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Original Research

Influencing Factors and Emission Reduction Paths of Industrial Carbon Emissions Under Target of "Carbon Peaking": Evidence from China

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Abstract

Jiangsu Province is a major industrialized province in China and its carbon emissions rank in the top five nationwide. It is of great significance to analyze Jiangsu's carbon-peaking path for achieving China's carbon peaking target by 2030. In this paper, based on the log-mean divisia index (LMDI) decomposition method, we calculate the main factors' contribution to the changes in industrial carbon emissions of Jiangsu Province during 2010-2021 and reveal that the reduction in energy intensity and the optimization of energy structure will suppress industrial CO_2 emissions, while the output per capita has a promoting effect on emissions. The results of the STIRPAT model fitted by ridge regression suggest that when the industrial employed population, the per capita output, and the carbon emission intensity, including technological progress, increase by 1%, the industrial CO_2 emissions in Jiangsu Province increase by 0.832%, 0.602%, and 0.815%, respectively. The discrete gray model DGM (1, 1) and the scenario analysis are used to forecast the carbon emissions between 2022 and 2035. The result indicates that Jiangsu can achieve the target of significant CO_2 emissions reduction without sacrificing industrial economic growth in a situation with a low population growth rate, a low per capita output growth rate, and a high carbon emission intensity reduction rate. In this case, it can reach the target of reaching the carbon emission peak by 2030 and thus lead to harmonious and sustainable socio-economic and environmental development.

Keywords: Industrial carbon emissions, LMDI decomposition method, STIRPAT model, DGM (1, 1) model, Scenario analysis

Introduction

The global greenhouse effect has long been an undeniable fact. In order to avoid the hazards of extreme climate caused by the greenhouse effect, it is essential to limit the increase in global temperature to below 1.5°C. The achievement of this goal needs to reduce net greenhouse gas emissions to zero worldwide by the mid-21st century [1]. On 9th August 2021, the Intergovernmental Panel on Climate Change (IPCC) released its Sixth Assessment Report, which stated that since the 1850s, the rise in greenhouse gas concentrations is largely due to human beings' activities. During the decade from 2011 to 2020, the global surface temperature was 1.09°C higher than

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that of the period 1850-1900, which is unprecedented since the ice age around 125,000 years ago [2]. According to the relevant studies, considering various greenhouse gas emissions, it is estimated that the global average temperature will increase more than 1.5°C in the next 20 years if effective measures are not taken in the future to control emissions. Overall, global climate change has become one of the greatest challenges that contemporary human society cannot ignore. It poses a severe threat to society, and thus, the transition towards a green-oriented and low-carbon economy has become an inevitable choice for global economic development.

Since the first industrial revolution, humans have already emitted over 1.5 trillion tons of carbon dioxide cumulatively because of the burning of fossil fuels [3]. Statistically, the total global CO_2 emissions are estimated to be 36.73 billion tons, 34.83 billion tons, and 36.42 billion tons in 2019, 2020, and 2021, respectively. Carbon dioxide will remain in the atmosphere for thousands of years, and then as the carbon dioxide emissions accumulate, the global temperatures will increase accordingly, even leading to some irreversible natural disasters. Consequently, setting carbon peaking targets has become a worldwide consensus.

As a responsible nation, China has initiatively implemented numerous policies and actively participated in international climate organizations to make its own contribution to mitigate global climate change. China has announced the measures that have been taken to combat climate change at various conferences, including the Copenhagen Climate Conference, the Paris Climate Conference, and the UN Climate Conference. In September 2020, at the United Nations General Assembly, President Xi Jinping committed that "China will strive to peak carbon dioxide emissions by 2030 and work towards carbon neutrality by 2060". Since then, the "dual carbon (carbon peaking and carbon neutrality)" target has been included in the Chinese government's work reports. In such cases, to fulfill the historic responsibility of achieving carbon neutrality while ensuring the steady growth of China's industrial economy at the same time, China must accelerate the transformation of its energy industry into a green-oriented and low-carbon one.

China is at a different development level from European countries and the United States, with a different industrial structure, a different energy consumption structure, and a different level of energy consumption per unit of GDP. The total carbon emissions of China are significantly higher than those of European countries and the United States and are currently on an upward trend. Industrial carbon emissions account for up to 70% of China's carbon emitting economic activities and are the major source of the rapid growth in carbon emissions [4][5]. As a major industrial province in China, Jiangsu's carbon emissions and carbon neutrality efforts are crucial components of the country's overall carbon emissions control. Jiangsu Province has a light-structure industry that is dominated by high energy-consuming industries. Also, its energy consumption depends seriously on coal and relies heavily on imports from other provinces and foreign countries. Moreover, Jiangsu's carbon emissions have been in the top five nationwide since 1997, placing itself under tremendous pressure to reduce carbon emissions. Meanwhile, Jiangsu Province is a typical representative of China in terms of its level of economic and social development, resource endowment, and carbon emission status.

Therefore, studying the factors influencing industrial carbon emissions and the development trend of Jiangsu Province in the context of carbon peaking and exploring ways to reduce CO_2 emissions without compromising economic development will not only provide evidence for carbon peaking and high-quality economic development in Jiangsu Province, but also be of great value to other regions. Based on the industrial energy consumption data and the industrial emission calculation methods of Jiangsu Province, this paper constructs an influencing factors system under the emission reduction target, proposes an emission reduction path that meets the characteristics of industrial carbon emissions in Jiangsu Province, and evaluates the economic effects.

Scholars have conducted a lot of research on issues related to carbon peaking and carbon emission reduction, mainly in the fields of carbon emission driving factors, carbon emission trends, and emission forecasts, as well as carbon peaking scenario analysis.

When studying carbon emission driving factors, Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) are widely used for decomposing carbon emission impact factors. In 1991, the IDA decomposition method was applied for the first time to studies of energy-related carbon dioxide emissions other than studies of energy consumption. Torvanger introduced a five-factor IDA approach to evaluate the contribution to the reduction in energy-related manufacturing carbon emissions for nine OECD countries and applied the Divisia index method to decompose the reduction in carbon intensity into fuel mix, emission coefficients, industry structure, energy intensities, and international structure [6]. Wang et al. studied the change in aggregated CO_2 emissions in China from 1957 to 2000 utilizing an index decomposition method and found that the improved energy intensity led to a considerable decrease in CO_2 emissions in China [7]. Hammond and Norman applied the IDA approach to separate the contributions of different factors to the CO_2 emissions reduction from UK manufacturing, which included changes in output, industrial structure, energy intensity, fuel mix, and electricity emission factor and pointed out that energy intensity was the primary factor in the reduction in CO_2 emissions [8]. Existing studies include national [9], regional [12], and industrial [13] perspectives to explore the factors that influence carbon emissions. Xu and Ang implemented a comprehensive literature survey on CO_2 emissions studies by reviewing 80 papers from 1991 to 2012 and confirmed that the IDA approach, which was regarded as a useful analytical tool, has been widely adopted by scholars worldwide in the research of CO_2 emissions [14].

In general, the IDA methodologies are grouped into four types; Laspeyres (LASP), Shapley/Sun (S/S), logarithmic mean Divisia index (LMDI), and other Divisia methods. As the Divisia index method was given attention by scholars in various countries in the late 1980s, the Divisia index decomposition method has been developed rapidly to form the logarithmic mean Divisia index (LMDI), which is widely used in the analysis of regional carbon emission driving factors [15] and the study of industrial carbon emission driving factors [16].

Ang stated that the LMDI method is shown to give no residual when applied, further supporting its practical use in decomposition studies [17]. The LMDI technique was adopted to analyze the factors influencing the changes in CO_2 emissions from electricity generation in China during the period 1991-2009 by Zhang et al. [18], and they found that the electricity generation efficiency effect played the dominant role in the CO_2 emissions reduction. Employing the LMDI method to explore the carbon density effect, the energy intensity effect, the economic effect in terms of per capita GDP, and the population effect on the total changes in CO_2 emissions in China and the ASEAN countries, Zhang et al. [19] identified that the economic effect in terms of per capita GDP played the dominant role in the CO_2 emissions growth, while energy intensity was the significant driving factor to decrease CO_2 emissions in most of the examined countries.

So far, there have been some attempts to use the LMDI to reduce China's CO_2 emissions. Therefore, the presented study selects the LMDI as a decomposition tool to analyze the reduction in CO_2 emissions in Jiangsu Province. Although extensive research has been undertaken to study the driving factors of CO_2 emissions changes at the single-country or regional level, studies specifically investigating the driving factors of the change in CO_2 emissions in Jiangsu are notably few. More importantly, Jiangsu Province is a leading manufacturing province whose carbon emissions have ranked in the top five nationwide since 1997. Therefore, investigating the factors that affect industrial carbon emissions and the development trend of Jiangsu Province will provide evidence for other provinces. Also, this research will offer valuable insights for other regions.

In order to quantify the impacts of driving factors on the changes in carbon emissions, the presented paper employed the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, which was proposed by Dietz and Rosa [20] in 1997 and is commonly employed for quantitative analysis related to the impacts arising from environmental changes. Fan et al. [21] applied the STIRPAT model to analyze the impact of population, affluence, and technology on CO_2 emissions of countries at different income levels during the 1975-2000 period. By utilizing the LMDI approach within the context of Jiangsu's industrial sectors, the presented paper seeks to integrate industrial employed population, carbon emission intensity, output per capita, and technological progress into an expanded STIRPAT framework to better assess their impact on carbon emissions in Jiangsu Province.

When analyzing carbon emission trends, three dominant research methods are adopted to calculate carbon emissions. The first type is mainly based on the carbon emission accounting methods introduced by the IPCC. This kind of method is usually used to calculate carbon dioxide emissions that participate in the carbon trading market, including the emission factor method, the mass balance approach, and the practical measurement method. The second type is based on input-output models to measure the macrocarbon emissions of national and provincial administrative units. The third category adopts large-scale carbon emissions accounting approaches, i.e., satellite remote sensing estimation methods.

Studies adopting the emission factors method to explore carbon emissions mostly focus on the energy consumption of industrial sectors and are classified at the national level [22], provincial level [23], and city level or below [24]. Raupach et al. employed the Kaya identity to express the global CO_2 emissions flux as a product of four driving factors [26]. Lu et al. applied the emission factors method to calculate the carbon emissions from China's building and construction industry from 1994 to 2012 [27]. Employing detailed energy consumption data for each fuel type and sector-specific emission factors, Ye et al. calculated both direct and indirect energy-related CO_2 emissions across some of China's provinces and offered provincially targeted policy proposals on emission reductions [28].

The mass balance method is a new approach to calculating carbon emissions in recent years. When accounting for carbon emissions, primarily based on the principle of the law of conservation of mass, quantitatively analyze the amount of energy used in the consumption. The advantage of this method is that it can clearly distinguish between natural emission sources and various energy-consuming devices. However, this approach pays more attention to intermediate emission processes, which are more likely to lead to systematic errors. Moreover, the relevant data is difficult to obtain, and therefore, this approach is not widely accepted in practice. The plot investigation method is essentially used to calculate carbon emissions according to the field monitoring data of emission sources [29]. The benefit of this methodology is that the measurement results are more accurate, and the intermediate process is simple. However, it is difficult to obtain the data, and it often requires a lot of human and material resources. Meanwhile, the data can be affected easily by the accuracy of the experimental apparatus, which leads to a relatively limited application and a restricted research scope for this methodology.

Besides, considering carbon emission trends and emission predictions, Steen-Olsen et al. combined environmentally extended input-output analysis with the global MRIO database to assess the carbon footprint of Norwegian households' consumption during 1999-2012 and analyze its trends [30]. Utilizing stochastic frontier analysis to identify the factors impacting carbon intensity and considering the carbon emission efficiency, Sun and Huang introduced a prediction model for carbon emission intensity based on the factor analysis and an extreme learning machine [31]. Based on the gray model GM (1, 1), an autoregressive integrated moving average model (ARIMA), and a second-order polynomial regression model (SOPR), Liu et al. constructed a forecasting model that enhances the accuracy of the forecasts by optimizing the coefficients of the three previously mentioned models with the Particle Swarm Optimization (PSO) method [32]. Operating on limited sample data, the gray prediction model processes and utilizes the available gray data information.

The presented study utilizes the emission factor methodology to accurately calculate industrial carbon emissions and influencing factors in Jiangsu Province. Further, the gray DGM (1, 1) model is employed to predict the key determinants decomposed by the LMDI method. The forecast results of these factors, which include the employed population, per capita output, carbon emission intensity, and technological advancement, are substituted into the STIRPAT model to estimate the carbon emissions in Jiangsu.

When considering studies of emission reduction, a variety of forecasting methodologies, such as data envelopment analysis (DEA), the grey prediction model (GM), the trend analysis, the long-range energy alternatives planning model (LEAP) model, the life cycle assessment (LCA) method, and the Asian-Pacific integrated model (AIM), are utilized to predict future CO_2 emissions reduction. Xu et al. applied dynamic simulation analysis to estimate the appropriate carbon intensity that can be achieved in China under the current situation [33]. Also, they forecasted China's CO_2 emissions and GDP development for 2008-2020 under different energy structure adjustments and carbon intensity constraints. Wang et al. used the LEAP model to generate and evaluate the reduction potential of China's steel industry from 2000 to 2030 under three different CO_2 emission scenarios [34].

As for carbon peaking scenario analysis, McCollum and Yang decomposed greenhouse gas emissions into four major driving factors and applied scenario analysis to evaluate the potential to reduce US transportation greenhouse gas emissions in the long term [35]. Scenario analysis was employed by Dong et al. to explore feasible mitigation pathways and estimate the reduction potential of changes to CO_2 emissions up to the year 2030 [36]. The result indicated that the Upper-Middle-Income (UMI) countries presented the most significant potential for mitigation. Ren and Long established nine scenarios to explore low-carbon development pathways according to different growth rates of factors influencing carbon emissions [37]. Lin and Ouyang [38] and Lin and Tan [39] suggested that scenario analysis is superior to other forecasting approaches in evaluating the uncertain future development of climate change, energy intensity, and energy consumption. Scenario analysis proved to be especially helpful for policymakers and government officials in formulating effective policies. However, upon reviewing the existing literature to date, there has been limited academic research applying scenario analysis to explore the potential for emissions reductions based on results from LMDI decomposition in an expanded STIRPAT framework.

In studies analyzing China's carbon peaking perspectives, Niu et al. stated that if the growth of China's GDP declines at a rate of 0.1% per year, then it is expected to be at its peak by the year 2035 [40]. Zhang et al. simulated the global energy model (C-GEM) and concluded that under the accelerated effort scenario, China is expected to reach the emission peak around 2030, with a peak value of around 1 billion tons [41]. Li et al. employed the gray GM (1,1) model to predict carbon emissions and pointed out that when the carbon emission intensity is within a certain interval, China will achieve the CO_2 emissions peak by 2030 [42]. Wang et al. predicted that China will peak carbon emissions at 13–16 megatons between 2021 and 2025 using Monte Carlo methods together with the Kuznets curve [43].

In conclusion, carbon emissions, carbon peaking, and carbon neutrality have become topical in academic research. Current research mainly focuses on carbon emission accounting, emission reduction potential, and future carbon emission predictions at the national, city, and industrial levels, as well as reasonable emission reduction proposals. Available research indicates that the carbon emission peak in China is predicted around 2030 by both domestic and foreign scholars, but the peak emission values estimated from different models and data vary significantly. Most of the studies in China focus on the national level, with insufficient evidence from the provincial level. It is difficult to separate the national carbon targets into various provincial targets, which leads to a lack of theoretical basis for developing provincial emission reduction policies. Additionally, although the previous studies have been abundant in carbon emission estimation methods and the driving factors, there are still some problems in the computing methods. For example, when it comes to carbon emission estimation methods, the existing methods suffer from a contradiction between calculation accuracy and the data processing dimension. The computational accuracy is supported by data accuracy and data processing speed, which are not compatible with the practicality of current annual statistics and 5-year input-output tables. In the decomposition of carbon emission impact factors, only direct emissions are taken into account, while indirect emissions are ignored.

In order to precisely calculate the industrial carbon emissions and the influencing factors in Jiangsu Province, this paper uses the emission factor methodology in emission measurement. Based on the emission factor database, it solves the model applicability problem when the data is partially missing and the computational quantity is large. Meanwhile, when investigating the emission influencing factors, the presented paper sets the power carbon emission coefficient as a variable to minimize the impact on emissions from the variations of the power carbon emission coefficient. Therefore, this paper focuses on the industrial sector in Jiangsu Province and investigates the changing characteristics of industrial carbon emission influencing factors in Jiangsu Province. An extended STIRPAT model is established to analyze the influencing factors and mechanisms of industrial carbon emissions and use the gray forecasting model to predict the primary influencing factors of industrial carbon emissions in Jiangsu Province. Additionally, after decomposing the carbon emissions changes, this study also carries out a scenario analysis of the carbon emissions reduction potential in Jiangsu up to the year 2035 to uncover feasible mitigation pathways. Combining with scenario analysis, we forecast and analyze the trend of industrial carbon emissions in Jiangsu Province and then find a more suitable path to achieve the emission peak at a provincial level, which is meant to provide a practical guide for achieving the target of carbon peaking in Jiangsu Province.

Material and Methods

Emission Factor Approach

Jiangsu is a major energy-consuming province lacking primary energy resources, whose industry sector is dominated by high energy-consuming industries. Meanwhile, it has a coal-based, multi-energy, complementary energy consumption system. Currently, industrial energy consumption in Jiangsu Province is mainly composed of raw coal, crude oil, gasoline, diesel, kerosene, fuel oil, liquefied petroleum gas, natural gas, and electricity. Therefore, this paper adopts CO_2 emissions to represent carbon emissions, and based on the energy consumption data of above-scale industrial sectors in Jiangsu Province, we get the expression of the emission factor method. See formula (1).

$$C = \sum_{i}^{9} C_i \times EF_i \times \frac{44}{12} \tag{1}$$

Where denotes the total CO_2 emissions of above-scale industrial sectors (tons); denotes the energy consumption of above-scale industrial sectors, including consumption of coal (tons), coke (tons), crude oil (tons), gasoline (tons), diesel (tons), kerosene (tons), fuel oil (tons), liquefied petroleum gas (tons), natural gas (ten thousand cubic meters), and electricity (million kWh), respectively; EF_i denotes the carbon emission coefficient of the energy source (tons CO_2/ton); 44/12 is the ratio of the molecular weight of carbon dioxide to the relative atomic mass of the element carbon.

LMDI Decomposition

Regional low-carbon development is influenced by a variety of factors. Thus, only through adequate analysis of these factors can we regulate the factors that affect regional low-carbon development and then promptly adjust the development concepts and policies. The studies on the factor decomposition of energy consumption and carbon emissions primarily adopt the factor decomposition method or the exponential decomposition method. Therefore, this paper adopts the exponential decomposition analysis method to analyze and investigate the factors influencing industrial carbon emissions and energy consumption in Jiangsu Province.

Exponential decomposition analysis was first proposed by Laspeyres in 1871 to weight indices with the base period price, which was mostly used to solve some economic problems but was not widespread in the field of energy or carbon emissions [44]. The fundamental idea of exponential decomposition analysis is to decompose variations in the target variable into a combination of several contributing factors. This paper mainly adopted the log-mean divisia index (LMDI) decomposition method introduced by Ang [45]. This decomposition method is based on Kaya's constant equation. We extend it by converting the original simple arithmetic average weight calculation method into the lower form of the log-mean formula, which solves the remaining problem of decomposition effectively and thereby avoids the subjectivity and randomness of parameter estimations.

The Kaya constant equation was first introduced at the IPCC meeting, where the scholar Kaya figured out the impact of economic, policy, and demographic factors on the environment [46] and pointed out that carbon emissions are not only associated with energy consumption and economic activities, but also with other factors such as energy efficiency and energy structure. Currently, the primary applications of the Kaya constant equation in analyzing carbon emission effects are decomposition analyses based on industrial structure and industrial distribution. The findings from different decomposition methods may be used to provide guidance for industrial structure and industrial distribution optimization on a regional or local level. As a major industrial and energy consumption province in China, Jiangsu has implemented policies of energy consumption control and green development for energy-intensive industries including flat glass, ethylene, ammonia, caustic soda, and papermaking industries in order to achieve the target of reducing energy intensity by 17% during the 13th Five-Year Plan period. Today, the output value of Jiangsu's high-tech industry sectors and strategically emerging industrial sectors accounts for 49.8% and 41.3% of the total output value of industrial enterprises above the designated size, respectively. Therefore, based on the LMDI decomposition method, we use a time-series analysis to identify the principal influencing factors affecting carbon emissions in Jiangsu Province, such as the above-scale industries employed population, carbon emission coefficients, energy consumption structure, energy intensity, and per capita output, and then statistically analyze the contribution accounted for by each factor [47].

According to the Kaya constant equation, the expression of carbon emissions of above-scaled industries in Jiangsu Province is set as the formula (2).

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} P \times \frac{G}{P} \times \frac{E}{G} \times \frac{E_i}{E} \times \frac{C_i}{E_i} = \sum_{i=1}^{n} p \times r \times m \times e \times f_i \quad (2)$$

where represents the total CO_2 emissions of above-scale enterprises in Jiangsu Province (million tons); represents different energy types, mainly including the major industrial consumption energy types in Jiangsu Province; represents the industrial employed population in Jiangsu Province (people); G represents the total industrial outputs in Jiangsu Province (million yuan); E_i represents the consumption quantity of the th energy source (million tons); represents the CO_2 emissions generated by the th energy source (million tons).

The variations in CO_2 emissions are divided into five impact factors according to the LMDI decomposition model (see Table 1).

Given the relatively minor rate of change of carbon emission coefficients for the nine fossil energy sources (raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and LPG) in different years, this paper assumes that the carbon emission coefficients for fossil energy sources remain constant over the study period and uses the default values provided by WRI.

Jiangsu Province is a major industrial province. The power sector is heavily dominated by thermal power due to Jiangsu's distribution of resources. It owns 8% of the total installed capacity in China. Additionally, Jiangsu is a major energy-consuming province. Therefore, Jiangsu's electricity consumption relies heavily on large-scale inter-provincial and inter-regional power transmission, which accounts for 14% of China's total imported electricity. This inverse relationship between Jiangsu's energy resources and energy loads determines the reliance on imported electricity. After the carbon market launch in China, the Ministry of Ecology and Environment (MOE) updated the national grid emission factor values in 2022 and 2023. The MOE published annual data on provincial power grid emission factors for 2010, 2012, 2018, and 2020. The carbon emission factors for electricity in Jiangsu are shown in Fig. 1.

Table 1. Symbols and meanings of each influencing factor in the LMDI decomposition method

Influencing Factors	**Symbol**	**Description**	**Units**
Employed population	ΔC_p	Employed population of industrial sectors in Jiangsu.	Ten thousand people
Output per capita	ΔC_r	Ratio of industrial output value to employed population.	CNY 10, 000 Yuan / Person
Energy intensity	ΔC_m	The ratio of total energy consumption to industrial output value.	Tons of standard coal / CNY 10, 000 Yuan
Energy structure	ΔC_e	The share of the th fuel in the total energy consumption.	%
Carbon emission coefficient	ΔC_f	CO_2 emissions per unit consumption of the th energy source.	ton/ton

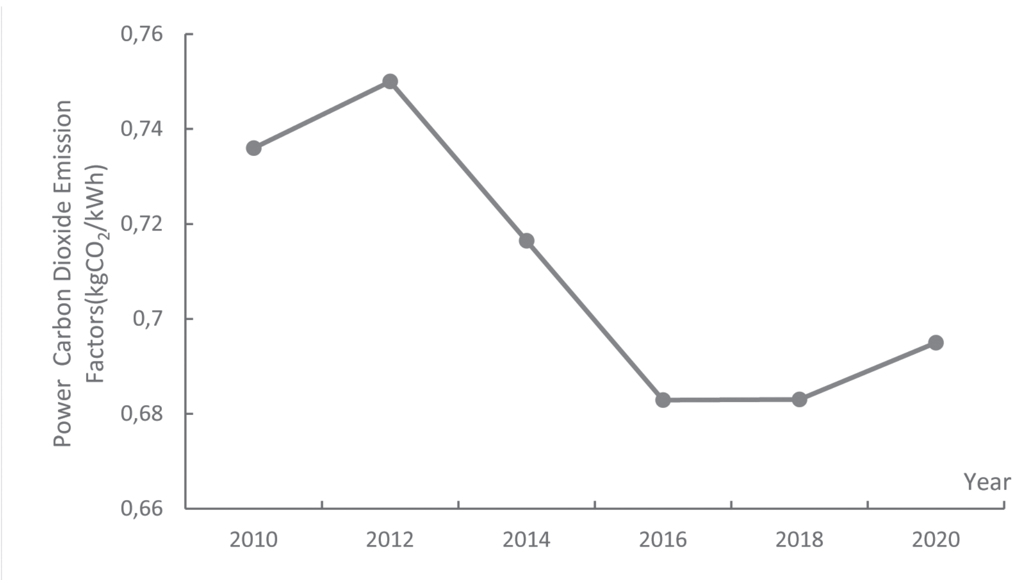


Fig. 1. Power Grid Carbon Dioxide Emission Factors in Jiangsu (2010-2020)

Carbon emissions from the power sector account for above 40% of China's total carbon dioxide emissions (in the mainland provinces and regions of China). Under the target of carbon neutrality, future power generation will be dominated by clean energy, whereas the proportion of non-fossil energy sources such as wind power and solar power will be significantly increased, which will enable the power industry to achieve a deep low-carbon and zero-carbon transition. Since the carbon emission factor of electric power continuously decreases, this paper considers that the carbon emission factor effect is mainly manifested as the effect caused by the impact of changes in the power carbon emission factor on CO_2 emissions variation. Based on the composition of different types of power sources in each province, inter-provincial power exchanges, and power consumption data, combined with the relevant contents of the "Ministry of Ecology and Environment: China's Regional Power Grid CO_2 Emission Factor Study 2023 Report" presented by Cai et al. [48], the carbon emission factors of Jiangsu's power grid in 2010, 2012, 2016, 2018, and 2020 were extracted, and the missing years were supplemented by the linear interpolation method. The finally derived formula for the comprehensive effect of CO_2 emission growth is shown in formula (3).

$$\Delta C = \Delta C_p + \Delta C_f + \Delta C_r + \Delta C_m + \Delta C_e \tag{3}$$

The formula for each factor is:

$$\Delta C_p = \sum_{i=1}^{n} \frac{C_i^t - C_i^{t-1}}{ln\, C_i^t - ln\, C_i^{t-1}} ln\left[\frac{p(t)}{p(t-1)}\right] \tag{4}$$

$$\Delta C_r = \sum_{i=1}^{n} \frac{C_i^t - C_i^{t-1}}{ln\, C_i^t - ln\, C_i^{t-1}} ln\left[\frac{r(t)}{r(t-1)}\right] \tag{5}$$

$$\Delta C_m = \sum_{i=1}^{n} \frac{C_j^t - C_j^{t-1}}{ln\, C_j^t - ln\, C_j^{t-1}} ln\left[\frac{m(t)}{m(t-1)}\right] \tag{6}$$

$$\Delta C_e = \sum_{i=1}^{n} \frac{C_i^t - C_i^{t-1}}{ln\, C_i^t - ln\, C_i^{i-1}} ln\left[\frac{e_i(t)}{e_i(t-1)}\right] \tag{7}$$

$$\Delta C_f = \sum_{i=1}^{n} \frac{C_i^t - C_i^{t-1}}{ln\, C_i^t - ln\, C_i^{i-1}} ln\left[\frac{f_i(t)}{f_i(t-1)}\right] \tag{8}$$

STIRPAT Model

The stochastic impacts by regression on population, affluence, and technology (STIRPAT) model is an evolution of the PAT model and was proposed by Dietz and Rosa [20], which completes the shortcomings of the Kaya constant equation and IPAT model and is broadly used in quantitative analysis of the impacts of environmental changes. This model enhances the analytical and explanatory power of the original model by adding and subtracting variables. Furthermore, the study reveals that the scale effect is the dominant influence on the growth of carbon emissions, which is in accordance with most scholars' conclusions, such as Gao et al. [49], who found that the economic development of coastal areas in southeastern China is the most significant factor among those that have a positive contribution to the growth of carbon emissions.

With reference to the study of Tan et al. [50], based on the LMDI decomposition method and combined with the characteristics of industrial sectors in Jiangsu Province, this paper intends to introduce industrial employed population, carbon emission intensity, output per capita, and technological progress as driving indicators into the STIRPAT model. This will enable a more comprehensive and accurate evaluation of the driving factors' contribution to the CO_2 emissions of industrial sectors in Jiangsu Province. The actual STIRPAT model applied in this paper is;

$$ln(C) = ln(a) + bln(P) + cln(I) + f(1-d)ln(TT) \tag{9}$$

where denotes CO_2 emissions from the industrial sector in Jiangsu Province; $ln(a)$ is a constant term; P denotes the industrial employed population in Jiangsu Province; TT denotes carbon emission intensity; I is output per capita; and d is technological progress.

The specific variables in Equation (9) are explained in Table 2.

Data Sources

Nowadays, China's manufacturing industry is pivotal in the world. China is the only country equipped with all 41 industrial sectors, and manufacturing value-added occupied nearly 1/3 of the global share last year, which ranked the first in the world for 12 consecutive years. While Jiangsu is equipped with 40 industrial categories, the total industrial

Table 2. Explanation of the variables in the STIRPAT model

Variables	Symbol	Description	Units
Employed population	*P*	Industrially employed population in Jiangsu Province	Person
Output per capita	*I*	Ratio of industrial output to industrial population	CNY 10, 000 Yuan /Person
Technological progress	*d*	Ratio of energy consumption to industrial output	Tons of standard coal / CNY 10, 000 Yuan
Carbon emission intensity	*TT*	Ratio of total CO_2 emissions to industrial output	Tons of CO_2 / CNY 10, 000 Yuan
CO_2 emissions	*C*	CO_2 from energy consumption in the industrial sector	Tons

economic volume has been ranked in the top three in China since the Reform and Opening-up. The manufacturing value-added sector occupies 13.3% of the country in 2021, and the manufacturing cluster is the largest in scale nationwide. Jiangsu is a large-scale industrial province. Its industry sector is not only a ‘high-energy user’, but also a ‘carbon-emissions consumer’. In terms of energy consumption, industrial energy consumption makes up more than 70% of the total energy consumption of society; in terms of carbon emissions, industrial carbon emissions account for 67.3% of the total carbon emissions of society, among which steel, petrochemicals and chemicals, building materials, weaving, and papermaking are the top five energy-intensive industries in the province, covering over 75% of the province’s industrial carbon emissions. As a leading economic province in eastern China, as well as a high energy-consuming and carbon-emitting province, the transformation to low-carbon industrial development in Jiangsu is essential for achieving carbon peaking and carbon neutrality in the province.

According to the “Jiangsu Statistical Yearbook”, the presented paper divides the major energy sources of industrial production in Jiangsu Province into ten categories. That is, for above-scale industrial enterprises, energy sources are classified into 10 types according to industrial group consumption, namely, raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, natural gas, and electricity. Table 3 presents the energy carbon emission factors and the discounted standard coal coefficients for the nine varieties.

Results and Discussion

Analysis of Industrial Carbon Emission Influencing Factors

Overall Industrial Emissions in Jiangsu Province

According to the industrial energy structure of Jiangsu in 2010-2021, the industrial energy consumption of Jiangsu Province is dominated by raw coal, coke, crude oil, electricity, and other energy consumption that is secondary. Apart from this, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and liquefied natural gas have a relatively low proportion, which is less than 2% in total. It indicates that Jiangsu’s industrial carbon emissions are largely derived from coal-based energy consumption. Since Jiangsu Province is in the process of optimizing its energy structure, the proportion of liquefied natural gas and electricity consumption has been rising, and the energy intensity has been substantially reduced. The emission factor method is used to measure and analyze the CO_2 emissions of above-scale industrial sectors in Jiangsu. In terms of the energy structure of industrial carbon emissions, the proportion of direct CO_2 emissions from fossil energy is relatively high in the above-scale industries in Jiangsu Province; on the contrary, the indirect emissions from electricity are under 6%. Fossil fuels are dominated by crude coal, which accounts for over 60%. Crude oil and coke make up 14.5% and 14.8%, respectively. In comparison, other fossil sources like gasoline, kerosene, diesel fuel, fuel oil, and liquefied petroleum gas (LPG) comprise relatively small shares. The trends of CO_2 emissions and carbon emissions per million of industrial output in the industrial sectors of Jiangsu from 2010 to 2021 are shown in Fig. 2.

It can be observed from Fig. 2 and 3 that, apart from 2020, which was affected by the epidemic, between 2010 and 2021, the total industrial energy consumption and the total carbon emissions followed a volatile increasing trend and the growth rate was essentially constant. However, total carbon emissions tend to be flat after 2016, at a rate lower than the growth rate of energy consumption. In addition, combining Fig. 2 and Fig. 3 indicates that:

a) Considering the current status of energy consumption, the province’s above-scale industrial energy consumption in 2021 was 345 million tons of standard coal, which increased by 17.87% compared to 2011, with an average annual growth rate of 1.79%. In terms of energy structure, “coal-based” energy structure remains relatively prominent.
b) Considering the carbon emissions and growth rate, the total carbon emissions of the above-scale industries in the province reached 787 million tons

Table 3. Energy sources’ CO_2 emission factors and standard coal coefficients

Energy Sources	**CO_2 emission factors**	**Standard coal coefficient**
Raw Coal	1.981 $kgCO_2/kg$	0.7143 kg/kg
Coke	2.860 $kgCO_2/kg$	0.9714 kg/kg
Crude Oil	3.020 $kgCO_2/kg$	1.4286 kg/kg
Gasoline	2.925 $kgCO_2/kg$	1.4714 kg/kg
Kerosene	3.033 $kgCO_2/kg$	1.4714 kg/kg
Diesel	3.096 $kgCO_2/kg$	1.4571 kg/kg
Fuel Oil	3.170 $kgCO_2/kg$	1.4286 kg/kg
Liquefied Petroleum Gas	3.101 $kgCO_2/kg$	1.7143 kg/kg
Natural Gas	2.162 $kgCO_2/m^3$	1.3300 kg/m^3
Electricity	/	0.1229 kg/kWh

Source: CO_2 emission factors from WRI and standard coal coefficients from the China Energy Statistical Yearbook.

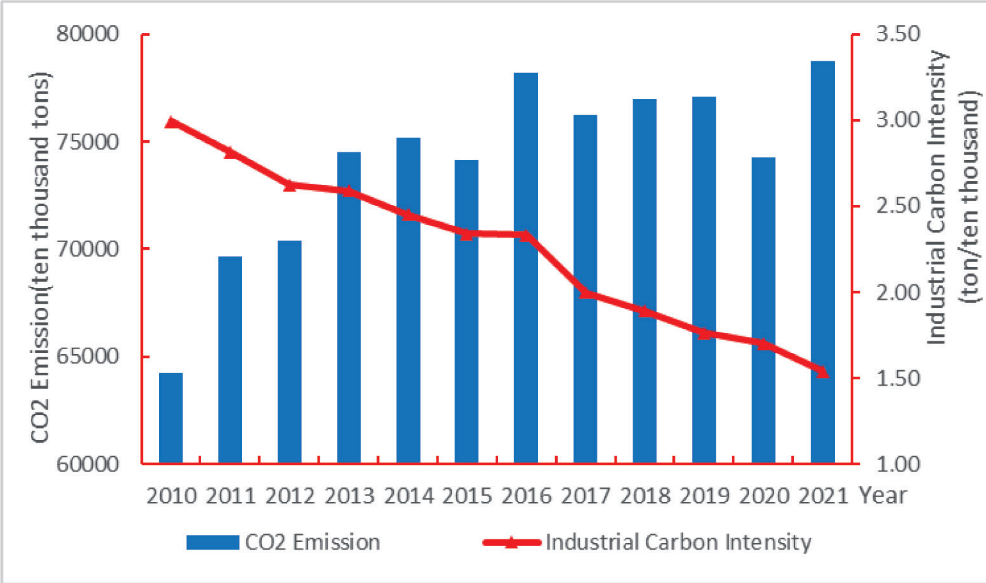


Fig. 2. Industrial CO_2 emissions and carbon intensity of Jiangsu from 2010 to 2021.

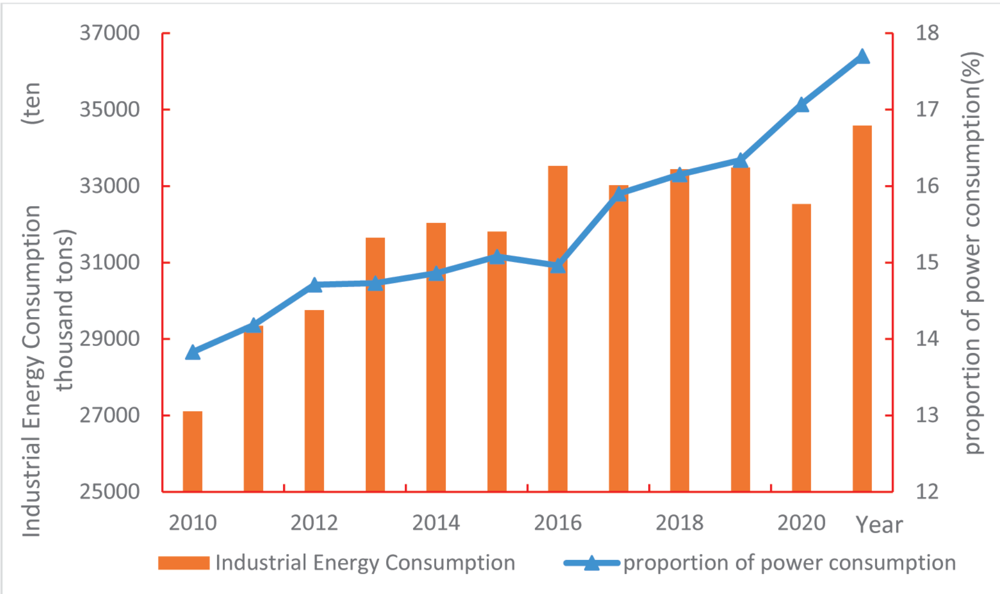


Fig. 3. Industrial power consumption shares and total energy consumption in Jiangsu Province from 2010-2021.

in 2021, an increase of 13.05% compared to 2011, but the growth rate of carbon emissions has slowed down, with an average annual growth rate of 1.31%.

c) Considering carbon emission intensity, during 2010-2021, the overall industrial carbon emission intensity showed a downtrend and declined significantly, dropping from a maximum of 29.5 thousand tons/billion yuan in 2010 to a minimum of 15.2 thousand tons/billion yuan in 2021. The average annual reduction rate is 4.41%. The results indicate that Jiangsu's above-scale industrial carbon emissions have been remarkably improved.

The above analysis shows that through low-carbon technological innovation and the spread of large-scale energy-saving technologies to reduce industrial energy consumption, the carbon emissions of Jiangsu's above-scale industries have been significantly improved. However, the "coal-based" energy structure of the industry still leads to greater pressure on carbon emission reduction.

LMDI Decomposition Results

From the addition formula of the LMDI decomposition model, it is apparent that when the contribution value is greater than zero, the driver has a facilitating effect on industrial CO_2 emissions and acts as a positive driver. However, when the contribution value is smaller than zero, the driver has a suppressing effect on industrial CO_2 emissions and acts as a negative driver. The decomposition results of CO_2 emissions from the industrial sector in Jiangsu Province based on the LMDI method are shown in Table 4, from which it can be seen:

a) Industrial energy intensity effect. Energy intensity is the measure of the efficiency of the total system energy consumption compared to the industrial output value, represented by the ratio of total energy consumption to the industrial output value. Therefore, a decrease in energy intensity indicates a rise in energy efficiency when other factors remain unchanged. The overall trend of industrial energy intensity in Jiangsu Province from 2010 to 2021 is downward, indicating that energy intensity has an inhibitory effect on carbon emissions. Combined with Fig. 3 and Table 4, energy intensity effectively suppressed CO_2 emissions from the industrial sectors over the study period, which offset 472.51 million tons of CO_2 emissions with a contribution rate of 347.03%. In terms of specific energy sources, the energy intensity effect of raw coal reduced emissions most significantly, with a contribution of 305.62 million tons to the reduction in carbon emissions. Coke and crude oil followed, which reduced carbon emissions by 70.39 million tons and 70.95 million tons, respectively. Additionally, natural gas and electric power decreased carbon emissions by 2.77 million tons and 18.08 million tons, respectively. Indeed, this result is highly dependent on the strict implementation of a series of energy efficiency measures in Jiangsu Province's industrial sector during the 13th Five-Year Plan period. Such a series of measures have been strictly conducted to control total energy consumption and energy intensity, promote total carbon emissions reductions and intensity, and effectively improve the industrial energy intensity effect.
b) Industrial energy consumption structure effect. Energy structure reflects the proportion of different energy sources over the total source consumption. During 2010-2021, the energy structure effect reduced CO_2 emissions by 29.02 million tons, with a contribution rate of 21.31%, and its suppression effect on carbon emissions is inferior only to that caused by the energy intensity effect. Combined with Fig. 3 and Table 4, the share of raw coal in Jiangsu Province's industrial energy consumption decreased from 59.07% in 2011 to 51.53% in 2021, with a decrease rate of 12.93%, which leads to a reduction of 62.53 million tons of industrial carbon emissions. The proportions of high carbon emission factors from energy sources like kerosene, diesel fuel, and fuel oil also declined by 53.64%, 51.96%, and 53.61%, respectively, which in turn resulted in a reduction of 0.07 million tons, 2.57 million tons, and 3.18 million tons in industrial carbon emissions, respectively. Further, the proportion of low carbon emission factor energy sources such as natural gas and electricity increased from 0.42% and 14.18% in 2011 to 1.21% and 17.7% in 2021, which led to an increase of 4.46 million tons and 7.08 million tons of carbon emissions in the industry sector, respectively. In 2011, the proportion of carbon emissions from coal, crude oil, and natural gas was 69.03%, 12.94%, and 0.32%, respectively, while in 2021 this changed to 62.77%, 15.41%, and 1.06%, respectively. It shows that in Jiangsu's industrial carbon emission structure, the structure of these three energy types - raw coal, crude oil, and natural gas - is continuously optimized and adjusted. There is a noticeable drop in the proportion of carbon emissions from raw coal and a rise in the proportion from natural gas. Jiangsu's industrial carbon emission structure also reveals that its industrial emissions are closely related to raw coal and crude oil, accounting for about 80% of total emissions. In order to accelerate the realization of Jiangsu's industrial "dual carbon" goals, it is essential to promote the development and application of clean energies, such as solar, wind, and hydrogen, to boost green, high-quality industrial development.
c) Industrial scale effect. The size of an industry is determined by the change in the number of employees within the industry. As shown in Table 4, during 2010-2013, the industry scale factors were positive, while during 2014-2021, the industry scale factors turned negative, and the industrial scale effect reduced CO_2 emissions by 17.84 million tons, which has a minor inhibiting effect on the increase in carbon emissions overall. The "13th Five-Year Plan for the Development of Modern Industrial System in Jiangsu Province" prioritized the development of emerging industries with high scale effects, such as new-generation information technology, high-tech software and information services, and digital creativity. In addition, Jiangsu has issued "Opinions on Further Accelerating the Development of Intelligent Manufacturing", "Three-Year Action Plan for Intelligent Manufacturing Demonstration Factory Construction in Jiangsu Province (2018-2020)", and other documents. These policies have been used to guide and encourage enterprises to pursue independent innovation and to promote the intelligent transformation and digital transformation of the manufacturing industry. Since the "13th Five-Year Plan", enterprises in Jiangsu Province have improved their productivity efficiency by 30% on average.
d) The carbon emission coefficient effect. The carbon emission coefficient effect is the weakest and reduces CO_2 emissions by 3.36 million tons. Considering the energy consumption structure, the carbon emission per kilowatt-hour of electricity continues to decline, dropping around 5.57% in 2021 compared to 2011, which suppressed the growth rate of industrial carbon emissions, demonstrating the coefficient-driven effect on carbon emission reduction. Although low-carbonization in electricity has made

significant achievements, the proportion of thermal power generation to total installed capacity in Jiangsu Province is high (83.63% of thermal power generation in 2021), resulting in a still relatively high carbon emission coefficient. Therefore, it is crucial to optimize the power generation structure, as this will make a significant contribution to reducing industrial carbon emissions in Jiangsu Province.

e) Industrial development level effect. The industrial development level effect is measured by the value of industrial output per capita. This indicates the growth in the industry's economic productivity and production capacity to some extent. Therefore, the region's expansive industrial capacity leads to high carbon emissions. Between 2010 and 2021, industrial development drove a carbon emissions increase of 658.89 million tons, with a contribution rate of 483.91% to the rise in emissions, which makes it the primary driving factor of the increased carbon emissions. Jiangsu Province is a major economic and industrial province with China's largest manufacturing sector. Jiangsu's industrial sector contributes over 40% of its GDP; however, its industrial sector accounts for about three-fourths of total energy consumption nationwide. Therefore, the industrial sector is the main industry increasing carbon emissions, and accordingly, it is critical for energy saving and emission reduction efforts.

Therefore, the analysis of CO_2 emission influencing factors based on the LMDI decomposition method indicates that the energy intensity, the energy structure, and the carbon emission coefficient are the principal factors that restrain industrial CO_2 emissions in Jiangsu Province, while influencing factors, such as employed population and per capita output, act to accelerate industrial CO_2 emissions in Jiangsu Province.

Jiangsu Province Industrial Carbon Emission Influencing Factors

In order to eliminate the multicollinearity problem in variables affecting industrial CO_2 emissions in Jiangsu, we consider a partial regression to improve the accuracy of the measurement of influencing factors for industrial CO_2 emissions in Jiangsu Province. The results of the ridge regression-fitted STIRPAT model are presented in Table 5.

The variance inflation factor (VIF) values of both technological progress and carbon emission intensity in Table 5 exceeded 10; that is, there was a rather strong multicollinearity between the variables. Applying SPSS21.0 software to perform ridge regression analysis on the STIRPAT model, the results of the ridge regression analysis yielded ridge trace plots, which are shown in Fig. 4 and 5.

Table 4. Results of the decomposition of CO_2 emission factors in the industrial sector in Jiangsu Province (Unit: million tons)

Year	Employed Population	Output per Capita	Energy Intensity	Energy Structure	Carbon Emission Coefficient	Total Effect
2010-2011	6.62	87.09	-41.28	0.78	-0.78	52.43
2011-2012	4.78	51.61	-47.10	-2.61	-0.13	6.55
2012-2013	3.24	47.60	-6.29	-2.64	-0.63	41.28
2013-2014	1.50	47.37	-39.96	-0.91	-0.71	7.29
2014-2015	-4.01	27.34	-29.85	-5.02	-0.28	-11.82
2015-2016	-2.66	44.54	-1.70	0.31	-0.87	39.62
2016-2017	-5.69	107.94	-116.02	-7.49	0.45	-20.81
2017-2018	-7.12	56.87	-41.11	-2.44	0.26	6.46
2018-2019	-12.86	67.12	-53.91	-0.33	-0.25	-0.23
2019-2020	-7.27	6.52	-21.94	-6.34	0.07	-28.96
2020-2021	5.63	114.89	-73.35	-2.33	-0.49	44.35
Total	-17.84	658.89	-472.51	-29.02	-3.36	136.16
Mean	-1.62	59.90	-42.96	-2.63	-0.31	12.38

Table 5. Least squares regression results of the STIRPAT model for industrial energy consumption CO_2 emissions in Jiangsu Province

	B	Beta	t value	Pr(>|t|)	VIF
Intercept	1.692		0.193	0.852	
	0.408	0.124	0.755	0.472	5.649
	0.714***	3.348	6.681	0.000	52.62
	1.083**	2.508	4.207	0.03	74.48

* significant at the significance level 90%, ** significant at the significance level 95%, *** significant at the significance level 99%.

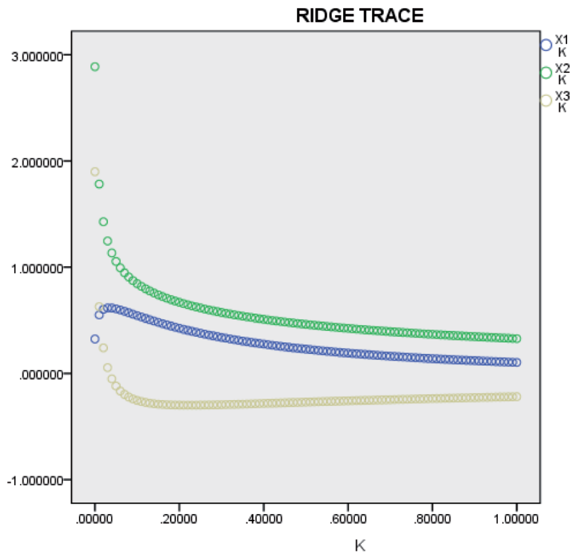


Fig. 4. Ridge trace plot

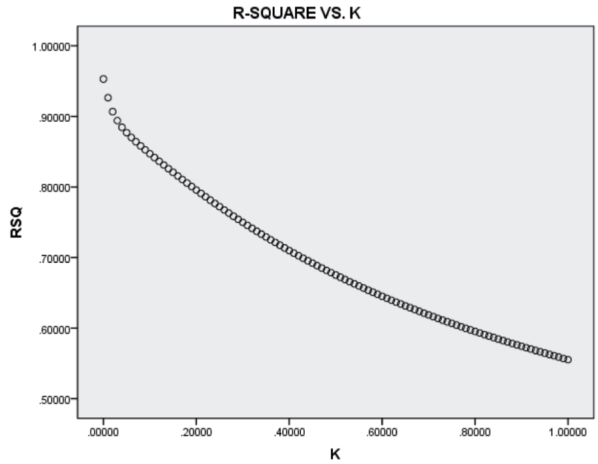


Fig. 5. K values correspond to the R^2 diagram.

Table 6. Results of ridge regression analysis for a K value of 0.002

	B	Beta	T	SIG
	0.8328	0.2529	1.6486	0.1378
	0.6021^{***}	2.8245	6.6217	0.0002
	0.8153^{**}	1.8883	3.7344	0.0575
Constant	-4.9736	0.0000	-0.6031	0.5632

** significant at the significance level 95%, *** significant at the significance level 99%.

The results of ridge regression analysis using SPSS 21.0 are shown in Table 6.

Table 6 shows that the results of the ridge regression for the industrial sector in Jiangsu Province are:

$$ln(C) = -4.9736 + 0.8328ln(P) + 0.6021ln(I) + 0.8153(1-d)ln(TT) \tag{10}$$

According to the formula of the ridge regression in equation (10), we compute the fitted values of the industrial CO_2 emissions in Jiangsu Province from 2010 to 2021. Then we analyze and compare the fitted values with the estimated values calculated by the emission factor method, as well as compute the relative errors, and the results are presented in Fig. 6.

The average percentage error between the actual and fitted values of the industrial CO_2 emissions in Jiangsu Province from 2010-2021 is 0.05%. It indicates that the difference between the fitted and actual values is minor and acceptable, which further indicates that the STIRPAT

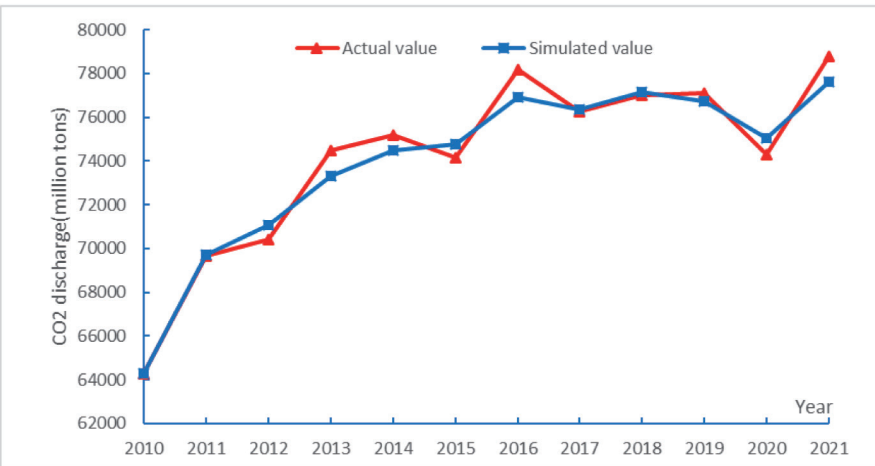


Fig. 6. Comparison between simulated and actual values of industrial carbon emissions in Jiangsu Province

regression equation is a satisfactory choice for the estimation.

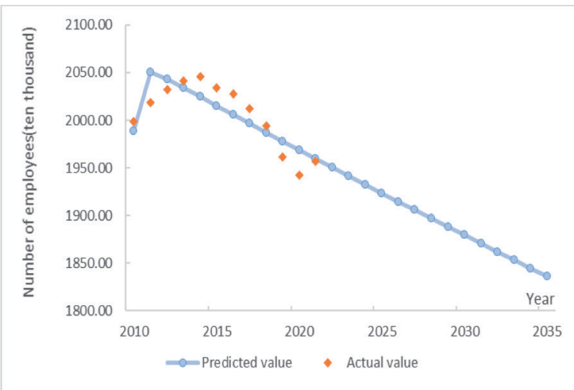
According to the results of the ridge regression, an increase of 1% in per capita output is associated with a 0.602% increment in CO_2 emissions. Although Jiangsu Province is gradually restructuring its industrial structure, the second industry still plays a vital role in its GDP, which accounts for over 50% of GDP. Among the four leading economic provinces of China, namely Guangdong, Jiangsu, Shandong, and Zhejiang, Jiangsu Province has the highest proportion of secondary industry. Furthermore, depending on the rapid development of the modern information technology industry in Jiangsu Province, Jiangsu Province is striving to combine the industry sector with modern information technology to promote industrial transformation in production, which will further enhance the output per capita and accordingly affect the level of industrial carbon emissions.

The lower carbon emission intensity with technological progress implies a higher energy utilization efficiency, which in turn leads to less industrial CO_2 consumption. Each 1% decrease in carbon emission intensity with technological progress lowers industrial CO_2 emissions by 0.815%. Thus, the carbon emission intensity with technological progress represents the technological level of the industrial sector in Jiangsu Province, and an improved technological level could effectively suppress CO_2 emissions.

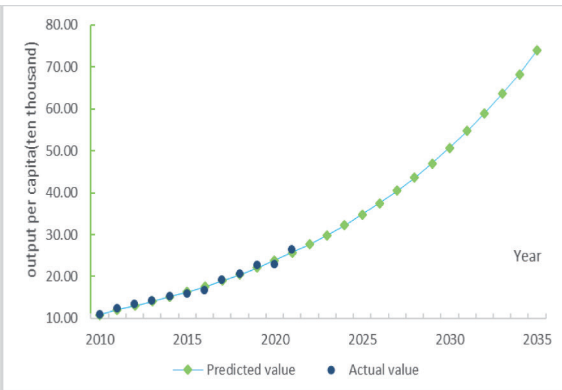
Industrial "Carbon Peaking" Forecast

In the crucial stage of post-epidemic global economic recovery, China's proposed "dual carbon" target is undoubtedly taking responsibility for global ecological conservation. Also, China effectively promotes the construction of global ecological civilization. Based on the decomposition of the influencing factors of industrial carbon emissions in Jiangsu Province and the regression analysis of the major influencing factors, we can derive the contribution and effect of energy consumption intensity, energy consumption structure, industrial output per capita, employed population size, and technological progress on industrial carbon emissions in Jiangsu Province.

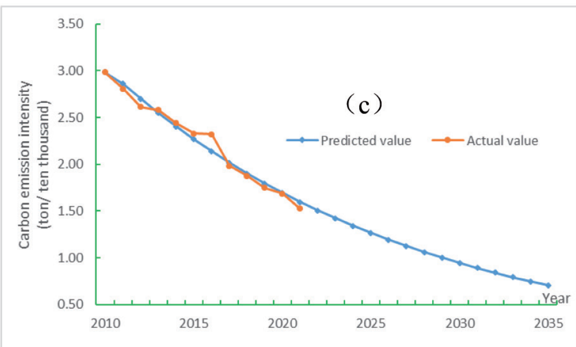
Based on the limited sample data, the gray prediction model develops and utilizes the available gray data information, which makes it possible to simulate the connections and patterns among uncertain systems and to explore the dynamic behaviors of uncertain systems. The core models are GM (1,1) model, GM (1,N) model, and the DGM (1,1) model. Currently, the model and its modified models are widely used in the fields of energy [51] and environment [52]. This paper utilizes the gray DGM (1,1) model to forecast the primary influencing factors on industrial carbon emissions in Jiangsu Province, such as the employed population, output per capita, carbon emission intensity, and technological progress. These forecast results of the fitting of DGM(1,1) model are presented in Fig. 7.



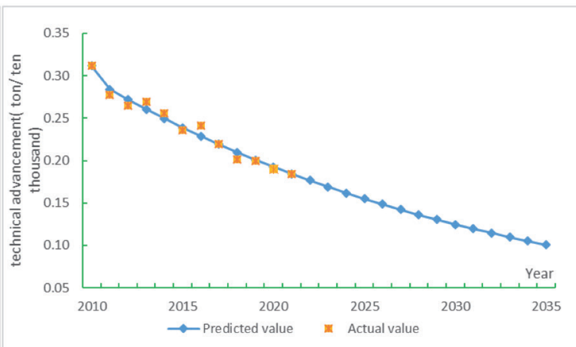
a. Employed population prediction



b. Per capita output prediction



c. Carbon emission intensity prediction



d. Technology progress prediction

Fig. 7. Prediction of industrial carbon emission influencing factors based on gray DGM (1,1)

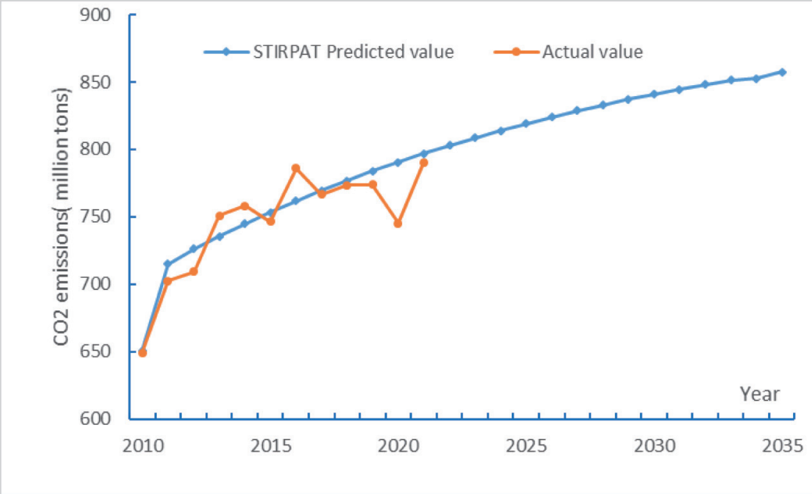


Fig. 8. Industrial carbon emission prediction based on the gray model and the STIRPAT model

Then, substitute the forecast results into the fitted STIRPAT model. The results are shown in Fig. 8. The predictions suggest that industrial carbon emissions in Jiangsu Province are expected to reach 857 million tons by 2035.

Furthermore, depending on the results of industrial carbon emissions in Jiangsu Province during 2010-2021, we can also apply the gray DGM (1,1) model directly, and the results of industrial carbon emissions measurement based on the DGM (1,1) model in Jiangsu Province are given in Fig. 9. When conducting time series forecasting, it is essential to estimate the value of relevant factors in the future period, and the prediction outcomes may have considerable errors. Therefore, in order to test the prediction performance of the model, we compare the real and predicted values of Jiangsu Province during 2010-2021. The average error rate is calculated to be merely 1.76% over 12 years, and it can be seen from Fig. 9 that the predicted carbon emission curve fits well with the real carbon emission curve, which indicates that the model is effective in forecasting the carbon emissions in Jiangsu Province for the next 15 years. From Fig. 9, it can also be observed that the industrial carbon emissions in Jiangsu Province will increase gradually from 2022 to 2035, but the annual growth rate declines year by year, and the average annual growth rate is 0.48. The industrial carbon emissions in Jiangsu Province will reach a peak of 852 million tons by 2035, which is consistent with the results of industrial carbon emissions prediction in Jiangsu Province based on the gray model and STIRPAT models. Therefore, in accordance with the prediction results of the gray DGM (1,1), the industrial carbon emissions of Jiangsu Province are expected to achieve their peak by 2035.

In this section, on the basis of the low-carbon economic development theory and scenario analysis method, combined with the analysis results above, we set different scenarios with different changing rates for the five influencing factors, that is, industrial energy intensity, energy consumption structure, per capita output, technological progress, and employed population in Jiangsu Province, and then forecast and analyze the long-term trend of industrial carbon emissions in Jiangsu Province through the gray prediction model and STIRPAT models. We propose the industrial

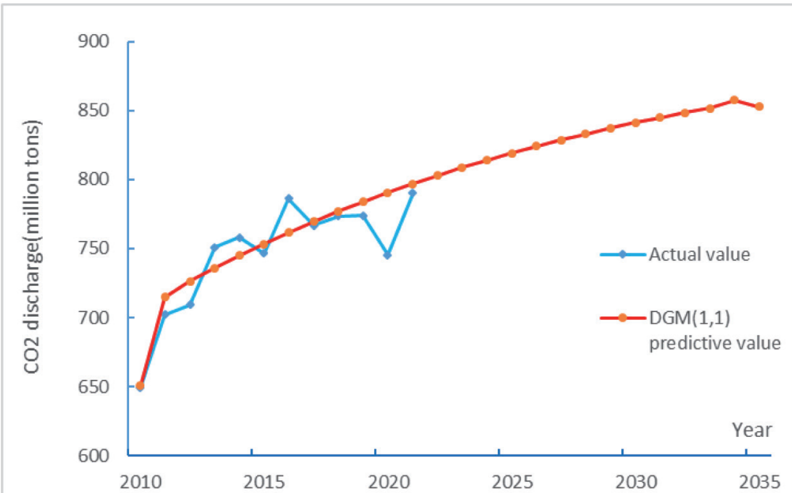


Fig. 9. Industrial carbon emission projection in Jiangsu Province based on gray DGM (1,1) model Industrial "Carbon Peaking" Path

emission reduction path under the goal of "carbon neutrality" and make suggestions for relevant policies.

Based on the prediction results in Fig. 9, according to the "Outline of the 14th Five-Year Plan for National Economic and Social Development of Jiangsu Province and Perspective Targets for the year 2035", "Master Plan for the Construction of Beautiful Jiangsu (2021-2035)", "Implementation Advice on Promoting High-Quality Development to Achieve Carbon Neutrality", "Implementation Proposals of Jiangsu Province to Achieve Carbon Neutrality", and given the current status of economic and social development and industrial carbon emissions in Jiangsu Province, as well as the historical evolution pattern, we take 2021 as the baseline year, and make basic assumptions on the future changes of four influencing factors, namely, the employed population, per capita output, carbon emission intensity and technological progress, for 2022-2035.

1) Employed Population Setting

The current population in China is still expanding every year. According to the statistical yearbook published by the Jiangsu Statistics Administration, the natural growth rate of the population in Jiangsu Province is constantly decreasing and has dropped from 2.85% in 2010 to -1.12% in 2021. Meanwhile, the industrially employed population in Jiangsu Province presents a volatile downward trend between 2010 and 2021, with an average reduction of 0.34% per year in the industrially employed population. Simultaneously, with the green development concept gaining popularity, a low-carbon and environment-friendly lifestyle receives attention. It can also be observed from the results in Table 4 that the industrially employed population size effect on carbon emissions in Jiangsu Province during 2010-2021 mainly exhibits a positive driving effect, but the total contribution is relatively small, and the annual average contribution of the population size effect on the energy consumption carbon emissions in Jiangsu Province is merely 9.12%. Therefore, there is little possibility that the impact of population size effects on carbon emissions will increase in the future. In addition, the "China and the New Climate Economy Report" shows that the difference in the average annual population growth rate under different development scenarios is 0.1%. The "National Population Development Plan (2016-2030)" suggests that the population in China will reach its peak around 2030. According to the "Outline of the 14th Five-Year Plan for National Economic and Social Development of Jiangsu Province and Perspective Targets for the Year 2035" and considering the population development requirements of Jiangsu Province and the current development status of the industrially employed population in Jiangsu Province, we set the low-speed and high-speed population growth patterns as shown in Table 7.

2) Carbon Emission Intensity

During 2010-2021, the carbon emission intensity of Jiangsu Province dropped from 2.985 tons of CO_2/ten thousand Yuan to 1.526 tons of CO_2/ten thousand Yuan, with an average annual decreasing rate of 6%. Moreover, the decreasing rate of carbon emission intensity has declined continuously in recent years, and the carbon emission intensity decreased by 7% from 2016-2021. Furthermore, China commits to achieving CO_2 emissions peak by 2030 and carbon neutrality by 2060. According to the new commitment of lowering CO_2 emissions per unit of GDP by over 65% by 2030 compared to 2005, China needs to reduce CO_2 emissions per unit of GDP by 17.6% on average during the 14th and 15th Five-Year Plans. As the reduction potential is gradually decreasing, the difficulty of emission reduction is growing. Therefore, the central government sets a target to realize an 18% reduction in cumulative CO_2 emissions per unit of GDP during the 14th Five-Year Plan.

In order to implement the "Implementation Opinions of the CPC Central Committee and the State Council on the complete and accurate implementation of the new development concept of carbon peaking and carbon neutrality work" and the "Notice of the State Council on the issuance of the action plan of carbon peaking by 2030", Jiangsu Province will strive to reduce energy consumption in various industrial sectors and improve energy efficiency. Jiangsu will continue to undertake energy efficiency leadership programs, paying more attention to the transportation equipment manufacturing, electrical equipment manufacturing, and communications devices industries, and will instruct those key industries to accelerate the application of energy-saving and emission-reducing technology. In order to further promote the energy revolution, Jiangsu will develop photoelectricity, wind power, nuclear power, hydrogen energy, and some other clean energy resources to reduce the proportion of thermal power in the power supply. Considering the target of reducing carbon dioxide emissions per unit of GDP by 18% in the 14th Five-Year Plan period, the development scenarios setting industrial carbon emission intensity in Jiangsu Province for 2022-2035 are shown in Table 8.

Table 7. Average annual growth rate of the industrially employed population in Jiangsu Province during 2022-2035

Scenario	2022-2025	2026-2030	2031-2035
High-speed growth	-1%	-2%	-3%
Low-speed growth	-0.5%	-1%	-2%

Table 8. Setting of the average annual growth rate of industrial carbon emission intensity in Jiangsu Province for 2022-2035

Scenarios	2022-2025	2026-2030	2031-2035
High-speed development	-7%	-6%	-5%
Low-speed development	-5%	-4%	-3%

3) Output Per Capita

The average annual growth rate of industrial output per capita in Jiangsu Province was 8.51% during 2010-2021. As the current economic development moves into a new step, the growth rate of industrial value-added in Jiangsu Province is gradually slowing down, which reveals that the industrial development of Jiangsu Province has encountered a bottleneck and has difficulties in the transition to high value-added industries. However, Jiangsu Province has realized that it is essential to upgrade the manufacturing industries and has also focused on industrial upgrading in the 14th Five-Year Plan. It is expected that by 2035, the industry in Jiangsu Province will release the limitations of development and devote itself to high-level manufacturing industries and emerging strategic industries. Accordingly, the output per capita is set as shown in Table 9.

Table 9. Setting of the average annual growth rate of output per capita in Jiangsu Province 2022-2035

Scenarios	2022-2025	2026-2030	2031-2035
High-speed development	8%	7%	6%
Low-speed development	7%	6%	5%

4) Technology Progress

We adopt industrial energy intensity to represent technological progress. From 2010 to 2021, the industrial energy intensity of Jiangsu Province dropped from 0.312 tons per ten thousand yuan to 0.184 tons per ten thousand, with an annual average decline of 4%, but the decline rate of energy intensity has become significantly slower in recent years. The "14th Five-Year Plan" states that, by 2025, compared with 2020, Jiangsu Province's energy consumption of regional gross product should fall around 14%, and energy consumption per unit of above-scale industrial add-value should decrease by 17%. Combined with the above-scale enterprise value-added ratio in Jiangsu Province, the industrial energy intensity is set to decrease by 17% in 2025, with an average annual rate of 3.5%. During 2025-2030, the industrial energy intensity will decrease by 16%, with an average annual rate of 3.2%, and during 2030-2035, the industrial energy intensity will decrease by 15%, with an average annual rate of 3%.

We set the future growth rate of the industrially employed population, output per capita, and carbon emission intensity in Jiangsu Province as both low and high growth rates. We can combine different cases of these variables to form eight different scenarios (Table 10).

Taking 2021 as the base period, according to the growth rates of different scenarios listed above, we calculate the industrial population, output per capita, and carbon emission intensity, including technological progress in Jiangsu Province for the future years 2022-2035, and then put them into the STIRPAT formula fitted by ridge regression to obtain the trend of industrial carbon emissions in Jiangsu Province for the years 2022-2035 under different scenarios, and the results are shown in Fig. 10. The overall trend of industrial carbon emissions is gradually falling up to 2035, and the rate of emission reduction is also progressively decreasing. In addition, the carbon emissions from the industrial sector in Jiangsu Province are expected to reach 695 million tons, 778 million tons, 737 million tons, 825 million tons, 726 million tons, 813 million tons, 770 million tons, and 862 million tons, respectively, by 2035 under eight scenarios.

The Jiangsu Provincial People's Government issued the "Jiangsu Province carbon emission peak implementation plan", which explicitly states that Jiangsu Province will achieve peak carbon emissions by 2030. According to the predicted trend of industrial carbon emissions in Jiangsu Province (Fig. 10), Scenario 2 (high-high-low), Scenario 4 (high-low-low), Scenario 6 (low-high-low), and Scenario 7 (low-low-high) will achieve the carbon emission peak target by 2030, with a peak value of 804 million tons, 829 million tons, 822 million tons, and 802 million tons, respectively.

From the simulation results of Scenario 2, Scenario 4, Scenario 6, and Scenario 7, it can be noted that Scenario 7 has the lowest peak value, which is also consistent with the findings of the previous studies. Therefore, accelerating energy technology innovation, reducing energy consumption per unit of output through technological improvement, and improving recycling

Table 10. Development scenarios setting in growth rates of influencing factors in Jiangsu Province for 2022-2035

Scenario	Growth rate of the industrial employed population	Growth rate of output per capita	Growth rate of carbon emission intensity
Scenario 1	High-speed development	High-speed development	High-speed development
Scenario 2	High-speed development	High-speed development	Low-speed development
Scenario 3	High-speed development	Low-speed development	High-speed development
Scenario 4	High-speed development	Low-speed development	Low-speed development
Scenario 5	Low-speed development	High-speed development	High-speed development
Scenario 6	Low-speed development	High-speed development	Low-speed development
Scenario 7	Low-speed development	Low-speed development	High-speed development
Scenario 8	Low-speed development	Low-speed development	Low-speed development

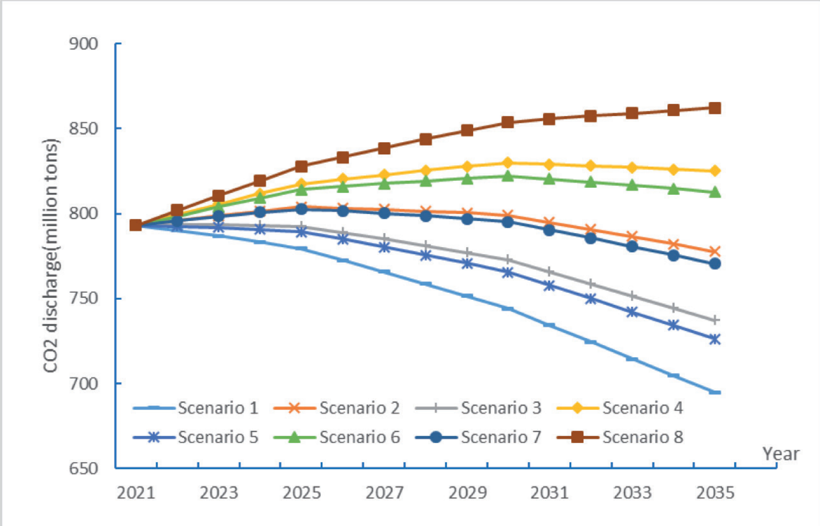


Fig. 10. Trend of industrial CO_2 emissions in Jiangsu Province for 2022-2035 under different scenarios

technology and low-carbon production technology will be beneficial to the steady industrial transition and stable economic development in the process of "carbon emission peak".

Overall, when the decline rate of carbon emission intensity is relatively small, industrial carbon emissions decrease at a slow rate. In order to achieve the targets of an emission peak in 2030 and carbon neutrality in 2060, Jiangsu Province needs to promote the application of low-carbon technologies. In order to fulfill people's demand for high-quality economic development and achieve the aim of constructing a modern and powerful country, Scenario 7 is the optimal path for industrial development in Jiangsu Province. Under the development scenario of a low employed population growth rate, a low per capita output growth rate, and a high rate of carbon emission intensity reduction, Jiangsu Province will reduce CO_2 emissions without sacrificing industrial economic development, and thereby, it will be possible to achieve a coordinated and sustainable development of socio-economic and environment aspects.

Conclusions

In this study, the LDMI decomposition method is applied to identify the key determinants of industrial carbon emissions in Jiangsu Province and then fitted these four driving factors - the employed population, per capita output, carbon emission intensity, and technological advancement - into the STIRPAT model to quantify the impacts of these factors on the changes in carbon emissions. The gray DGM (1,1) model is employed to predict the key determining variables, and the forecast results are substituted into the fitted STIRPAT model. Combining different scenario analysis settings, we forecast and analyze the industrial carbon emission trend in Jiangsu Province, as well as explore low-carbon development pathways. It can help policymakers develop more practical plans for green development at the provincial level and contribute to low-carbon development.

Firstly, our study indicates that from 2010 to 2021, industrial CO_2 emissions in Jiangsu Province exhibit an overall fluctuating growth trend, but with a relatively small growth rate. The analysis of CO_2 emission influencing factors based on the LMDI decomposition method indicates that energy intensity and carbon emission coefficient are the primary factors that inhibit industrial CO_2 emissions in Jiangsu Province. While other factors, including employed population, per capita output, and energy structure, are acting to promote industrial CO_2 emissions in Jiangsu Province. The findings show that reductions in energy intensity significantly restrained CO_2 emissions over the study period, offsetting 472.51 million tons of CO_2 emissions with an impact of 347.03%. This suppression effect from improved energy intensity outperforms the other two factors. But overall, the changes in carbon emissions due to energy structure are declining gradually throughout the years. While the output per capita is a major contributor to industrial CO_2 emissions, it leads to 658.89 million tons of CO_2 emissions with a contribution rate of 483.91%, which is the main driving factor to increase carbon emissions.

Secondly, the results of the STIRPAT model obtained by ridge regression fitting suggest that when the employed population, output per capita, and carbon emission intensity, including technological progress, increase by 1%, CO_2 emissions would then rise by 0.832%, 0.602%, and 0.815%, respectively. The mean percentage error between actual and fitted values for industrial CO_2 emissions in Jiangsu Province from 2010-2021 is 0.05%. This small margin of error suggests the gray DGM (1,1) model effectively captures trends in the historical data, fitting the real emissions values closely throughout the analyzed period.

Thirdly, through the analysis of the eight scenarios, Jiangsu Province can achieve the target of carbon reduction without compromising industrial economic growth under the development scenarios of a low population growth rate, a low per capita output growth rate, and a high carbon emission intensity reduction rate, so that the coordinated and sustainable development of socio-economic and environmental factors will be realized. Therefore, accelerating improvements in energy technologies, enhancing production efficiencies through technological innovation, and upgrading recycling technologies will help Jiangsu's industries transition to a stable and energy-efficient one and achieve their carbon peaking goals.

In the process of realizing the "dual carbon" path, optimizing the industrial and energy structures is an effective measure to control carbon emissions. Currently, Jiangsu Province is facing the dilemma that industrial structure optimization becomes difficult, and the marginal cost of emission reduction increases. The only way to achieve the target of "dual carbon" without compromising economic efficiency is through industrial transformation and upgrading. Based on the results of the scenario analysis and the existing emission reduction policies of Jiangsu Province, the following policy recommendations are proposed for Jiangsu Province to achieve industrial carbon peaking.

Firstly, it is crucial to optimize the energy structure and limit total fossil energy consumption. Currently, fossil energy consumption is a major factor affecting industrial carbon emissions in Jiangsu Province. In order to achieve the "dual carbon" target, it is vital to reduce fossil energy consumption. In addition, the industrial energy consumption structure of Jiangsu Province remains dominated by fossil energy, with a relatively low proportion of non-fossil energy. Also, we shall fully utilize the industry's proprietary capital and technology advantages to develop new-type power and new energy equipment clusters, intelligent power grids, and electrochemical energy storage technologies. In this way, we shall accelerate the transformation of the energy-intensive structure to a clean, power-based one and achieve high-quality development and a green transformation of the industrial economy at the same time. It is also necessary to continuously improve the policies and regulations for energy structure adjustment and optimization and to promote the low-carbon transformation in energy consumption structure.

Secondly, promoting technological progress is fundamental to achieving the dual targets of carbon peaking and economic growth. From the findings above, the annual reduction in energy intensity indicates that technological progress has a restraining effect on industrial carbon emissions in Jiangsu Province. Therefore, while adapting the energy structure of Jiangsu Province, we will encourage enterprises to accelerate the new generation of information technology as well as to develop and utilize new energy and materials. In this way, enterprises can improve technological innovation and use digital technology to promote the integration of green industry and information technology, so as to replace low-end energy-consuming output with high-value ones, and further promote the green and low-carbon development of industry, which will eventually increase energy efficiency and reduce carbon emissions. Furthermore, we should strive to develop strategic emerging industries and promote the deep integration and development of artificial intelligence and green, low-carbon industries.

Furthermore, according to the LMDI decomposition result, energy intensity and the optimization of energy structure will suppress industrial CO_2 emissions, and energy intensity plays an important role between them, which is consistent with the findings of other scholars. Wu and Xu [53] suggested that a reduction in energy intensity is the most important driving factor in the decrease in carbon emissions in Zhejiang, Guizhou, and Shaanxi provinces. Therefore, provinces with a developed economy and high industrial concentration, which is similar to Jiangsu Province, also need to strive to achieve green development through the adoption of new technologies and reduce carbon emissions. In order to achieve the carbon emission peak by 2030, policies to improve energy efficiency and reduce energy intensity need to be implemented in these regions. Industrial structure optimization and energy intensity reduction will contribute to a decrease in carbon emissions in different provinces to different degrees, no matter the various driving mechanisms among provinces.

Industrial carbon emissions are constrained by various social factors and closely correlated with elements such as regional economy, population, technology level, energy, and industrial structure. This article primarily analyzes the influencing factors on industrial carbon emissions in Jiangsu Province, which include energy consumption structure, carbon emission coefficients, energy intensity, employed population, and output per capita. Combined with the STIRPAT model, gray prediction model, and scenario setting, this article analyzes the path of industrial carbon peaking in Jiangsu. However, a detailed analysis of the influences of industrial distribution, industrial structure, and other factors on industrial carbon emissions in Jiangsu Province has not been conducted. This requires further refinement in future research. Additionally, carbon emissions among various industrial sub-sectors exhibit a complex correlational structure. Therefore, analyzing the carbon emission characteristics of Jiangsu Province's industrial sectors, constructing an industrial carbon emission framework detailing the linkages between sub-industrial sectors, exploring the roles and positions of each sub-sector within this structure, and proposing targeted paths and recommendations to reach industrial carbon peaking in Jiangsu represent worthwhile research endeavors.

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Conflict of Interest

The authors declare no conflict of interest.

Reference

1. IPCC special report. https://www.ipcc.ch/sr15/
2. IPCC circulates final draft of Synthesis Report to Sixth Assessment Report. https://www.ipcc.ch/2022/11/25/ipcc-circulates-final-draft-ar6-synthesis-report/
3. CHAVAILLAZ Y., ROY P., PARTANEN A.I., DA SILVA L., BRESSON É., MENGIS N., CHAUMONT D., MATTHEWS H.D. Exposure to excessive heat and impacts on labour productivity linked to cumulative CO_2 emissions. Scientific Reports, **9**, 13711, **2019**.
4. WANG F., CHAI W., LIU J., REN J., SHAN J., LI Z. City Size, Urban-rural Income Gap and Environmental Pollution: Empirical Evidence from 283 Cities in China. Polish Journal of Environmental Studies, **30** (4), 3287, **2021**.
5. FAN W., WANG F., LIU S., CHEN T., BAI X., ZHANG Y. How does financial and manufacturing co-agglomeration affect environmental pollution? Evidence from China. Journal of Environmental Management, **325**, 116544, **2023**.
6. TORVANGER A. Manufacturing sector carbon dioxide emissions in nine OECD countries, 1973–87: A Divisia index decomposition to changes in fuel mix, emission coefficients, industry structure, energy intensities and international structure. Energy Economics, **13** (3), 168, **1991**.
7. WANG C., CHEN J.N., ZOU J. Decomposition of energy-related CO2 emission in China: 1957–2000. Energy, **30** (1), 73, **2005**
8. HAMMOND G.P., NORMAN J.B. Decomposition analysis of energy-related carbon emissions from UK manufacturing. Energy, **41** (1), 220, **2012**
9. WÓJTOWICZ K.A., SZOŁNO-KOGUC J.M., BRAUN J. The Role of Public Spending in CO_2 Emissions Reduction in Polish Regions: An LMDI Decomposition Approach. Energies, **15**, 103, **2021**.
10. HASAN M.M., LIU K. Decomposition analysis of natural gas consumption in Bangladesh using an LMDI approach. Energy Strategy Reviews, **40**, 100724, **2022**.
11. LIN B., AHMAD I. Analysis of energy related carbon dioxide emission and reduction potential in Pakistan. Journal of Cleaner Production, **143**, 278, **2017**.
12. PETERS G.P., MINX J.C., WEBER C.L., EDENHOFER O. Growth in emission transfers via international trade from 1990 to 2008. Proceedings of the national academy of sciences, **108**, 8903, **2011**.
13. MOHAMMADI V., TABAR A.M.M., DASHTI N. Inter-fuel substitution and decomposition analysis of energy intensity: Empirical evidence from Iran. Energy Strategy Reviews, **39**, 100773, **2022**.
14. XU X.Y., ANG B.W. Index decomposition analysis applied to CO2 emission studies. Ecological Economics, **93**, 313, **2013**.
15. 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. Journal of Cleaner Production, **142**, 783, **2017**.
16. LIANG W., GAN T., ZHANG W. Dynamic evolution of characteristics and decomposition of factors influencing industrial carbon dioxide emissions in China: 1991–2015. Structural Change and Economic Dynamics, **49**, 93, **2019**.
17. ANG B.W., ZHANG F.Q., CHOI K.H. Factorizing changes in energy and environmental indicators through decomposition. Energy, **23** (6), 489, **1998**.
18. ZHANG M., LIU X., WANG W, ZHOU M. Decomposition analysis of CO2 emissions from electricity generation in China. Energy Policy, **52**, 159, **2013**.
19. ZHANG J., FAN Z., CHEN Y., GAO J., LIU W. Decomposition and decoupling analysis of carbon dioxide emissions from economic growth in the context of China and the ASEAN countries. Science of the Total Environment, **714**, 136649, **2020**.
20. DIETZ T., ROSA E.A. Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences, **94** (1), 175, **1997**.
21. FAN Y., LIU L.C., WU G., WEI Y.M. Analyzing impact factors of CO2 emissions using the STIRPAT model. Environmental Impact Assessment Review, **26** (4), 377, **2006**.
22. LIU S., XIAO Q. An empirical analysis on spatial correlation investigation of industrial carbon emissions using SNA-ICE model. Energy, **224**, 120183, **2021**.
23. HAN X., YU J., XIA Y., WANG J. Spatiotemporal characteristics of carbon emissions in energy-enriched areas and the evolution of regional types. Energy Reports, **7**, 7224, **2021**.
24. CHEN L., XU L., CAI Y., YANG Z. Spatiotemporal patterns of industrial carbon emissions at the city level. Resources, Conservation and Recycling, **169**, 105499, **2021**.
25. ZHENG Y., DU S., ZHANG X., BAI L., WANG H. Estimating carbon emissions in urban functional zones using multi-source data: A case study in Beijing. Building and Environment, **212**, 108804, **2022**.
26. RAUPACH M.R., MARLAND G., CIAIS P., LE QUÉRÉ C., CANADELL J.G., KLEPPER G., FIELD C.B. Global and regional drivers of accelerating CO2 emissions. Proceedings of the National Academy of Sciences, **104** (24), 10288, **2007**.
27. LU Y., CUI P., LI D. Carbon emissions and policies in China's building and construction industry: Evidence from 1994 to 2012. Building and Environment, **95**, 94, **2016**.
28. YE B., JIANG J., LI C., MIAO L., TANG J. Quantification and driving force analysis of provincial-level carbon emissions in China. Applied Energy, **198**, 223, **2017**.
29. OHYAMA H., SHIOMI K., KIKUCHI N., MORINO I., MATSUNAGA T. Quantifying CO_2 emissions from a thermal power plant based on CO_2 column measurements by portable Fourier transform spectrometers. Remote Sensing of Environment, **267**, 112714, **2021**.
30. STEEN-OLSEN K., WOOD R., HERTWICH E.G. The carbon footprint of Norwegian household consumption 1999–2012. Journal of Industrial Ecology, **20**, 582, **2016**.
31. SUN W., HUANG C. Predictions of carbon emission intensity based on factor analysis and an improved extreme learning machine from the perspective of carbon emission efficiency. Journal of Cleaner Production, **338**, 130414, **2022**.
32. LIU L., ZONG H., ZHAO E., CHEN C., WANG J. Can China realize its carbon emission reduction goal in 2020: From the perspective of thermal power development. Applied Energy, **124**, 199, **2014**.
33. XU F., XIANG N., YAN J., CHEN L., NIJKAMP P., HIGANO Y. Dynamic simulation of China's carbon emission reduction potential by 2020. Letters in Spatial and Resource Sciences, **8**, 15, **2015**.
34. WANG K., WANG C., LU X., CHEN J. Scenario analysis on CO2 emissions reduction potential in China's iron and steel industry. Energy Policy, **35**, 2320, **2007**.

35. MCCOLLUM D., YANG C. Achieving deep reductions in US transport greenhouse gas emissions: Scenario analysis and policy implications. Energy Policy, **37** (12), 5580, **2009**.
36. DONG K., JIANG H., SUN R., DONG X. Driving forces and mitigation potential of global CO2 emissions from 1980 through 2030: Evidence from countries with different income levels. Science of the Total Environment, **649**, 335, **2019**.
37. REN F., LONG D. Carbon emission forecasting and scenario analysis in Guangdong Province based on optimized Fast Learning Network. Journal of Cleaner Production, **317**, 128408, **2021**.
38. LIN B., OUYANG X. Energy demand in China: Comparison of characteristics between the US and China in rapid urbanization stage. Energy conversion and management, **79**, 128, **2014**.
39. LIN B., TAN R. Estimating energy conservation potential in China's energy intensive industries with rebound effect. Journal of Cleaner Production, **156**, 899, **2017**.
40. NIU S., LIU Y., DING Y., QU W. China's energy systems transformation and emissions peak. Renewable and Sustainable Energy Reviews, **58**, 782, **2016**.
41. ZHANG X., KARPLUS V.J., QI T., ZHANG D., HE J. Carbon emissions in China: How far can new efforts bend the curve? Energy Economics, **54**, 388, **2016**.
42. LI F., XU Z., MA H. Can China achieve its CO2 emissions peak by 2030? Ecological Indicators, **84**, 337, **2018**.
43. WANG H., LU X., DENG Y., SUN Y., NIELSEN C.P., LIU Y.F., ZHU G., BU M.L., BI J., MCELROY M.B. China's CO2 peak before 2030 implied from characteristics and growth of cities. Nature Sustainability, **2**, 748, **2019**.
44. LASPEYRES E. Die berechnung einer mittleren waarenpreissteigerung. Jahrbücher für Nationalökonomie und Statistik, **196**, 218, **1981**.
45. ANG B.W. The LMDI approach to decomposition analysis: a practical guide. Energy Policy, **33**, 867, **2005**.
46. YANG J., CAI W., MA M.D., LI L., LIU C.H., MA X., LI L.L., CHEN X.Z. Driving forces of China's CO_2 emissions from energy consumption based on Kaya-LMDI methods. Science of the Total Environment, **711**, 134569, **2020**.
47. JEHLIČKA P., JACOBSSON K. The importance of recognizing difference: Rethinking Central and East European environmentalism. Political Geography, **87**, 102379, **2021**.
48. CAI B., ZHAO L, ZHANG Z, LU X., JIA M., ZHANG L., LIU M., LEI Y., JIANG L., GAO Y., NING L., GUO J., WU P. China Regional Power Grids Carbon Dioxide Emission Factors. Ministry of Ecology and Environment of the People's Republic of China, **2023** [In Chinese].
49. GAO C., LIU Y., JIN J., WEI T., ZHANG J., ZHU L. Driving forces in energy-related carbon dioxide emissions in east and south coastal China: commonality and variations. Journal of Cleaner Production, **135**, 240, **2016**.
50. TAN X., DONG L., CHEN D., GU B., ZENG Y. China's regional CO_2 emissions reduction potential: A study of Chongqing city. Applied Energy, **162**, 1345, **2016.**
51. MOONCHAI S., CHUTSAGULPROM N. Short-term forecasting of renewable energy consumption: Augmentation of a modified grey model with a Kalman filter. Applied Soft Computing, **87**, 105994, **2020**.
52. YE L.L., XIE N.M., HU A.Q. A novel time-delay multivariate grey model for impact analysis of CO_2 emissions from China's transportation sectors. Applied Mathematical Modelling, **91**, 493, **2021**.
53. WU Y., XU B. When will China's carbon emissions peak? Evidence from judgment criteria and emissions reduction paths. Energy Reports, **8**, 8722, **2022**.