward trends after 2013, with both regions reaching their peak emissions in 2021. The carbon emission intensity in all four regions showed a fluctuating downward trend, with Regions I and III peaking in 2006, and Regions II and IV peaking in 2005. The lowest carbon emission intensities for Regions I, III, and IV were in 2021, while Region II reached its lowest intensity in 2020.

Second, according to the disparities indicated by the Theil index, there were significant regional disparities in carbon emission intensity, with inter-regional disparities being the main source of these regional disparities. The total Theil index for the national carbon emission intensity showed a trend of first increasing and then decreasing. The Theil index for intra-regional carbon emission intensity in China initially showed a fluctuating decline, followed by a continuous increase and then another decline. Moreover, the Theil index for inter-regional carbon emission intensity exhibited an upward trend, followed by a decline.

Third, based on the disparities obtained by the kernel density estimation method, the distribution of carbon emission intensity in China underwent an evolutionary process of first shifting to the right and then to the left, but overall showed a trend of a leftward shift. The presence of multiple peaks in the kernel density estimation curve of carbon emission intensity indicates a weak multi-polarization phenomenon in the distribution of national carbon emission intensity. Observing the main peak and tail, there are significant disparities in national carbon emission intensity, although these disparities are narrowing. Regionally, the distribution of carbon emission intensity in Regions I, II, and IV has undergone the same evolution process of first shifting to the right and then to the left, but overall, it shows a trend of shifting to the left. Region III exhibits a leftward shift in carbon emission intensity distribution. Additionally, different regions exhibit varying degrees of multi-polarization.

Based on the above conclusions, the following three policy recommendations are proposed:

Implement differentiated regional emission reduction strategies: Given that Region I and Region II have significantly higher and continuously growing total carbon emissions, stricter total carbon emission controls and earlier peaking deadlines should be imposed on them, alongside mandatory promotion of clean energy transition. For instance, in the case of Hebei Province and Shandong Province within Region I, where total carbon emissions have continuously increased during the study period, corresponding emission reduction measures should prioritize strict control over total emissions. For Region III and Region IV, the focus should be on setting aggressive targets for reducing carbon emission intensity and strictly capping their total emission growth, guiding them to leapfrog traditional high-carbon development pathways.

Establish a collaborative governance mechanism aimed at narrowing regional disparities: Since inter-regional differences are the primary source of overall inequality, a cross-regional mechanism linking carbon markets, facilitating green technology transfer, and implementing horizontal fiscal compensation should be established. Through policy guidance, high-emission regions should effectively provide financial and technological support to low-emission regions, thereby promoting regional equity within the broader national effort to reduce emissions. For example, Hebei Province,

having undertaken substantial industrial relocation within the Beijing-Tianjin-Hebei regional development, represents a key contributing factor to its continuously high total carbon emissions.

Transition the policy framework from "intensity control" to "dual control of both intensity and total volume": Although the carbon emission intensity shows an overall declining trend nationally and across all regions, total carbon emissions continue to rise, indicating the inadequacy of current intensity-based controls. It is recommended that, at the national level, and particularly for high-emission regions, binding targets for achieving an absolute reduction in total carbon emissions should be established and implemented promptly to ensure emissions peak as early as possible.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflicts of interest.

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