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Decomposition Analysis and Trend Prediction of Energy-Consumption CO_2 Emissions in China's Yangtze River Delta Region

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Abstract: This study calculated CO_2 emissions related to the consumption of primary energy by five sectors in the Yangtze River Delta region over 2000 to 2019. The Logarithmic Mean Divisia Index (LMDI) decomposition method was used to establish the factor decomposition model of CO_2 emissions change. The LMDI model was modified to assess the impact of five influencing factors, namely energy structure, energy intensity, industrial structure, economic output, and population size, on CO_2 emissions in the Yangtze River Delta region over the study period. The empirical results show that economic output has the largest positive effect on the growth in CO_2 emissions. Population size is the second most important factor promoting the growth in CO_2 emissions. Energy intensity is the most inhibitory factor to restrain CO_2 emissions, with a significant negative effect. Energy structure and industrial structure contribute insignificantly to CO_2 emissions. Using data on CO_2 emissions in the Yangtze River Delta region from 2000 to 2019, the GM (1, 1) model was applied for future forecasts of primary energy consumption and CO_2 emissions. Specific policy suggestions to mitigate CO_2 emissions in Yangtze River Delta region are provided.

Keywords: Yangtze River Delta region; CO_2 emissions; LMDI method; grey prediction GM (1, 1) model

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1. Introduction

Climate change caused by greenhouse gas emissions poses an ever-increasing threat to social development and human health; therefore, lowering carbon dioxide (CO_2) emissions has emerged as a critical international concern. The main source of CO_2 emissions is energy consumption, and many scholars have conducted related research on energy consumption in human life and production activities [1–4]. In 2019, China's yearly greenhouse gas emissions amounted to 27% of global emissions, surpassing the total emissions of Organization for Economic Cooperation and Development (OECD) countries for the first time [5], and in 2021 it consumed 26.49% of world primary energy and created 31.06% of global CO_2 emissions [6]. The country's latest Five-Year Plan includes a set of regional emission reduction targets to control CO_2 emissions. As is commonly known, the greenhouse effect is directly caused by the large amounts of greenhouse gas emissions—mainly comprising CO_2. Effective control of CO_2 emissions is therefore imperative to mitigating global warming.

China, as the world's largest developing country, continues to prioritize economic development, particularly regional economic development. Its most developed region, the Yangtze River Delta region, holds a crucial strategic position and is a driving force in modernizing China's economy and society. As seen in Figure 1, it comprises Jiangsu and Zhejiang provinces, centered on Shanghai, is a region of rapid industrialization and has China's densest population, highest urbanization, and most developed economy.

Figure 1. The Yangtze River Delta region of China.

According to the China Statistical Yearbook [7], gross domestic product (GDP) of the Yangtze River Delta region in 2021 was around 23.3 trillion yuan at the current price, accounting for nearly 20% of China's national economy. The region's GDP increased at a high average annual growth rate of 10% from 2000 to 2019, mainly accounted for by Jiangsu province with a rate of 6 trillion yuan in 2019, followed by Zhejiang Province and Shanghai. During the same period, the Yangtze River Delta region's energy consumption increased from 200.71 million tons to 666.15 million tons of standard coal, representing nearly 15% of China's total energy consumption. In particular, energy consumption in the region's industry sector increased from 59.91 million tons of standard coal in 2000 to 130.63 million tons in 2019, accounting for the largest sectoral share. The Yangtze River Delta region's CO_2 emissions rose considerably as a result of its usage of coal, the primary energy utilized, which has led to a number of environmental issues.

In recent years, global warming has become a major concern, and numerous studies have attempted, using various methodologies, to determine the factors that influence CO_2 emissions. The main methodologies used are the environmental Kuznets curve approach, STIRPAT, IPAT, and regression, and decomposition analysis. While each method has its advantages, that of decomposition analysis is its ability to quantitatively depict how driving forces influence changes based on an aggregation. As decomposition analysis methods, both structural decomposition analysis (SDA) and index decomposition analysis (IDA) are frequently employed; however, the IDA method is more widely used due to the availability of data [8]. In-depth investigations are not appropriate for SDA since it requires input-output data, which are typically released every five years in China—IDA simply utilizes departmental aggregate data, making it appropriate for time series modeling. The LMDI approach was first proposed by Ang and Choi [9], and is highly regarded as an IDA technique due to its theoretical base, adaptability, ease of usage, and result interpretation [8,10]. Compared with other IDA approaches, the LMDI method has several practical advantages in terms of its applicability, including perfect decomposition, the additive property of results and consistency in aggregation [10]. These advantages explain the wide use of LMDI in research over many fields, such as in energy supply and demand [11,12], and in energy-related gas emissions [13,14]. Decomposition studies have been conducted in numerous countries and regions around the world, and this study focuses on CO_2 emissions research in China. In addition to studying CO_2 emissions throughout whole China [15,16], many studies adopt sectoral and regional perspectives to identify the driving factors of CO_2 emissions. Studies relative to China have assessed CO_2 emissions at the sectoral level, specific to industry [17], construction [18], cement industry [19], chemical industry [20], petroleum refining and coking industry [21], transport [22,23], and manufacturing industry [24], identifying the driving factors for reducing CO_2 emissions by sector. In addition to sector-level studies, several scholars have investigated CO_2 emissions from a regional perspective [25–29].

Estimating and projecting CO_2 emissions into the atmosphere is critical for analyzing and planning mitigation activities, as well as establishing scenarios for future emissions. Deng [30] was the first to propose utilizing the grey model (GM) to analyze uncertainty and information deficiency. As a result of this concept, the grey model has been used in a range of complex applications [31–35].

Thus, in this study, we examined the factors influencing CO_2 emissions in the Yangtze River Delta region from 2000 to 2019 using the LMDI method, and the GM (1,1) model was applied to forecast primary energy consumption and CO_2 emissions in the short term. The goal of this study was to demonstrate the potential of each influencing factor in reducing CO_2 emissions by exploring the impact of each factor on CO_2 emissions changes and predict future trends in CO_2 emissions changes to explore potential future pathways for efficient CO_2 emissions and execute low-carbon development strategies. This novel study reveals the insight for investigating CO_2 emissions on production activities in the past and for future timepoints.

2. Materials and Methods

2.1. The LMDI Decomposition Method

The LMDI method is a popular decomposition technique in energy and environmental research. In terms of theoretical background, zero residual, adaptability, result interpretation, and other qualities, Ang [8] argued that LMDI was the most preferable decomposition method. Using the additive LMDI decomposition model, we incorporate qualitative and quantitative analysis in the research process to investigate the effects of different factors on CO_2 emissions in the Yangtze River Delta region.

The analysis process involves categorizing by industry sectors and energy types based on the extended Kaya decomposition method. Changes in CO_2 emissions may be broken down into emission coefficient effect, energy structure effect, energy intensity effect, industrial structure effect, economic output effect, and population size effect.

We decomposed the carbon emissions of the Yangtze River Delta region by the LMDI method from the following Kaya identity:

$$C = \frac{C}{E} \cdot \frac{E}{GDP} \cdot \frac{GDP}{P} \cdot P \tag{1}$$

where C denotes the total carbon emissions, E denotes the total energy consumption, GDP denotes gross domestic product and P denotes population scale.

We then extended Kaya's identity, as follows:

$$\boldsymbol{C = \sum_{i,j} C_{i,j} = \sum_{i,j} \frac{C_{i,j}}{E_{i,j}} \cdot \frac{E_{i,j}}{E_i} \cdot \frac{E_i}{Q_i} \cdot \frac{Q_i}{Y} \cdot \frac{Y}{P} \cdot P = \sum_{i,j} F_{i,j} \cdot S_{i,j} \cdot I_i \cdot R_i \cdot G \cdot P} \tag{2}$$

where i denotes sector, j denotes energy type, $C_{i,j}$ denotes carbon emission from energy j consumption by sector i (in units of 10,000 tons), $E_{i,j}$ denotes energy j consumption by sector i (in units of 10,000 tons of standard coal), E_i represents total energy consumption of sector i (in units of 10,000 tons of standard coal), Q_i represents value added of sector i (in units of 100 million yuan), Y refers to GDP (in units of 100 million yuan), and P refers to resident population (in units of million people). $F_{i,j} = C_{i,j} / E_{i,j}$ denotes the carbon emission coefficient of energy j in sector i (the carbon emission coefficient factor); $S_{i,j} = E_{i,j} / E_i$ denotes the proportion of energy j in sector i (the energy structure factor); $I_i = E_i / Q_i$ denotes energy intensity of sector i (the energy intensity factor); $R_i = Q_i / Y$ denotes sector i value added proportion in GDP (the industrial structure factor); $G = Y / P$ denotes economic output per capita in a period (the economic output factor); and P denotes resident population (the population size factor).

Applying the LMDI additive method, the carbon emission factors can be decomposed as below:

$$\Delta C = C^t - C^0 = \Delta C_F^t + \Delta C_S^t + \Delta C_I^t + \Delta C_R^t + \Delta C_G^t + \Delta C_P^t \tag{3}$$

The expressions for determining the decomposition factors' contribution values are as follows:

Emission coefficient effect:

$$\Delta \boldsymbol{C}_F^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{F}_{i,j}^t}{\boldsymbol{F}_{i,j}^0} \tag{4}$$

Energy structure effect:

$$\Delta \boldsymbol{C}_S^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{S}_{i,j}^t}{\boldsymbol{S}_{i,j}^0} \tag{5}$$

Energy intensity effect:

$$\Delta \boldsymbol{C}_I^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{I}_{i}^t}{\boldsymbol{I}_{i}^0} \tag{6}$$

Industrial structure effect:

$$\Delta \boldsymbol{C}_R^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{R}_{i}^t}{\boldsymbol{R}_{i}^0} \tag{7}$$

Economic output effect:

$$\Delta \boldsymbol{C}_G^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{G}^t}{\boldsymbol{G}^0} \tag{8}$$

Population size effect:

$$\Delta \boldsymbol{C}_P^t = \sum_{i,j} \frac{\boldsymbol{C}_{i,j}^t - \boldsymbol{C}_{i,j}^0}{\boldsymbol{ln}\boldsymbol{C}_{i,j}^t - \boldsymbol{ln}\boldsymbol{C}_{i,j}^0} \cdot \boldsymbol{ln}\frac{\boldsymbol{P}^t}{\boldsymbol{P}^0} \tag{9}$$

where C^0 and C^t denote total CO_2 emissions of a region in period 0 and period t, respectively. ΔC denotes the change in CO_2 emissions from period 0 to period t. Accordingly, ΔC can be decomposed into the emission coefficient effect (ΔC_F), energy structure effect (ΔC_S), energy intensity effect (ΔC_I), industrial structure effect (ΔC_R), economic output effect (ΔC_G) and population size effect (ΔC_P).

As there is little change in the carbon emission coefficient of the same energy type stated in IPCC 2006 [36], in Equation (3), ΔC_F is therefore always equal to 0. Therefore, only the latter five factors need to be considered. Equation (3) can be simplified as below.

Total effect:

$$\Delta \boldsymbol{C} = \boldsymbol{C}^t - \boldsymbol{C}^0 = \Delta \boldsymbol{C}_S^t + \Delta \boldsymbol{C}_I^t + \Delta \boldsymbol{C}_R^t + \Delta \boldsymbol{C}_G^t + \Delta \boldsymbol{C}_P^t \tag{10}$$

2.2. GM (1, 1) Model

Many scholars use different models to test the CO_2 emissions of various regions. Among the current numerous prediction methods, the grey prediction model has the advantages of simple modeling, use with limited samples, simple data requirements, convenient operation, and high practicability. Grey prediction is based on the grey dynamic model, which is a method enabling effective control over a system with insufficient data and incomplete information, thus is widely favored by many scholars. It is widely used across broad-ranging fields including industry, agriculture, economy and society, and has achieved good results. Moreover, much research on the theory of the model has been conducted to improve its test accuracy. In terms of the complex issues surrounding energy, these are usually accompanied by low information amount, few samples, and incomplete data, which makes grey prediction unique as it only has low data requirements to make accurate predictions. Therefore, it is reasonable to use the grey prediction GM (1, 1) model to make short-term predictions for the Yangtze River Delta region.

The construction of GM (1, 1) grey prediction model is as follows:

Original series $X^{(0)}$ is defined as:

$$\boldsymbol{X^{(0)}} = \left\{\boldsymbol{x^{(0)}(1),\ x^{(0)}(2), \ldots, x^{(0)}(n)}\right\} \tag{11}$$

where n $\geq$ 3.

Get a new series $X^{(1)}$:

$$\boldsymbol{X^{(1)}} = \left\{\boldsymbol{x^{(1)}(1),\ x^{(1)}(2), \ldots, x^{(1)}(n)}\right\} \tag{12}$$

where $x^{(1)}(n) = \sum_{k=1}^{n} x^{(0)}(k)$.

The basic form of GM (1, 1) is:

$$\boldsymbol{X^{(0)}(t) + \alpha \cdot X^{(1)}(t) = u} \tag{13}$$

where t is the independent variable, α is the developed coefficient, and u is the grey controlled variable, which are estimated by the ordinary least-squares method. A grey prediction model can be constructed from α and u. α represents the developed law and trend of the sequence, and u reflects the change relationship of the sequence.

A response equation can be generated using the estimated coefficients α and u:

$$\boldsymbol{\hat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{u}{\alpha}\right)e^{-\alpha t} + \frac{u}{\alpha}} \tag{14}$$

The prediction formula is expressed as:

$$\boldsymbol{\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}(t)} \tag{15}$$

The fitting and prediction results are discussed using the posterior variance test to show how reliable the GM (1, 1) model is. Posterior variance ratio C and small error probability P are both criteria for the posterior variance test.

The following is the definition of the posterior variance ratio C and small error probability P:

$$\boldsymbol{C = \frac{S_2}{S_1} = \sqrt{\frac{{S_2}^2}{{S_1}^2}}} \tag{16}$$

$$\boldsymbol{P = \left\{ \left| \varepsilon^{(0)}(t) - \overline{\varepsilon}^{(0)}(t) \right| < 0.6745 S_1 \right\}} \tag{17}$$

where $C > 0$, $0 \leq P \leq 1$, ${S_2}^2 = \frac{1}{m-1}\sum_{t=1}^{m-1}\left(\varepsilon^{(0)}(t) - \overline{\varepsilon}^{(0)}(t)\right)^2$, and ${S_1}^2 = \frac{1}{m-1}\sum_{t=1}^{m}\left(x^{(0)}(t) - \overline{x}^{(0)}(t)\right)^2$. $\varepsilon^{(0)}(t)$ is the residual between the predicted value $\hat{x}^{(0)}(t)$ and the actual value

$x^{(0)}(t)$ at time t. $P > 0.95$ and $C < 0.35$ indicates excellent prediction accuracy, $P > 0.60$ and $C < 0.80$ indicates qualified prediction accuracy, and $P < 0.60$ and $C > 0.80$ indicates unqualified prediction accuracy.

2.3. Data

All available data are from the study period, 2000–2019. Data on GDP, value added of each sub-sector and population were obtained from the China Statistical Yearbook (2001–2020) [7], Jiangsu Statistical Yearbook (2001–2020) [37], Zhejiang Statistical Yearbook (2001–2020) [38] and Shanghai Statistical Yearbook (2001–2020) [39] for the period 2000−2019. Data on the resident population is used as population data, while GDP and value-added of each sub-sector are converted into constant 2000 prices (base year is 2000) to remove the effects of price volatility. Energy consumption is the total amount of energy consumed based on eight energy sources: coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and natural gas. Five sectors contribute to economic output: (1) agriculture, forestry, animal husbandry and fishery, (2) industry, (3) construction, (4) transport, storage and post, (5) wholesale, retail trade, hotels and catering services. The energy consumption data are total final consumption quantities, obtained from the Jiangsu Statistical Yearbook (2001−2020) [37], Zhejiang Statistical Yearbook (2001–2020) [38], Shanghai Statistical Yearbook (2001−2020) [39], and China Energy Statistical Yearbook (2001−2020) [40] for 2000−2019. The eight energy types involve quantities in different units, which are converted into standard coal consumption quantities in units of 10,000 tce (tce: tons of standard coal equivalent) using conversion coefficients (see Table 1). There are no direct CO_2 emissions figures available, and none are included in any statistical yearbook or government website. As a result, the majority of research on CO_2 emissions has calculated emissions using energy consumption. Therefore, we calculated amounts of provincial CO_2 emissions of the eight energy types in five sectors using Equation (18) as follows:

$$C = \sum_j C_j = \sum_j E_j \cdot F_j \tag{18}$$

where C refers to the total CO_2 emissions related to energy consumption; j refers to eight energy types; C_j is the CO_2 emissions of energy j; E_j is the energy j consumption (standard coal equivalent); and F_j represents the carbon emission coefficient of energy j. Table 1 shows the standard coal reference coefficient and carbon emission coefficient by energy type.

Table 1. Standard coal reference coefficient and carbon emission coefficient.

Energy Types	Standard Coal Reference Coefficient (kgce/kg)	Carbon Emission Coefficient (kg/kgce)
Coal	0.7143	0.7476
Coke	0.9714	0.8550
Crude oil	1.4286	0.5825
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel oil	1.4571	0.5921
Fuel oil	1.4286	0.6185
Natural gas [a]	1.3300	0.4435

Source: China Energy Statistical Yearbook [40] and IPCC 2006 [36].Notes: [a]: Standard coal reference coefficient of nature gas is in the range of 1.1000−1.3300 kgce/kg. Here, we chose 1.3300 kgce/kg based on the commonly used value for research.

2.4. Limitations

Firstly, this study was limited to a focus on the CO_2 emissions research of the five major sectors related to production activities, exploring the emission reduction pathways in the Yangtze River Delta region from the perspective of the overall industry. Secondly, a short-term forecast was chosen as it could be more appropriately adapted to regional low carbon development. For further study, decomposition analysis and prediction of CO_2 emissions can be conducted and compared by sector.

3. Results and Discussion

3.1. Energy-Consumption CO_2 Emissions of Yangtze River Delta Region

In parallel with the rapid social and economic development of the Yangtze River Delta region, CO_2 emissions from energy consumption have increased. Figure 2 depicts the energy-consumption CO_2 emissions by sector for Jiangsu Province, Zhejiang Province, Shanghai, and the Yangtze River Delta region, during 2000–2019.

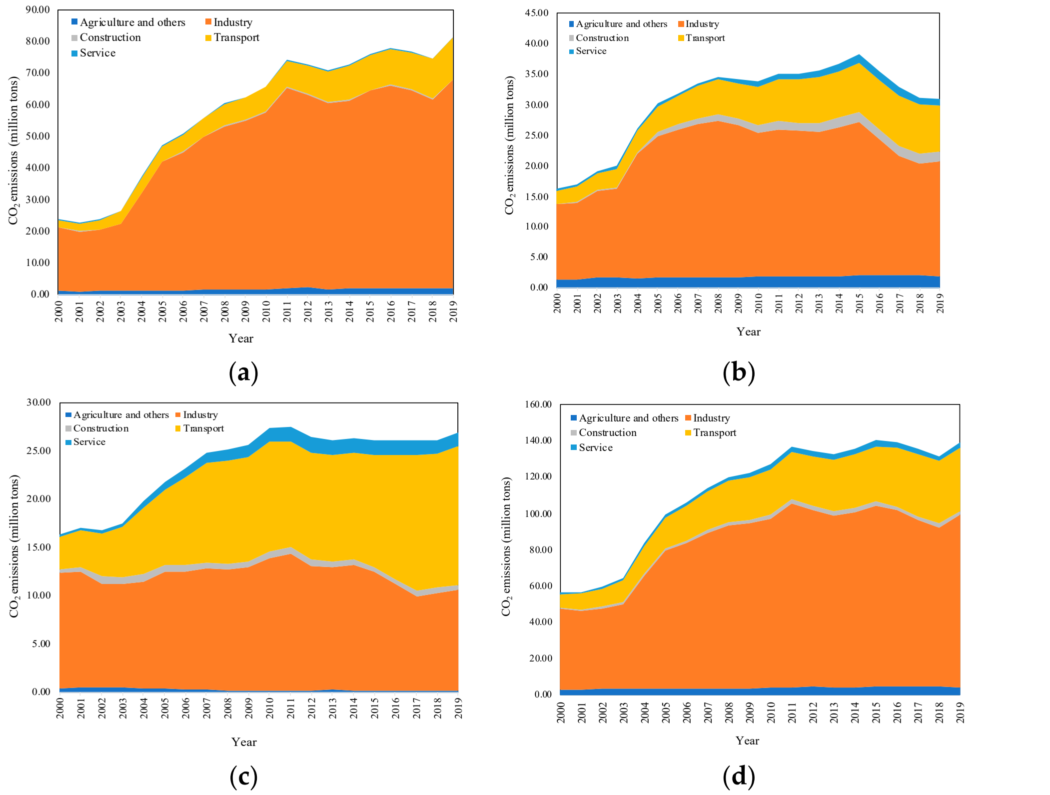

Figure 2. Energy-consumption CO_2 emissions by sector over 2000−2019. (**a**) Jiangsu Province; (**b**) Zhejiang Province; (**c**) Shanghai; (**d**) Yangtze River Delta region.

Figure 2d shows that CO_2 emissions in the Yangtze River Delta region increased rapidly before 2011, and then increased steadily during 2011–2019. Industrial CO_2 emissions have the largest share for the region, followed by the transport sector. Figure 2a,b show that industrial CO_2 emissions account for the largest proportion for Jiangsu and Zhejiang Provinces, tendencies of which varied over recent years. However, differing from Jiangsu and Zhejiang Provinces, Figure 2c depicts that since 2016, the proportion of CO_2 emissions from transport has exceeded that of industry in Shanghai. Industrial CO_2 emissions slowly declined from 2011, and the proportion of CO_2 emissions from transport has an upward trend.

As shown in Figure 3, energy-consumption CO_2 emissions in the Yangtze River Delta region show an increasing trend as a whole, from 56.51 million tons in 2000 to 139.05 million tons in 2019. This represents an average annual growth rate of 4.85%. Jiangsu Province contributed the largest amount of CO_2 emissions in the region.

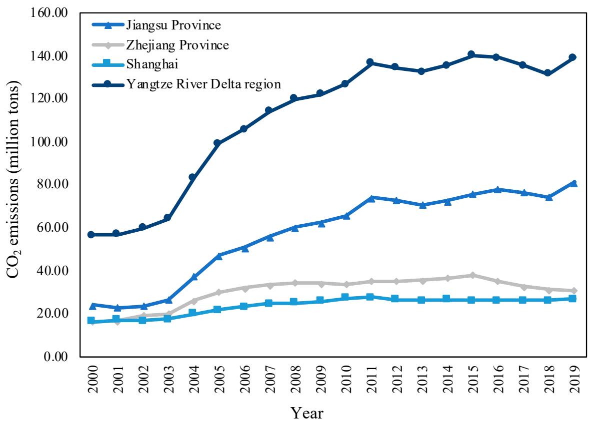

Figure 3. Energy-consumption CO_2 emissions in the Yangtze River delta region, Jiangsu Province, Zhejiang Province and Shanghai, 2000−2019.

3.2. Decomposition Analysis of CO_2 Emissions Factor

Using Equations (5)–(9), the driving factor effects on CO_2 emissions can be calculated, including the energy structure effect (ΔC_S), energy intensity effect (ΔC_I), industrial structure effect (ΔC_R), economic output effect (ΔC_G) and population size effect (ΔC_P). The results of annual change and cumulative change in CO_2 emissions relative to 2000 are shown in Table A1 in Appendix A.

The effects of economic output, population size, and energy intensity on CO_2 emissions are significant, as shown in Figures 4 and 5, while the effects of energy structure and industrial structure are negligible. Economic output and population size have predominantly positive effects on the rise in CO_2 emissions, implying that changes in these factors caused the increase in CO_2 emissions. Economic output is the greatest pull factor on the increase in CO_2 emissions, and population size is the second most important factor promoting the growth in CO_2 emissions. Energy intensity has a negative effect on CO_2 emissions, and acts as an inhibitory factor, implying that the impact of changes in energy intensity lowered the CO_2 emissions decrease. Energy intensity is the most inhibitory factor to restrain CO_2 emissions, with a significant negative effect, other than for 2004 and 2005. Although energy structure had both positive and negative effects during the study period, the effect was negative overall. Industrial structure had a positive effect on CO_2 emissions except for 2007, although the pull effect was not significant.

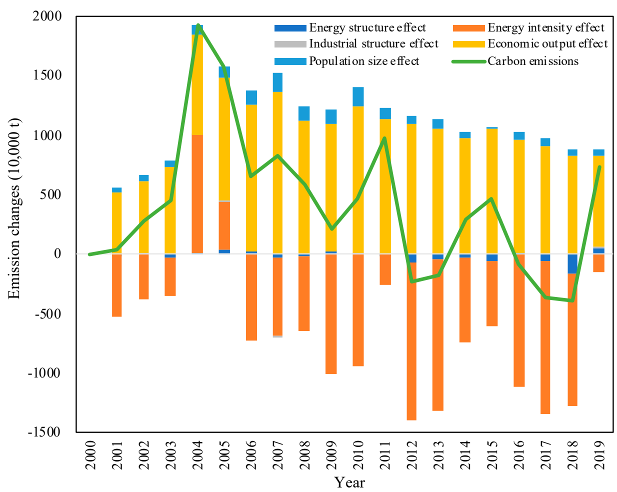

Figure 4. Time series of decomposition of CO_2 emissions of the Yangtze River Delta region, based on the five factors (compared to 2000 level).

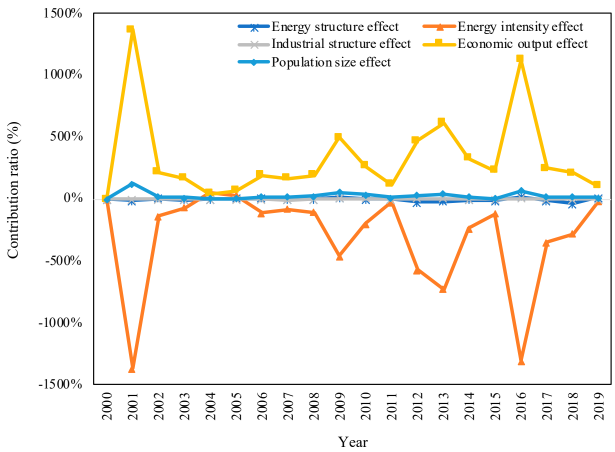

Figure 5. Contribution ratio of five factors to CO_2 emissions change in Yangtze River Delta region.

As shown in Figure 6, owing to the Yangtze River Delta region's large-scale economic boom from 2000 to 2019, cumulative CO_2 emissions increased by 18,562.57 $\times$ 10^4 tons, and the economic output effect contributed the most to energy-consumption CO_2 emissions (i.e., up to 224.90%); additionally, population growth resulted in an increase in CO_2 emissions of 1535.83 $\times$ 10^4 tons. Energy intensity led to a CO_2 emissions drop of 11,577.14 $\times$ 10^4 tons. Energy structure adjustments resulted in a total decrease of 309.57 $\times$ 10^4 tons of CO_2 emissions. Energy intensity, population size, and energy structure contributed −140.27%, 18.61%, and −3.75%, respectively. Industrial structure adjustments showed an insignificant positive effect on CO_2 emissions, with an increase of 42.04 $\times$ 10^4 tons and a cumulative contribution ratio of 0.51%. It can be concluded, therefore, that the decisive factor leading to increased CO_2 emissions in the Yangtze River Delta region is economic output; population size is the second-highest driving factor leading to the rapid growth in CO_2 emissions, while reduction in energy intensity is the decisive factor in slowing the growth in CO_2 emissions, followed by energy structure. Industrial structure is not associated with the release of significant emissions.

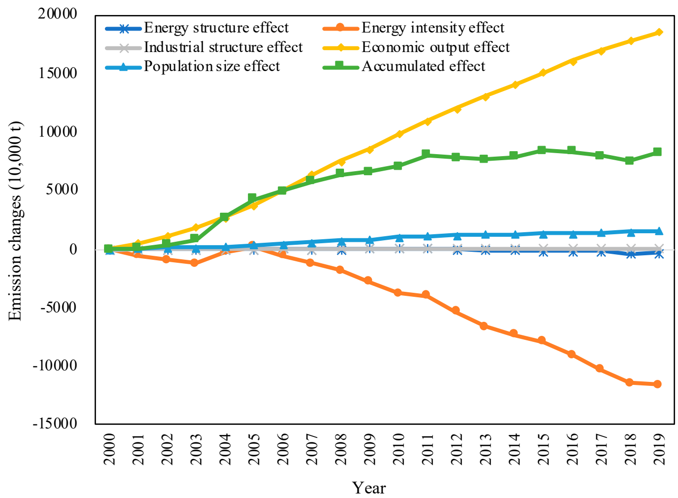

Figure 6. Accumulative effect of the five factors in the Yangtze River Delta region.

3.2.1. Energy Structure Effect

Cumulative CO_2 emissions increased during 2000−2019, but energy structure had both positive and negative effects on CO_2 emissions, with an overall trend of lowering CO_2 emissions. In 2019, cumulative CO_2 emissions in the region were 8253.73 $\times$ 10^4 tons, of which the contribution value of energy structure was −309.57 $\times$ 10^4 tons, with a cumulative contribution rate of only 4%. Regarding the eight energy types considered in this study, coal has a carbon emission coefficient of 0.7476, but coke has a coefficient of 0.8550, which is higher. The increase in the coke proportion plays a significant role in CO_2 emissions change. Figure 7 shows that the proportion of coal consumption in the Yangtze River Delta region decreased from 49.78% in 2000 to 18.98% in 2019. However, the proportion of coke consumption increased from 13.15% in 2000 to 24.27% in 2019, and in 2018 it surpassed coal for the first time, indicating that coke acts as an alternative high-carbon energy type for coal. In addition, the proportion of low-carbon energy increased year by year. Although the proportion of low-carbon energy consumption has increased, energy structure is still dominated by coal and coke, which are high-carbon energy sources. While the annual contribution value of the energy structure effect varied significantly due to changes in the proportion of energy types, the contribution ratio of energy structure is relatively small compared to the annual and cumulative CO_2 emissions change. Therefore, it can be considered that the negative effect of energy structure on CO_2 emissions is not significant.

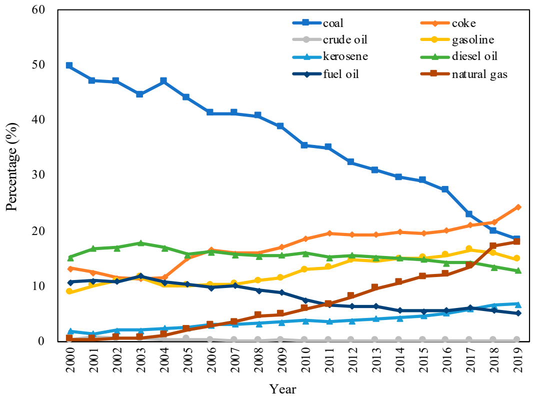

Figure 7. Proportion of primary energy consumption in Yangtze River Delta region, 2000−2019.

It should be noted that though the coal proportion has declined, the proportion of coke as a high-carbon energy increased each year. As a result, on the one hand, the energy structure has been optimized, which has stifled a rise in CO_2 emissions and had a negative impact. As a high-carbon energy source, however, coke consumption grew yearly. In general, therefore, the optimization of energy structure has not effectively curbed the rise in CO_2 emissions, reflecting a weak inhibition on CO_2 emissions. Currently, coal is the primary energy source in the region, while the proportion of solar, wind, and nuclear energy consumed is relatively minor. Therefore, it is essential to optimize the energy structure. This indicates that aggressive development of low-carbon energy sources such as solar, wind, nuclear, and other clean energies with low carbon emission coefficients is required, as well as the replacement of high-carbon energy sources with low-carbon energy sources and an increase in the supply of clean energy. Only by these measures can the energy structure procure a significantly inhibitive effect.

3.2.2. Energy Intensity Effect

Except for 2004 and 2005, the cumulative change in energy intensity in CO_2 emissions is shown to be −11,577.14104 tons (see Figure 4), indicating a negative effect on CO_2 emissions change in the region. Therefore, energy intensity is the most inhibitory factor, leading to a decrease in CO_2 emissions. In addition, energy intensity also shows a positive effect in some years, even though the value of its contribution to the reduction in CO_2 emissions is small.

As shown in Figure 8, energy intensity in the Yangtze River Delta region has demonstrated a general downward trend since 2000, achieving its lowest value in 2019; from 0.44 t standard coal/10^4 yuan in 2000 to 0.19 t standard coal/10^4 yuan in 2019, signifying a 42% drop. From 2000 to 2019, even though the energy intensity in the region generally showed a downward trend, it rebounded slightly from 2003 to 2005, showing a growth trend and leading to an increase in CO_2 emissions change. This could be because technological progress, on the one hand, improved energy efficiency and reduced energy demand, while on the other hand it fostered economic expansion and increased energy demand. These processes connected with these two findings cancel each other out, resulting in an insignificant positive effect on the change in CO_2 emissions from 2003 to 2005. Due to energy efficiency regulations and measures implemented between 2000 and 2002, energy intensity decreased significantly, producing an inhibitory effect of reducing CO_2 emissions. Due to technological innovation, the region's energy intensity continued to decline after 2005, which explains why the reduction in CO_2 emissions is significantly impacted by energy intensity. In general, the change in energy intensity explains the considerable contribution to CO_2 emissions reduction, but also shows that there is still much room to improve CO_2 emissions reductions.

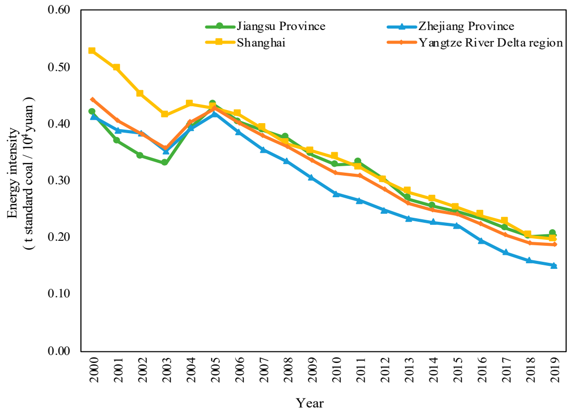

Figure 8. Changes in energy intensity in the Yangtze River Delta region, 2000−2019.

3.2.3. Industrial Structure Effect

Figure 4 reveals that excluding 2007, the industrial structure positively affected CO_2 emissions, although this effect was negligible during 2000−2019. This demonstrates that industrial structure is incapable of reducing CO_2 emissions effectively. China focused on industry structure reform and maintaining stable economic growth during the 13th Five-Year Plan (2016–2020), but how to effectively mitigate CO_2 emissions with economic development represents a challenging task. As a developed region, it is more difficult for industrial structure to exert an inhibitory effect on CO_2 emissions. Table 2 demonstrates that the industrial sector remains the region's major pillar sector, followed by the service sector, which includes retail commerce and hotels. However, the agriculture, transport, and construction sectors have relatively small shares. Furthermore, the proportion of value added of each sector remained nearly stable from 2000 to 2019, indicating that there was little change to the industrial structure during the study period, which explains the negligible impact of industrial structure on CO_2 emissions.

Table 2. Proportion of value added of sub-sector in Yangtze River Delta region during 2000−2019 (unit: %).

Year	Agriculture, Forestry, Animal Husbandry, and Fishery	Industry	Construction	Transport, Storage, and Post	Wholesale, Retail Trade, Hotels, and Catering Services
2000	9.11	44.49	5.60	6.66	11.11
2005	9.19	44.53	5.62	6.66	11.13
2010	9.33	44.57	5.67	6.66	11.10
2015	9.46	44.61	5.71	6.66	11.07
2019	9.48	44.63	5.71	6.66	11.08

3.2.4. Economic Output Effect

Figures 4 and 6 show that economic output in the Yangtze River Delta region is the key driving factor behind the rise in CO_2 emissions from 2000 to 2019—that is, it has a significantly positive effect on the growth in CO_2 emissions. The amount of energy consumption can reflect the regional economic situation to some extent, in terms of the amount needed to maintain steady economic activities, and as CO_2 emissions are the direct product of energy consumption, there is little doubt that CO_2 emissions and economic output are closely linked. China's economy grew rapidly after the start, in 1978, of the period of reform and opening up. The region's GDP grew from 1.95 trillion yuan in 2000 to 12.65 trillion yuan in 2019 at constant 2000 prices. GDP per capita increased from 14,534.90 yuan in 2000 to 81,420.03 yuan in 2019, with an average annual growth rate of 9%. Furthermore, the region's primary energy consumption increased from 86.46 million tons of standard coal in 2000 to 227.87 million tons of standard coal in 2019—a 2.64-fold increase, which led to CO_2 emissions in 2019 reaching 139.05 million tons, 2.46 times the figure in 2000. This clarifies why GDP growth was the key factor in the exponential rise in CO_2 emissions. Therefore, maintaining a stable economic development rate and making adjustments to the economic transformation may reduce the dependence on energy demand and relieve the pull effect on CO_2 emissions.

3.2.5. Population Size Effect

According to Figure 4, population size has the second-highest positive impact on the growth in CO_2 emissions in the Yangtze River Delta region during the study period. The population grew on a yearly basis, and urbanization growth is significant, as a result of development of the economy and society. The residential population grew by 1% each year from 134.37 million in 2000 to 155.37 million in 2019. From 2000 to 2010, population size contributed increasingly to the change in CO_2 emissions; however, in recent years, the contribution value of population size has tended to remain stable, and the positive effect on CO_2 emissions has become limited. Figure 9 shows that the GDP per capita of the Yangtze River Delta region is much higher than that of China overall. Although the average annual growth rate of GDP per capita in Yangtze River Delta region is 9%, and that of China as a whole is 8%, economic development in the Yangtze River Delta region has far outpaced that of the nation as a whole. This, in consequence, led to a large population inflow, further accelerating population growth and the related consumer market of the region, which increased energy needs and the incentive to boost production, eventually leading to an increase in CO_2 emissions.

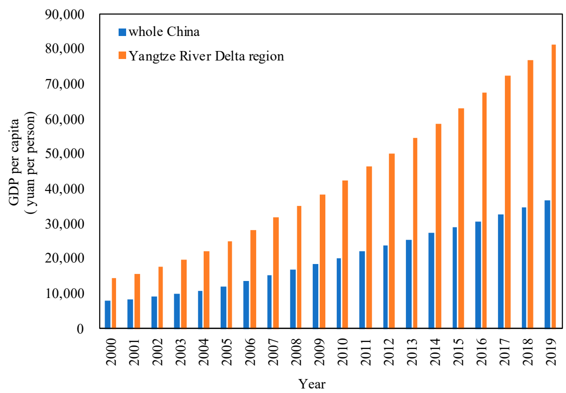

Figure 9. Comparison of GDP per capita between whole China and Yangtze River Delta region, 2000−2019.

3.3. Forecasting Results

The grey prediction GM (1, 1) model was used to forecast future CO_2 emissions during 2020–2026 using the calculation results of CO_2 emissions over 2000–2019 as the original sequence. The prediction results and trend are shown in Table 3 and Figure 10a, respectively.

Table 3. Prediction results of energy-consumption CO_2 emissions in 2020–2026 (million tons).

Year	2020	2021	2022	2023	2024	2025	2026
Predicted value	160.528	165.669	170.897	176.214	181.621	187.121	192.715

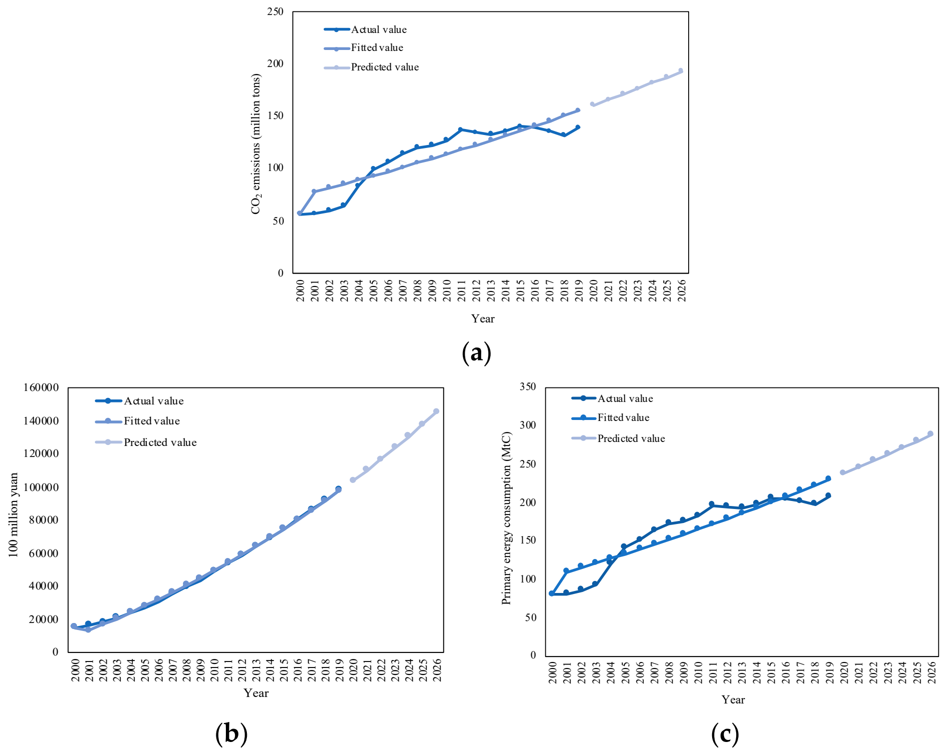

Figure 10. Prediction trend of (**a**) energy-consumption CO_2 emissions, (**b**) GDP and (**c**) primary energy consumption in Yangtze River Delta region over 2020–2026.

Based on the calculation results of the GM (1, 1) model, Table 4 shows that the average relative error of the GM (1, 1) model was 11.97%, implying the model had a good fit. The developed coefficient α is -0.017, grey controlled variable u is 213.516, small error probability P is 0.850, and posterior variance ratio C is 0.197. As $C < 0.35$, $P < 0.95$, thus the forecast is deemed to demonstrate qualified accuracy, which indicates that the consequences were satisfactory for model construction. This model can therefore be utilized to predict CO_2 emissions in the region.

Based on Figure 10a, CO_2 emissions in the Yangtze River Delta region will rise from 2020 to 2026. If the economic policy, energy policy, and population policy of the region remain unchanged, CO_2 emissions from primary energy consumption will reach 192.715 million tons by 2026.

According to the energy conservation and emission reduction plan of the 14th Five-Year Plan (2021–2025), China set a target of 13.5% reduction in energy consumption per unit of GDP compared with the 2020 level. However, by 2025, the Yangtze River Delta region's energy consumption per unit of GDP is extremely likely to be 11.6% lower than that in 2020, according to Figure 10b,c. This implies that relative to China's general goal, the Yangtze River Delta region may be unable to meet the expected target.

Table 4. GM (1, 1) model error test results of energy-consumption CO_2 emissions.

Year	Actual Value	Fitted Value	Residual	Relative Error (%)
2000	56.508	56.508	0	0
2001	56.886	77.698	−20.812	36.585
2002	59.69	81.426	−21.737	36.416
2003	64.179	85.218	−21.039	32.782
2004	83.504	89.075	−5.571	6.671
2005	99.344	92.997	6.347	6.389
2006	105.864	96.986	8.878	8.386
2007	114.144	101.043	13.101	11.478
2008	120.078	105.169	14.908	12.416
2009	122.264	109.366	12.898	10.549
2010	126.91	113.634	13.277	10.461
2011	136.622	117.975	18.647	13.649
2012	134.297	122.39	11.907	8.866
2013	132.558	126.88	5.679	4.284
2014	135.518	131.446	4.072	3.005
2015	140.167	136.091	4.077	2.908
2016	139.317	140.815	−1.498	1.075
2017	135.633	145.619	−9.986	7.363
2018	131.679	150.505	−18.826	14.297
2019	139.046	155.474	−16.429	11.815

At present, the Yangtze River Delta region is undergoing industrial development, which means much energy is consumed for the purposes of production and living. From Figure 10a, it can be clearly seen that the CO_2 emissions of primary energy consumption in the Yangtze River Delta region will increase yearly from 2020 to 2026. Although the local government is actively exploring the path of low-carbon economic development, and the measures taken to reduce emissions have also achieved certain results, based on the above results it can be clearly seen that CO_2 emissions will increase yearly in the future. Based on this study's results, achieving the goal of mitigating CO_2 emissions in the short term therefore represents a substantial challenge. With reference to economic development of the Yangtze River Delta region, the region will only be able achieve CO_2 emissions reduction through the concerted efforts of the market, government, and individuals. From this it can be concluded sustainable economic development of the region will take some time to achieve.

4. Conclusions

For this study, CO_2 emissions from energy consumption were calculated using data from eight energy types and five sectors from the Yangtze River Delta region, which included two provinces and one city, from 2000 to 2019. Annual changes and cumulative changes in CO_2 emissions are quantitatively calculated, as well as the contributions of those changes to CO_2 emissions. The Grey prediction GM (1, 1) model was applied to forecast primary energy consumption and CO_2 emissions during 2020–2026. The main findings in this study are as follows.

(1) Primary energy consumption and CO_2 emissions will continue to rise in the Yangtze River Delta region from 2020 to 2026, with total CO_2 emissions rising by 192.715 million tons over the forecast period;

(2) Economic output and population size have mainly positive effects on the increase in CO_2 emissions, and the impacts of changes in these two factors led to growth in CO_2 emissions. Economic output is the biggest force pulling up CO_2 emissions, contributing 224.90% in the study period. Population size is the second-most important factor promoting the growth in CO_2 emissions, the cumulative contribution ratio of which is 18.61%;

(3) Except for 2004 and 2005, energy intensity is the greatest inhibitory factor in reducing CO_2 emissions, with a significant negative effect. The energy intensity effect contributed −140.27% to the change in CO_2 emissions;
(4) Energy structure and industrial structure have insignificant contributions to CO_2 emissions, contributing −3.75% and 0.51%, respectively. Although energy structure had a positive and negative effect during the study period, it showed a negative effect in terms of the cumulative contribution. Industrial structure had a positive effect on CO_2 emissions except in 2007, although the pull effect was not significant;
(5) Changes in energy structure and energy intensity had a restraining effect, but they were insufficient to counteract the rise in CO_2 emissions, which led to an overall trend of rising CO_2 emissions.

Global warming has become a complex problem for human civilization. It has also resulted in great challenges to the sustainable development of the Yangtze River Delta region. An important measure to effectively deal with climate change is to reduce greenhouse gas emissions, especially CO_2 emissions due to energy consumption. Based on the results of the above analysis, the following policy recommendations are made.

(1) Formulating appropriate economic development goals.

According to the results, CO_2 emissions from energy consumption in the Yangtze River Delta region exhibited a general upward trend in 2000–2019, as economic development and energy consumption would tend to commonly inhibit CO_2 emissions decreasing. Local governments must consequently set acceptable economic development goals rather than focusing exclusively on economic growth.

(2) Optimizing the energy consumption structure.

Despite the recent trend toward declining coal usage, the Yangtze River Delta region still relies heavily on coal for its energy supply. The Yangtze River Delta region should continually optimize the energy structure to reduce environmental pollution and ecological risks. On the one hand, it is efficient to promote the development of clean coal technology and improve coal utilization efficiency. On the other hand, the proportion of green energy consumption needs to be promoted as well as the proportions of wind energy, solar energy, hydropower, and other clean and renewable energy consumption.

(3) Promoting technological progress and innovation.

Technological progress and innovation are the main driving factors for improving energy efficiency. From the mining of fossil energy to the final use, many processes are involved, resulting in the loss and waste of fossil energy. On the one hand, the government should increase investment in energy technology research and research institutions to carry out technological development and innovation, and on the other, through international cooperation, advanced energy technologies need to be introduced to change the energy use patterns.

(4) Adjusting industrial structure and developing low-carbon industries.

Rapid economic growth in the Yangtze River Delta region is primarily attributable to the expansion of secondary industry, the region's main industry sector. This sector is also the largest contributor to energy consumption and CO_2 emissions. The government therefore needs to comprehensively consider the economic and environmental conditions, put forward a development plan to restrain high-polluting enterprises, and formulate relevant regulations for those that are polluting and harmful to the environment. At the same time, local governments should encourage and support enterprises that use clean energy and produce low-carbon products.

(5) Optimizing the population structure and promoting low-carbon living.

The Yangtze River Delta region has one of the greatest population growth rates in China, and the problems of urbanization and aging are becoming increasingly prominent.

On the one hand, the population structure needs to be optimized, and on the other, the government needs to encourage citizens to adopt a low-carbon mindset and help shape their consumption habits. Although some behaviors may not directly lead to resource and energy savings, they can help to create a positive social environment, and raise overall understanding and awareness of energy conservation, towards ultimately living low-carbon lifestyles.

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Appendix A

Table A1. Decomposition analysis of five factors on CO_2 emissions in the Yangtze River Delta region (10^4 t) (AC = annual change, CC = cumulative change).

Time	Energy Structure ΔC_S^t		Energy Intensity ΔC_I^t		Industrial Structure ΔC_R^t		Economic Output ΔC_G^t		Population Size ΔC_P^t		Carbon Emissions ΔC^t	
	AC	CC	AC	CC	AC	CC	AC	CC	AC	CC	AC	CC
2000	0	0	0	0	0	0	0	0	0	0	0	0
2001	−6.29	−6.29	−517.43	−517.43	0.02	0.02	515.49	515.49	45.98	45.98	37.77	37.77
2002	4.66	−1.63	−382.31	−899.74	1.40	1.42	610.48	1125.97	46.11	92.09	280.34	318.12
2003	−27.65	−29.28	−317.00	−1216.75	3.10	4.52	736.06	1862.04	54.43	146.52	448.94	767.05
2004	5.88	−23.40	992.71	−224.04	0.22	4.74	849.03	2711.07	84.67	231.19	1932.50	2699.55
2005	33.82	10.42	413.17	189.13	3.83	8.57	1038.69	3749.76	94.49	325.68	1583.99	4283.55
2006	20.46	30.88	−724.67	−535.54	3.22	11.79	1230.99	4980.75	121.98	447.65	651.99	4935.54
2007	−22.14	8.74	−669.59	−1205.13	−1.32	10.48	1370.27	6351.02	150.79	598.45	828.02	5763.56
2008	−19.22	−10.48	−629.10	−1834.23	2.81	13.28	1122.03	7473.05	116.84	715.29	593.35	6356.91
2009	22.47	11.99	−1005.80	−2840.04	3.92	17.20	1077.65	8550.70	120.38	835.67	218.62	6575.53
2010	3.75	15.75	−940.68	−3780.72	4.85	22.05	1243.00	9793.70	153.75	989.42	464.67	7040.19
2011	−3.21	12.54	−255.60	−4036.31	3.43	25.48	1131.92	10,925.62	94.57	1083.98	971.12	8011.31
2012	−66.29	−53.75	−1330.18	−5366.49	3.36	28.84	1095.75	12,021.37	64.87	1148.85	−232.49	7778.82
2013	−39.37	−93.12	−1270.88	−6637.37	2.14	30.98	1062.22	13,083.59	72.04	1220.89	−173.84	7604.97
2014	−22.60	−115.72	−714.37	−7351.74	2.24	33.22	974.90	14,058.49	55.81	1276.70	295.98	7900.95
2015	−55.41	−171.13	−552.31	−7904.05	3.14	36.36	1051.48	15,109.97	18.05	1294.75	464.95	8365.90
2016	14.40	−156.74	−1113.74	−9017.79	1.85	38.21	953.78	16,063.75	58.66	1353.42	−85.05	8280.85
2017	−53.51	−210.24	−1289.07	−10,306.85	1.71	39.91	904.44	16,968.19	68.00	1421.41	−368.43	7912.42
2018	−157.47	−367.72	−1121.95	−11,428.80	0.51	40.42	823.82	17,792.01	59.70	1481.12	−395.39	7517.04
2019	58.15	−309.57	−148.33	−11,577.14	1.62	42.04	770.56	18,562.57	54.71	1535.83	736.69	8253.73

References

1. Fu, X.; Zhou, Y. Collaborative Optimization of PV Greenhouses and Clean Energy Systems in Rural Areas. *IEEE Trans. Sustain. Energy* **2023**, *14*, 642–656. [CrossRef]
2. Song, S.; Long, J.; Jiang, H.; Ran, B.; Yao, L. Characteristics of Office Lighting Energy Consumption and Its Impact on Air Conditioning Energy Consumption. *Energy Built Environ.* **2023**, *in press*. [CrossRef]
3. Fu, X. Statistical Machine Learning Model for Capacitor Planning Considering Uncertainties in Photovoltaic Power. *Prot. Control. Mod. Power Syst.* **2022**, *7*, 5. [CrossRef]
4. Tsemekidi Tzeiranaki, S.; Bertoldi, P.; Economidou, M.; Clementi, E.L.; Gonzalez-Torres, M. Determinants of Energy Consumption in the Tertiary Sector: Evidence at European Level. *Energy Rep.* **2023**, *9*, 5125–5143. [CrossRef]
5. China's Greenhouse Gas Emissions Exceeded the Developed World for the First Time in 2019. Available online: https://rhg.com/research/chinas-emissions-surpass-developed-countries/ (accessed on 20 April 2023).
6. British Petroleum. *bp Statistical Review of World Energy 2022*; British Petroleum Press: London, UK, 2022.
7. China Statistical Yearbook. Available online: http://www.stats.gov.cn/sj/ndsj/ (accessed on 24 April 2023).
8. Ang, B.W. Decomposition Analysis for Policymaking in Energy: Which Is the Preferred Method? *Energy Policy* **2004**, *32*, 1131–1139. [CrossRef]

9. Ang, B.W.; Choi, K.-H. Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *Energy J.* **1997**, *18*, 59–73. [CrossRef]
10. Ang, B.W. The LMDI Approach to Decomposition Analysis: A Practical Guide. *Energy Policy* **2005**, *33*, 867–871. [CrossRef]
11. Wang, W.; Liu, X.; Zhang, M.; Song, X. Using a New Generalized LMDI (Logarithmic Mean Divisia Index) Method to Analyze China's Energy Consumption. *Energy* **2014**, *67*, 617–622. [CrossRef]
12. Chong, C.H.; Ma, L.; Li, Z.; Ni, W.; Song, S. Logarithmic Mean Divisia Index (LMDI) Decomposition of Coal Consumption in China Based on the Energy Allocation Diagram of Coal Flows. *Energy* **2015**, *85*, 366–378. [CrossRef]
13. Chang, Y.F.; Lewis, C.; Lin, S.J. Comprehensive Evaluation of Industrial CO_2 Emission (1989–2004) in Taiwan by Input-Output Structural Decomposition. *Energy Policy* **2008**, *36*, 2471–2480. [CrossRef]
14. Wang, M.; Feng, C. Decomposition of Energy-Related CO_2 Emissions in China: An Empirical Analysis Based on Provincial Panel Data of Three Sectors. *Appl. Energy* **2017**, *190*, 772–787. [CrossRef]
15. Wang, C.; Chen, J.; Zou, J. Decomposition of Energy-Related CO_2 Emission in China: 1957–2000. *Energy* **2005**, *30*, 73–83. [CrossRef]
16. Xu, S.C.; He, Z.X.; Long, R.Y. Factors That Influence Carbon Emissions Due to Energy Consumption in China: Decomposition Analysis Using LMDI. *Appl. Energy* **2014**, *127*, 182–193. [CrossRef]
17. Liu, L.C.; Fan, Y.; Wu, G.; Wei, Y.M. Using LMDI Method to Analyze the Change of China's Industrial CO_2 Emissions from Final Fuel Use: An Empirical Analysis. *Energy Policy* **2007**, *35*, 5892–5900. [CrossRef]
18. Wu, P.; Song, Y.; Zhu, J.; Chang, R. Analyzing the Influence Factors of the Carbon Emissions from China's Building and Construction Industry from 2000 to 2015. *J. Clean. Prod.* **2019**, *221*, 552–566. [CrossRef]
19. Xu, J.H.; Fleiter, T.; Eichhammer, W.; Fan, Y. Energy Consumption and CO_2 Emissions in China's Cement Industry: A Perspective from LMDI Decomposition Analysis. *Energy Policy* **2012**, *50*, 821–832. [CrossRef]
20. Lin, B.; Long, H. Emissions Reduction in China's Chemical Industry—Based on LMDI. *Renew. Sustain. Energy Rev.* **2016**, *53*, 1348–1355. [CrossRef]
21. Xie, X.; Shao, S.; Lin, B. Exploring the Driving Forces and Mitigation Pathways of CO_2 Emissions in China's Petroleum Refining and Coking Industry: 1995–2031. *Appl. Energy* **2016**, *184*, 1004–1015. [CrossRef]
22. Zhang, M.; Li, H.; Zhou, M.; Mu, H. Decomposition Analysis of Energy Consumption in Chinese Transportation Sector. *Appl. Energy* **2011**, *88*, 2279–2285. [CrossRef]
23. Wang, W.W.; Zhang, M.; Zhou, M. Using LMDI Method to Analyze Transport Sector CO_2 Emissions in China. *Energy* **2011**, *36*, 5909–5915. [CrossRef]
24. Ren, S.; Yin, H.; Chen, X.H. Using LMDI to Analyze the Decoupling of Carbon Dioxide Emissions by China's Manufacturing Industry. *Environ. Dev.* **2014**, *9*, 61–75. [CrossRef]
25. Zhao, M.; Tan, L.; Zhang, W.; Ji, M.; Liu, Y.; Yu, L. Decomposing the Influencing Factors of Industrial Carbon Emissions in Shanghai Using the LMDI Method. *Energy* **2010**, *35*, 2505–2510. [CrossRef]
26. Song, M.; Guo, X.; Wu, K.; Wang, G. Driving Effect Analysis of Energy-Consumption Carbon Emissions in the Yangtze River Delta Region. *J. Clean. Prod.* **2015**, *103*, 620–628. [CrossRef]
27. Chen, L.; Xu, L.; Xu, Q.; Yang, Z. Optimization of Urban Industrial Structure under the Low-Carbon Goal and the Water Constraints: A Case in Dalian, China. *J. Clean. Prod.* **2016**, *114*, 323–333. [CrossRef]
28. Zhang, W.; Li, K.; Zhou, D.; Zhang, W.; Gao, H. Decomposition of Intensity of Energy-Related CO_2 Emission in Chinese Provinces Using the LMDI Method. *Energy Policy* **2016**, *92*, 369–381. [CrossRef]
29. Zhou, X.; Zhang, M.; Zhou, M.; Zhou, M. A Comparative Study on Decoupling Relationship and Influence Factors between China's Regional Economic Development and Industrial Energy–Related Carbon Emissions. *J. Clean. Prod.* **2017**, *142*, 783–800. [CrossRef]
30. Ju-Long, D. Control Problems of Grey Systems. *Syst. Control Lett.* **1982**, *1*, 288–294. [CrossRef]
31. Wu, L.; Liu, S.; Liu, D.; Fang, Z.; Xu, H. Modelling and Forecasting CO_2 Emissions in the BRICS (Brazil, Russia, India, China, and South Africa) Countries Using a Novel Multi-Variable Grey Model. *Energy* **2015**, *79*, 489–495. [CrossRef]
32. Pao, H.T.; Fu, H.C.; Tseng, C.L. Forecasting of CO_2 Emissions, Energy Consumption and Economic Growth in China Using an Improved Grey Model. *Energy* **2012**, *40*, 400–409. [CrossRef]
33. Wang, X.; Cai, Y.; Xu, Y.; Zhao, H.; Chen, J. Optimal Strategies for Carbon Reduction at Dual Levels in China Based on a Hybrid Nonlinear Grey-Prediction and Quota-Allocation Model. *J. Clean. Prod.* **2014**, *83*, 185–193. [CrossRef]
34. Tang, D.; Ma, T.; Li, Z.; Tang, J.; Bethel, B.J. Trend Prediction and Decomposed Driving Factors of Carbon Emissions in Jiangsu Province during 2015–2020. *Sustainability* **2016**, *8*, 1018. [CrossRef]
35. Liu, X.; Peng, H.; Bai, Y.; Zhu, Y.; Liao, L. Tourism Flows Prediction Based on an Improved Grey GM(1,1) Model. *Procedia Soc. Behav. Sci.* **2014**, *138*, 767–775. [CrossRef]
36. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Available online: https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (accessed on 24 April 2023).
37. Jiangsu Statistical Yearbook. Available online: https://tj.jiangsu.gov.cn/col/col87172/index.html (accessed on 24 April 2023).
38. Zhejiang Statistical Yearbook. Available online: http://tjj.zj.gov.cn/col/col1525563/index.html (accessed on 24 April 2023).

39. Shanghai Statistical Yearbook. Available online: https://tjj.sh.gov.cn/tjnj/index.html (accessed on 24 April 2023).
40. National Bureau of Statistics of China. *China Energy Statistical Yearbook (2001–2020)*; China Statistics Press: Beijing, China, 2020.