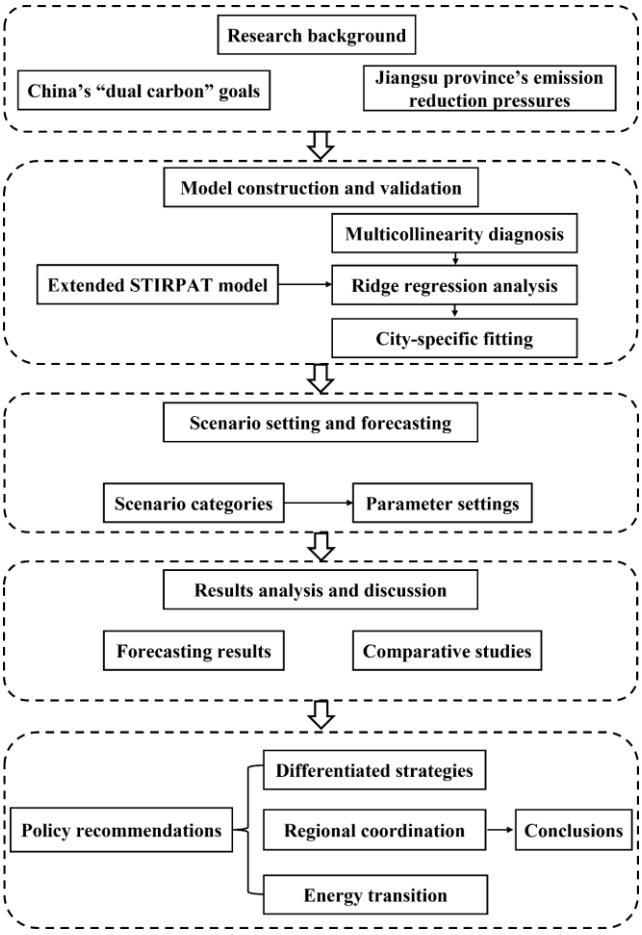
Global NEST Journal, Vol 27, No 10, 07678
Copyright© 2025 Global NEST
Printed in Greece. All rights reserved

Forecasting carbon emission peaking in Jiangsu province from a multi-city perspective: An extended STIRPAT model and differentiated scenario analysis

Xuelin Zhang[A], Mingjun Liao[A] and Shenghai Fan[A]
[A]School of Materials Engineering, Yancheng Institute of Technology, Yancheng, 224051, China
Received: 21/05/2025, Accepted: 05/10/2025, Available online: 11/11/2025
*to whom all correspondence should be addressed: e-mail: dahaitg@163.com
https://doi.org/10.30955/gnj.07678

Graphical abstract



Abstract

Carbon emissions have consistently been a focal point of attention for the Chinese government. As one of the key drivers of China's economy, Jiangsu province plays a pivotal role in achieving the dual carbon goals. This study is grounded in data from Jiangsu province spanning 2003 to 2022 and constructs an extended STIRPAT model to delve into the impact of factors such as population, GDP per capita, urbanization rate, industrial structure, energy consumption intensity, and per capita energy consumption on carbon emissions. Additionally, this paper forecasts the future carbon emission trends of the 13 cities in Jiangsu province under different scenarios and explores the possibility of the province reaching its carbon peak. The findings reveal that cities exhibit varying degrees of sensitivity to influencing factors. Under the baseline scenario, cities like Wuxi and Zhenjiang are expected to achieve carbon peaking by 2030, whereas in more economically developed areas such as Nanjing and Suzhou, the timing of carbon peak may be relatively delayed. In the green development scenario, all cities across the province are projected to reach carbon peak ahead of schedule. Moreover, scenarios of industrial structure optimization and energy conservation are also found to accelerate the process of carbon peaking. However, under the extensive development scenario, only a few cities are likely to achieve carbon peaking before 2030. Accordingly, Jiangsu province should formulate differentiated carbon peak targets based on the specific circumstances of each city and strengthen inter-regional coordinated development. Simultaneously, the government needs to adopt more robust policy measures to facilitate the optimization and adjustment of the energy structure, the upgrading of industrial structures, and the enhancement of energy efficiency, thereby ensuring the successful realization of the province's carbon peak goals.

Keywords: STIRPAT model; carbon emissions; carbon peak; scenario analysis

1. Introduction

Global climate change is undoubtedly one of the greatest challenges for future economic and social development, with human activities being the primary driving force (IPCC, 2014). This has compelled governments worldwide to attach great importance and assume the responsibility of addressing climate change. As the largest emitter of carbon dioxide in the world, China faces immense pressure to reduce emissions (Yu and Qu, 2013; Liu *et al.*, 2022; Bai *et al.*, 2024). On September 22, 2020, China solemnly announced at the 75th United Nations General

Assembly its commitment to peaking carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060. The realization of these goals requires not only top-level design at the national level but also effective carbon reduction measures in regions, especially in economically developed and densely populated provinces like Jiangsu. As an economically prominent province, Jiangsu faces substantial energy demands from both its population and industrial sectors, making energy conservation and emission reduction particularly challenging (Zhang and Huang, 2012; Long *et al.*, 2015; Li *et al.*, 2023). Therefore, a thorough analysis of the factors influencing carbon emissions in Jiangsu and the prediction of the timing and peak of carbon emission peaking are crucial for formulating regional carbon reduction strategies.

In terms of research methods for predicting carbon emission trends and timing of carbon peak, the main approaches include the input-output model, system dynamics model, neural network model, and STIRPAT model, among others (Tarancon and Del Rio, 2012; Anser, 2019; Huo *et al.*, 2022). Qiao *et al.* (2021) used a new cumulative grey model (DGM (β,1)) to predict the CO_2 emissions of 17 APEC member countries through taking 2014-2019 data as the original data and testing the model accuracy by the MAPE value, suggesting that among these 17 countries, 13 are expected to show an upward trend in CO_2 emissions while 4 present a downward trend during 2020-2023, and all countries should pay more attention to the issue of CO_2 emissions and adjust their climate and energy policies. Chaudry *et al.* (2022) employed a novel coupled multi-scale energy and transport system model to simulate Britain's net-zero carbon emission scenario for 2050, concluding that smart electrification of heat and transport is the most cost-effective pathway for Britain to achieve net-zero carbon emissions by 2050. Sang and Shen (2024) employed an innovative two-step method (Mann-Kendall trend test + Tapio decoupling model) to analyze the carbon peaking status of 154 countries in three dimensions, classified the countries into four income groups, and provided references for targeted carbon reduction and global carbon neutrality. Yang *et al.* (2024) used a data-driven rule-based model to predict the carbon peak trajectories of China's 30 provinces through time-series forecasting, suggesting that most provinces are expected to achieve carbon peak before 2030 under policy interventions. Xia *et al.* (2024) categorized provinces based on the Environmental Kuznets Curve theory and constructed a carbon emission prediction model integrating time-series and impact factor models, combined with Monte Carlo simulation for scenario analysis, concluding that there are differences in carbon peak timing among China's provinces. Zhang and Luo (2023) utilized the LEAP model for scenario analysis of carbon emissions from public buildings in China, exploring carbon peak predictions and pathways through setting baseline and mitigation scenarios, suggesting that the carbon peak may occur between 2030 and 2035. Tian *et al.* (2022) analyzed the driving factors of carbon emissions in different cities in Shandong province using an extended STIRPAT model and predicted the timing and peak of carbon emissions for various cities and the province through scenario analysis. Yin *et al.* (2023) proposed a novel grey model PGM (1, N) based on multi-parameter combination optimization for predicting China's CO_2 emissions, which optimizes the driving terms by differentiating the definition and optimization of variable orders and introducing a smoothing generation operator, suggesting that China's carbon emissions will continue to grow.

Nevertheless, there is still controversy among scholars regarding whether China can achieve its carbon emission peaking target by 2030. Particularly for Jiangsu, an economically developed region, the analysis of carbon emissions and their peaking predictions at the municipal level is insufficient, lacking a comprehensive regional prediction of peaking scenarios and corresponding policy recommendations. Therefore, this paper employs the extended STIRPAT model and ridge regression analysis method to predict the future trends of carbon dioxide emissions for Jiangsu's 13 prefecture-level cities and to formulate targeted peaking strategies, thereby providing a scientific basis for China to achieve its overall carbon emission peaking goal.

2. Method and data

Due to the differences in social and economic development and carbon emissions among the 13 prefecture-level cities within Jiangsu province, including Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yancheng, Yangzhou, Zhenjiang, Taizhou, and Suqian, this article first assesses the energy-related carbon emissions of each city from 2003 to 2022. Then, using the STIRPAT model, factors such as population, per capita GDP, urbanization rate, industrial structure, energy consumption intensity, and per capita energy consumption are selected as influencing factors. Through regression fitting, a carbon emission prediction model for the 13 prefecture-level cities in Jiangsu province is constructed. Different scenarios are then set to predict the future carbon emission trends of the 13 cities in Jiangsu province. Based on this analysis, the peak carbon emissions of Jiangsu province as a whole are analyzed, and policy recommendations are provided for the early achievement of peak carbon emissions in Jiangsu province and its 13 prefecture-level cities.

2.1. Data sources

This paper has collated data on population, per capita GDP, urbanization rate, industrial structure, per capita energy consumption, energy consumption intensity, and CO_2 emissions for the 13 cities in Jiangsu province from 2003 to 2022 through various channels. Among these, data on population, per capita GDP, urbanization rate, and industrial structure are primarily sourced from the "Statistical Yearbooks" (2003-2022) and "Bulletins of National Economic and Social Development" (2003-2022) published by the statistical bureaus of each city. Data on energy consumption are derived from the "Energy Statistical Yearbooks" of various cities. The CO_2 emissions from energy consumption are calculated by multiplying

the energy consumption by the carbon emission factors and then aggregating the results. The conversion coefficients for standard coal and carbon emission factors for various types of energy are presented in **Table 1**. **Figure 1** presents the carbon emissions for various cities as calculated through accounting measures.

Table 1. Conversion coefficients to standard coal and carbon emission factors for various types of energy

Type of Energy	Unit	Conversion Coefficient to Standard Coal	Carbon Emission Factor
Raw Coal	10,000 tons	0.7143	0.7559
Gasoline	10,000 tons	1.4714	0.5538
Kerosene	10,000 tons	1.4714	0.5714
Diesel Oil	10,000 tons	1.4571	0.5921
Fuel Oil	10,000 tons	1.4286	0.6185
Liquefied Petroleum Gas	10,000 tons	1.7143	0.5042
Natural Gas	billion cubic meters	13.3	0.4483

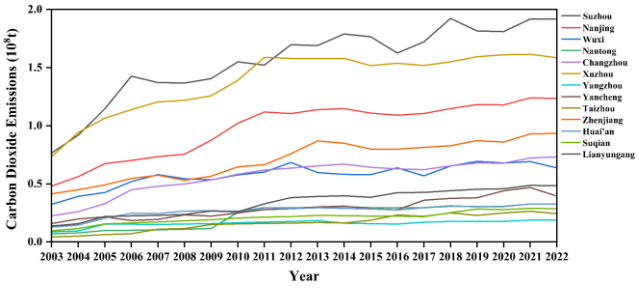


Figure 1. Carbon emission data for the 13 cities in Jiangsu province from 2003 to 2022

2.2. STIRPAT model

The IPAT model, first proposed by American ecologist Ehrlich and Holden (1971), is used to assess the impact of human activities on the environment. The name of the model is derived from its four main variables: environmental impact (*I*), population (*P*), affluence or per capita consumption (*A*), and technology (*T*). The formula is expressed as:

$$I = P \times A \times T \quad (1)$$

However, the IPAT model has certain linear limitations, as it assumes that different factors contribute equally to environmental pressure, which contradicts the Environmental Kuznets Curve hypothesis. To overcome the limitations of the model, Dietz and Rosa proposed the STIRPAT model based on the IPAT model (Dietz and Rosa, 1997; York *et al.*, 2003), with its expression shown in Equation (2):

$$I = a \times P^b \times A^c \times T^d \times e \quad (2)$$

In the equation, *I* represents environmental pressure, *P* denotes population, *A* stands for affluence, *T* indicates technology level, *a* is the model coefficient, *b*, *c*, and *d* are the elasticity coefficients for *P*, *A*, and *T* respectively, and *e* is the random error term. The IPAT model is a special form of the STIRPAT model, where $a = b = c = d = e = 1$.

The STIRPAT model is a multivariate nonlinear model. In empirical analysis, the logarithm of both sides of equation (2) is generally taken:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \quad (3)$$

Using *lnI* as the dependent variable, *lnP*, *lnA*, and *lnT* as independent variables, *lna* as the constant term, and *lne* as the error term, the logarithmic model can be fitted with multiple linear regression to obtain *a*, *b*, *c*, and *d*. The elasticity coefficients indicate that a 1 % change in *P*, *A*, and *T* will result in *b* %, *c* %, and *d* % changes in *I*, respectively.

The STIRPAT model rejects the unit elasticity hypothesis, introduces randomness, and facilitates empirical analysis. Additionally, the STIRPAT model can incorporate various factors affecting environmental pressure, such as urbanization, industrial structure, and energy consumption intensity (Tang and Hu, 2021). Therefore, the STIRPAT model is most widely used in quantifying the relationship between carbon emissions and various influencing factors (Ofori *et al.*, 2023). It is the most commonly used and recognized model for studying carbon emission peak issues.

Based on existing research, population (*p*), per capita GDP (*A*), urbanization rate (*U*), industrial structure (*IS*), and energy consumption intensity (*EI*) are widely used in carbon emission studies and can significantly impact carbon emissions (Wang *et al.*, 2013; Lin and Du, 2015; Lin *et al.*, 2017; Xue *et al.*, 2022). However, few studies have explored the impact of per capita energy consumption (*PEC*) on carbon emissions. Since per capita energy consumption is a crucial indicator of energy utilization efficiency, reducing it is a key pathway to achieving green and low-carbon energy transformation. Therefore, this paper supplements per capita energy consumption as a major influencing factor. In summary, this paper selects these six factors as the influencing factors of carbon emissions and constructs an extended STIRPAT model, with its expression as follows:

$$\ln I = b\ln P + c\ln A + d\ln U + f\ln IS + g\ln PEC + h\ln EI + j \quad (4)$$

The equation is as follows: *I* represents carbon dioxide emissions, *P* stands for population, *A* is per capita GDP, *U* denotes urbanization rate, *IS* is industrial structure, *PEC* refers to per capita energy consumption, and *EI* is energy consumption intensity. The coefficients *b*, *c*, *d*, *f*, *g*, and *h* represent the elasticity of each variable, while *j* is a constant, calculated as: *lna* + *lne*, where *a* is the model coefficient and *e* is the random error term. The explanations of each variable in the model are shown in **Table 2**.

Table 2. Model variable description

Variable	Explanation or Description	Unit
Carbon dioxide emissions(*I*)	Energy consumption carbon dioxide emissions	10^8t
Population (*P*)	Year-end permanent population	Ten thousand people
Per capita GDP(*A*)	Gross Domestic Product (GDP) / Year-end Permanent Population	Yuan per person
Urbanization rate(*U*)	Proportion of Urban Residents in Total Population	%
Industrial structure(*IS*)	Proportion of the Secondary Industry in Gross Domestic Product (GDP)	%
Per capita energy consumption(*PEC*)	Energy consumption / Year-end Permanent Population	Tonnes of coal equivalent per person
Energy consumption intensity(*EI*)	Energy Consumption per Unit of Gross Domestic Product (GDP)	Million tonnes of coal equivalent per billion yuan

3. Analysis of model regression fitting results

3.1. Analysis of multicollinearity

When performing multiple regression calculations, if there is a correlation among multiple independent variables, it will cause the coefficients in the model to lose practical significance. Therefore, it is necessary to perform multicollinearity diagnosis on the logarithmic values of the original data of the independent variables in the model (Xu and Wang, 2020). Taking Nanjing as an example, based on the collected data, SPSS software was used to perform multiple regression analysis and calculate the variance inflation factor, as shown in **Table 3**. By analyzing the model fitting situation through the R^2 value, and analyzing the variance inflation factor (VIF), if VIF is greater than 10 or 5, strictly 10, then the model exhibits collinearity (Shrestha, 2020). From **Table 3**, it can be seen that the variance inflation factors of various factors are much higher than 10, and the variance inflation factor of per capita GDP is as high as 760.6, indicating that there is severe multicollinearity among variables. Therefore, it is not possible to make judgments based on the results fitted by ordinary least squares, and the multicollinearity of independent variables must be eliminated to obtain reasonable results.

Table 3. Multicollinearity test of independent variables

Influencing factors	Coefficient	Standard error(S)	t-statistic	Probability(P)	VIF
Constant	-14.367	8.55	-1.68	0.117	—
Population (ln*P*)	1.594	1.054	1.512	0.154	130.4
Per capita GDP(ln*A*)	-0.687	0.523	-1.314	0.212	760.6
Urbanization rate(ln*U*)	0.565	0.917	0.616	0.548	28.4
Industrial structure(ln*IS*)	1.756	0.545	3.225	0.007	39.4
Per capita energy consumption(ln*PEC*)	1.174	0.532	2.208	0.046	70.5
Energy consumption intensity(ln*EI*)	-1.057	0.508	-2.08	0.058	525.1
R^2	0.979				
F	F=100.752 P=0.000				

Table 4. Estimates by ridge regression

Influencing factors	Unstandardized coefficients		t-statistic	Probability(P)
	B	Standard error(S)		
Constant	-10.383	1.542	-6.733	0.000***
Population (ln*P*)	0.691	0.112	6.149	0.000***
Per capita GDP(ln*A*)	0.083	0.012	7.155	0.000***
Urbanization rate(ln*U*)	0.842	0.268	3.135	0.008***
Industrial structure(ln*IS*)	0.158	0.139	1.135	0.277
Per capita energy consumption(ln*PEC*)	0.33	0.107	3.086	0.009***
Energy consumption intensity(ln*EI*)	-0.093	0.022	-4.337	0.001***
R^2	0.927			
F	F=27.529 P=0.000			

Note: **** indicates P<0.01.*

3.2. Ridge regression analysis

Due to the issue of multicollinearity among the logarithms of the five influencing factors, the ridge regression analysis method can be employed to address this problem (Meng *et al.*, 2021). Ridge regression analysis serves as a complement to the ordinary least squares regression, effectively mitigating the multicollinearity issue, and enhancing the computational accuracy, stability, and reliability of the model (Shariff and Duzan, 2018). Therefore, this paper selects ridge regression analysis to resolve the multicollinearity problem, taking Nanjing as an example. The ridge regression function in SPSS software is utilized to fit Equation (4), with the ridge regression coefficient k ranging within the interval (0,1) and taking values at a step size of 0.01. When k equals 0.184, the Ridge trace plot exhibits a gradual stabilization, as shown in **Figure 2**. The specific Ridge Regression estimation results are presented in **Table 4**.

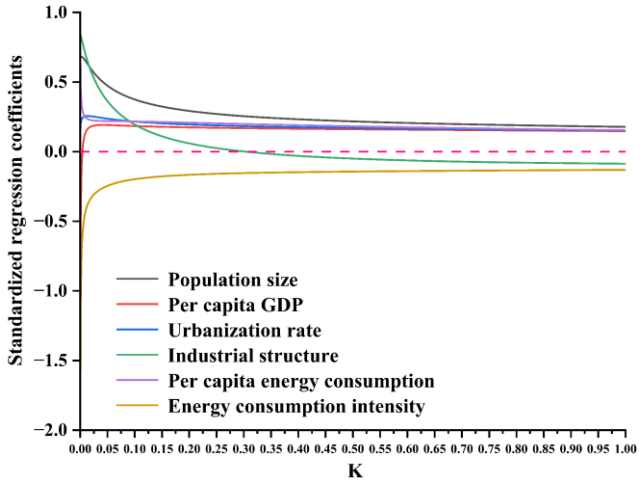


Figure 2. Ridge trace

The coefficients of the ridge regression, with the exception of the industrial structure, have all passed the significance level test at 1%. The R^2 value is 0.927, indicating a good overall fit, and the F-statistic has also passed the significance level test at 1%, suggesting that the six factors including population, per capita GDP, urbanization rate, industrial structure, per capita energy consumption and energy consumption intensity can explain 92.7% of the variation in carbon emissions from energy consumption. This validates the rationality of selecting these six factors. Consequently, a carbon emission prediction model for Nanjing can be derived, with the model equation as follows:

$$\ln I = 0.691\ln P+0.083\ln A+0.842\ln U+0.158\ln IS +0.33\ln PEC-0.093\ln EI-10.383 \quad (5)$$

Based on the positive and negative effects reflected by the elasticity coefficients, the elasticity coefficients for population, per capita GDP, urbanization rate, industrial structure, and per capita energy consumption are positive, indicating a positive effect. This suggests a significant positive correlation between these factors and carbon emissions, with their changes driving the increase in carbon emissions from energy consumption in Nanjing. Conversely, the elasticity coefficient for energy consumption intensity is negative, indicating a negative effect and a significant negative correlation with carbon emissions. The results demonstrate that economic and social development drives the growth in energy demand, leading to increased carbon emissions. The peak of carbon emissions and the time to reach this peak depend on the combined action of these factors. The comparison between the fitted values of carbon emissions by the model and the actual values is illustrated in **Figure 3**. It can be observed that the model effectively simulates the growth and trends in carbon emissions from energy consumption in Nanjing.

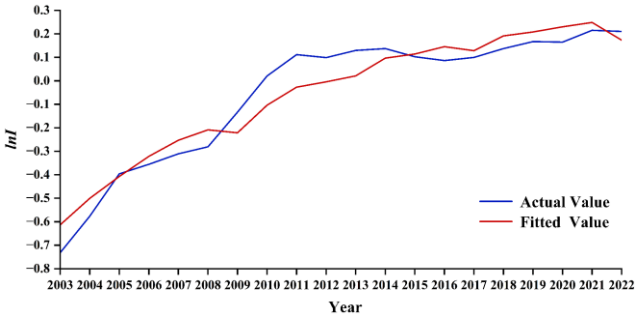


Figure 3. Comparison chart of fitted and actual carbon emissions from energy consumption

Similarly, through ridge regression analysis, fitting the carbon emissions with various influencing factors, carbon emission prediction models were constructed for the remaining 12 cities in Jiangsu province, with the relevant results shown in **Table 5**. The table indicates that carbon emissions in different cities exhibit varying sensitivities to influencing factors. This discrepancy may arise from the unequal economic development among cities, or it could be due to the differing resource endowments and technological capabilities across these urban areas. In **Table 5**, we note an anomalous phenomenon: the population regression coefficients for cities such as Xuzhou, Yancheng, and Taizhou exhibit negative values, which is contrary to our general understanding. A deeper analysis reveals that this phenomenon is due to the year-on-year decline in the population of these cities, as residents increasingly migrate to more developed areas in search of opportunities. However, the carbon emissions of these cities have not decreased correspondingly; on the contrary, they have been increasing annually. Therefore, the observed negative coefficients are actually an illusion. When assessing the positive or negative impact of regression coefficients, we must consider a variety of specific circumstances and influencing factors, and conduct a systematic analysis and judgment.

4. Analysis of future carbon emission trends in the 13 cities of Jiangsu province

4.1. Future carbon emission scenario setting

Based on the extended STIRPAT model, scenario analysis is employed to simulate the peak and timing of energy carbon emissions in the 13 cities of Jiangsu from 2023 to 2040. In line with the future economic and social development of Jiangsu and the trend towards green and low-carbon energy transformation, five carbon emission growth scenarios are established: the baseline

scenario(S1), green development scenario(S2), industrial structure optimization scenario(S3), energy conservation scenario(S4) and extensive development scenario(S5). The parameter settings for the six influencing factors refer to relevant policies and historical data trends in population, energy, and urbanization. The rates of change for each influencing factor are set based on the median values, with adjustments made to reflect the low and high ends of the spectrum.

Table 5. Carbon emission regression fitting results of the 13 cities in Jiangsu province

City	lnP	lnA	lnU	lnIS	lnPEC	lnEI	Cons	k	R^2
Suzhou	0.196*	0.132***	0.833***	0.353*	0.269***	-0.108***	-7.934***	0.075	0.959
Nanjing	0.691***	0.083***	0.842***	0.158	0.33***	-0.093***	-10.383***	0.184	0.927
Wuxi	0.558***	0.114***	0.439**	0.46**	0.256**	-0.064**	-9.642***	0.116	0.899
Nantong	0.25	0.177***	0.295	-0.537	0.622***	-0.179	-5.184	0.102	0.885
Changzhou	1.491***	0.139***	-1.034***	0.149	0.477***	-0.154***	-8.337***	0.115	0.973
Xuzhou	-2.12***	0.095***	-0.135	-0.186	0.278***	-0.094***	14.633***	0.155	0.956
Yangzhou	1.288	0.055***	0.58***	0.872*	0.307**	0.022	-16.544	0.083	0.837
Yancheng	-1.18*	0.069***	0.26**	-0.903**	0.244***	-0.054	7.859*	0.097	0.939
Taizhou	-3.021	0.181***	0.684***	0.36	0.544***	-0.177***	9.639	0.156	0.957
Zhenjiang	1.815***	0.063***	0.205*	-0.316	0.134**	-0.131***	-11.348***	0.143	0.952
Huai'an	-0.773	0.05***	0.345***	0.498	0.262***	0.011	-0.604	0.2	0.863
Suqian	-0.585	0.085***	0.211***	0.038	0.357***	-0.036	-0.128	0.14	0.949
Lianyungang	2.029	0.145***	0.263**	1.078*	0.328***	-0.163***	-20.567*	0.083	0.964

*Note: ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.*

Table 6. Annual average rate of change settings for each factor in different scenarios

Years	Scenario	P	A	U	IS	PEC	EI
2023-2025	S1	1%	6%	0.9%	-2.2%	-3.2%	-3.3%
	S2	0.95%	5.5%	0.85%	-2.6%	-3.6%	-3.7%
	S3	1%	6%	0.9%	-2.6%	-3.2%	-3.3%
	S4	1%	6%	0.9%	-2.2%	-3.6%	-3.7%
	S5	1.05%	6.5%	0.95%	-2%	-3%	-2.9%
2026-2030	S1	0.95%	5.5%	0.7%	-2.4%	-3.4%	-3.5%
	S2	0.9%	5%	0.65%	-2.8%	-3.8%	-3.9%
	S3	0.95%	5.5%	0.7%	-2.8%	-3.4%	-3.5%
	S4	0.95%	5.5%	0.7%	-2.4%	-3.8%	-3.9%
	S5	1%	6%	0.75%	-2.2%	-3.2%	-3.1%
2031-2035	S1	0.9%	5%	0.5%	-2.6%	-3.6%	-3.7%
	S2	0.85%	4.5%	0.45%	-3%	-4%	-4.1%
	S3	0.9%	5%	0.5%	-3%	-3.6%	-3.7%
	S4	0.9%	5%	0.5%	-2.6%	-4%	-4.1%
	S5	0.95%	5.5%	0.55%	-2.4%	-3.4%	-3.3%
2036-2040	S1	0.85%	4.5%	0.3%	-2.8%	-3.8%	-3.9%
	S2	0.8%	4%	0.25%	-3.2%	-4.2%	-4.3%
	S3	0.85%	4.5%	0.3%	-3.2%	-3.8%	-3.9%
	S4	0.85%	4.5%	0.3%	-2.8%	-4.2%	-4.3%
	S5	0.9%	5%	0.35%	-2.6%	-3.6%	-3.5%

Despite the issuance of policies such as the "14th Five-Year Plan for National Economic and Social Development of Jiangsu province and the Long-Range Objectives for 2035" and the "Implementation Plan for Carbon Peaking in Industrial Sectors and Key Industries in Jiangsu province," which offer some constructive suggestions on the change rates of various factors in the future, it is necessary to tailor these rates to the actual conditions of each city. Under the guidance of relevant policy documents and in conjunction with the historical data trends of each city, the change rates of influencing factors are set for each city. Taking Nanjing as an example, **Table 6** presents the change rates of influencing factors from 2023 to 2040 for Nanjing.

Nanjing has achieved significant success in controlling population, improving the quality of economic growth, and optimizing the process of urbanization. Through the implementation of stringent ecological and environmental protection policies and the promotion of high-quality economic development, Nanjing has progressively decoupled population growth from economic expansion. As a result, although the growth rates of population(*P*), per capita GDP(*A*), and urbanization(*U*) continue to be positive, the magnitude of growth has been decreasing annually.

Simultaneously, Nanjing has accelerated the optimization and upgrading of its industrial structure, encouraging the development of low-energy-consuming and high-value-added industries, while intensifying the elimination of high-energy-consuming industries. In addition, the effective promotion of energy-saving technologies and clean energy has led to a significant reduction in per

capita energy consumption and energy consumption intensity. Consequently, the growth rates for industrial structure(*IS*), per capita energy consumption(*PEC*), and energy consumption intensity(*EI*) are set to be negative, with the magnitude of decline increasing year by year.

4.2. Analysis of future carbon emission trends in cities of Jiangsu province

Based on the carbon emission prediction models for various cities, this paper calculates the carbon emissions from 2023 to 2040 under five different scenarios (**Figure 4**) and determines the peak carbon emission times for each city under these scenarios (**Table 7**).

Figure 4. Carbon emission forecasting for cities in Jiangsu province.

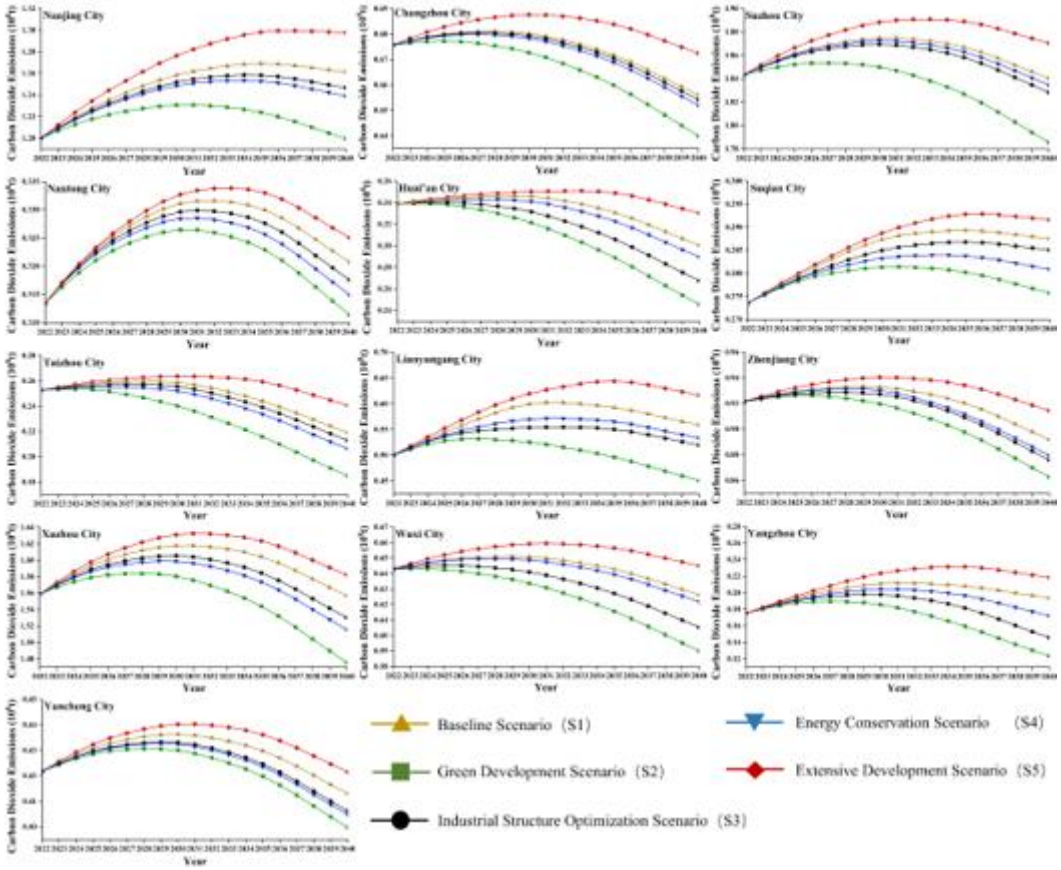


Table 7. Peak carbon emission times for various cities in Jiangsu under different scenarios.

City	Peak emission time				
	S1	S2	S3	S4	S5
Nanjing	2035	2031	2034	2034	2037
Changzhou	2028	2025	2027	2027	2031
Suzhou	2031	2027	2030	2030	2033
Nantong	2032	2030	2031	2031	2033
Huai'an	2029	2025	2024	2028	2033
Suqian	2035	2031	2035	2033	2036
Taizhou	2028	2024	2027	2026	2030
Lianyungang	2031	2027	2030	2030	2035
Zhenjiang	2029	2025	2027	2028	2030
Xuzhou	2031	2028	2030	2029	2031
Wuxi	2029	2025	2025	2028	2031
Yangzhou	2031	2027	2029	2030	2034
Yancheng	2030	2028	2029	2029	2031

Table 7 reveals that the timing of carbon peak varies across cities in Jiangsu province under distinct scenarios. In the baseline scenario (S1), most cities are anticipated to achieve carbon peak around 2030, whereas cities such as Changzhou, Huai'an, and Taizhou have already reached this milestone prior to 2030. However, in economically advanced regions like Nanjing and Suzhou, the carbon peak is projected to occur somewhat later than in other urban areas. Within the green development scenario (S2), all cities notably bring forward their carbon peak, with the majority achieving it between 2025 and 2030, which

demonstrates that green development strategies are instrumental in expediting carbon neutrality. In scenarios focused on industrial structure optimization (S3) and energy conservation (S4), the timing of carbon peak is also earlier, though marginally later than under the green development scenario, indicating that structural adjustments and energy-saving initiatives can moderately hasten the emission reduction process, despite some cities experiencing a slight delay. In the extensive development scenario (S5), only Taizhou and Zhenjiang are projected to reach carbon peak by 2030, while all other cities will see this event occur after 2030, with certain cities not achieving it until after 2035.

These findings underscore the pronounced influence of diverse policy contexts on the timing of carbon peak, emphasizing the critical role of governmental involvement. Policies promoting green development and energy efficiency are particularly effective in fostering early carbon neutrality. Given the higher carbon emissions in economically prosperous regions, it is imperative to enhance environmental conservation measures alongside economic pursuits. The varying abilities of cities to address climate change, due to disparities in location, resource availability, and development status, necessitate tailored policy approaches. The extensive development scenario (S5) cautions that a passive reliance on spontaneous economic transformation is inadequate and could result in prolonged negative impacts.

5. Discussion

Through comparative analysis with other related studies, it is evident that the peak carbon emission predictions for most cities in this paper are largely consistent with findings from other research. For instance, Chen *et al.* (2023) utilized the LEAP model to study the peak time for Nanjing and concluded that the target for carbon peak by 2030 would not be achieved; Sun *et al.* (2022) suggested that the total CO_2 emissions in Suzhou are expected to peak around 2030; According to the study by Qin *et al.* (2024), they invoked the KAYA identity model and posited that under the optimal scenario, the peak carbon emissions for Wuxi city would materialize in either 2025 or 2026.

While the current study provides valuable insights, it's important to acknowledge that certain peak predictions deviate from findings in another research. For instance, our analysis suggests that Nantong may reach its carbon emissions peak between 2030 and 2033, which contrasts with the prediction by Wang and Dong (2024) that Nantong could achieve carbon neutrality before 2030 under specific scenarios. Similarly, regarding Suqian, our study indicates that reaching the peak before 2030 under various scenarios might be challenging, whereas Wang and Dong (2024) propose a potential peak between 2025 and 2029. These discrepancies likely stem from the distinct approaches each study employs in assigning policy implications to different scenarios, ultimately leading to variations in projected future change rates for influencing factors.

6. Policy suggestions

Achieving carbon peak in the 13 cities of Jiangsu province by 2030 is an arduous task. Significant variations are observed in the future carbon emission trends across the cities of Jiangsu. The timing and magnitude of carbon peak differ among cities. Therefore, the emphasis of peak mitigation measures should be distinct for each city.

(1) Jiangsu province should establish differentiated peak targets based on the specific circumstances of each city. Economically developed cities such as Nanjing, Suzhou, Wuxi, and Changzhou should aim to achieve carbon peak by 2025. Cities like Zhenjiang, Yangzhou, and Taizhou should reach the peak between 2025 and 2030. Cities like Suqian and Lianyungang, facing greater challenges, should implement stricter policy measures to strive for an earlier realization of the peak.

(2) Within Jiangsu province, there should be a strengthening of regional coordinated development. The economically advanced southern region should enhance cooperation with the central and northern regions to promote technological progress and industrial structural transformation. There should be an increase in industrial symbiosis among regions, reducing carbon emissions through industrial chain collaboration and resource sharing.

(3) As an important province in the eastern region of China, Jiangsu should develop a unified plan and adjust the policies of each city in a timely manner to ensure that the province's carbon emissions peak before 2030, and as early as possible. This will help alleviate the peak pressure on other regions and provide experience and a model for other provinces in China to achieve their carbon peak targets.

To ensure the target is met on schedule, it is imperative to introduce more policies and exert greater efforts in accelerating the adjustment of energy mix, optimizing industrial structure, and improving energy efficiency. It is recommended to expedite the pace of green and low-carbon energy transformation by vigorously developing new energy sources such as wind and solar power, focusing on increasing the proportion of non-fossil energy consumption and reducing the share of fossil energy, to swiftly achieve the stock replacement of traditional fossil energy with new energy.

7. Conclusions

Among the cities in Jiangsu province, Changzhou, Huai'an, Taizhou, Zhenjiang, Wuxi, and Yancheng are likely to reach their carbon emission peaks before 2030. Among these, Changzhou and Taizhou are expected to be the first to experience peak carbon emissions, both occurring in 2028, while other cities may struggle to peak their carbon emissions before 2030.

The future carbon emission trends in Jiangsu's cities exhibit significant differences, with varying peak times and magnitudes of peak emissions. It is necessary to establish differentiated peak targets based on the specific circumstances of each city in Jiangsu.

Overall, the carbon emissions of Jiangsu province are projected to peak between 2028 and 2033. Consequently, it is feasible for Jiangsu province to reach its overall carbon emission peak before 2030. In order to better achieve the emission reduction goals of the entire province and the nation, Jiangsu should prioritize green development strategies, promoting the transformation towards a low-carbon economy and development.

References

Anser, M. K. (2019), Impact of energy consumption and human activities on carbon emissions in Pakistan: application of STIRPAT model. *Environmental Science and Pollution Research*, **26(13)**, 13453–13463.

Bai, C., Yi, X., Wang, D. (2024), Does the rebound effect offset low-carbon gains from technological progress in China's transportation sector? *Science of the Total Environment*, **954**, 176520.

Chaudry, M., Jayasuriya, L., Blainey, S., *et al.* (2022), The implications of ambitious decarbonisation of heat and road transport for Britain's net zero carbon energy systems. *Applied Energy*, **305**, 117905.

Chen, M., Zhang, C., Chen, C., *et al.* (2023), Main pathways of carbon reduction in cities under the target of carbon peaking: A case study of Nanjing, China, *Sustainability*, **15 (11)**, 8917.

Dietz, T., Rosa, E.A. (1997), Effects of population and affluence on CO_2 emissions, *Proceedings of the National Academy of Sciences of the United States of America*, **94 (1)**, 175–179.

Ehrlich, P., Holden, J. (1971), Impact of population growth, *Science*, **171 (3977)**, 1212–1217.

Huo, T., Xu, L., Liu, B., *et al.* (2022), China's commercial building carbon emissions toward 2060: An integrated dynamic emission assessment model. *Applied Energy*, **325**, 119828.

Intergovernmental Panel on Climate Change. (2015), Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report, Cambridge University Press, Cambridge.

Li, R., Liu, Q., Cai, W., *et al.* (2023), Echelon peaking path of China's provincial building carbon emissions: Considering peak and time constraints, *Energy*, **271**, 127003.

Lin, B., Du, Z. (2015), How China's urbanization impacts transport energy consumption in the face of income disparity, *Renewable and Sustainable Energy Reviews*, **52**, 1693–1701.

Lin, S., Wang, S., Marinova, D., *et al.* (2017), Impacts of urbanization and real economic development on CO_2 emissions in non-high income countries: Empirical research based on the extended STIRPAT model, *Journal of Cleaner Production*, **166**, 952–966.

Liu, Z., Deng, Z., He, G., *et al.* (2022), Challenges and opportunities for carbon neutrality in China, *Nature Reviews Earth & Environment*, **3**, 141–155.

Long, R., Yang, R., Song, M., *et al.* (2015), Measurement and calculation of carbon intensity based on ImPACT model and scenario analysis: A case of three regions of Jiangsu province, *Ecological Indicators*, **51**, 180–190.

Meng, W., He, C., Zhou, Z., *et al.* (2021), Application of the ridge regression in the back analysis of a virgin stress field, *Bulletin of Engineering Geology and the Environment*, **80**, 2215–2235.

Ofori, E.K., Li, J., Gyamfi, B.A., *et al.* (2023), Green industrial transition: Leveraging environmental innovation and environmental tax to achieve carbon neutrality. Expanding on STRIPAT model, *Journal of Environmental Management*, **343**, 118121.

Qiao, Z., Meng, X., Wu, L.F. (2021), Forecasting carbon dioxide emissions in APEC member countries by a new cumulative grey model. *Ecological Indicators*, **125**, 107593.

Qin, X., Xu, X., Yang, Q. (2024), Carbon peak prediction and emission reduction pathways of China's low-carbon pilot cities: A case study of Wuxi city in Jiangsu province, *Journal of Cleaner Production*, **447**, 141385.

Shariff, N.S.M., Duzan, H.M.B. (2018), A comparison of OLS and ridge regression methods in the presence of multicollinearity problem in the data, *International Journal of Engineering & Technology*, **7**, 36–38.

Shrestha, N. (2020), Detecting multicollinearity in regression analysis, *American Journal of Applied Mathematics and Statistics*, **8 (2)**, 39–42.

Sang, M., Shen, L.Y. (2024), An international perspective on carbon peaking status between a sample of 154 countries. *Applied Energy*, **369**, 123580.

Sun, W., Zhao, Y., Li, Z., *et al.* (2022), Carbon emission peak paths under different scenarios based on the LEAP model—A case study of Suzhou, China, *Frontiers in Environmental Science*, **10**, 905471.

Tarancon, M. A., Del Rio, P. (2012). Assessing energy-related CO_2 emissions with sensitivity analysis and input-output techniques. *Energy*, **37(1)**, 161–170.

Tang, M., Hu, F. (2021), How does land urbanization promote CO_2 emissions reduction? Evidence from Chinese prefectural-level cities, *Frontiers in Environmental Science*, **9**, 766839.

Tian, S., Xu, Y., Wang, Q., *et al.* (2022), Research on peak prediction of urban differentiated carbon emissions—A case study of Shandong Province, China, *Journal of Cleaner Production*, **374**, 134050.

Wang, P., Wu, W., Zhu, B., *et al.* (2013), Examining the impact factors of energy-related CO_2 emissions using the STIRPAT model in Guangdong Province, China, *Applied Energy*, **106**, 65–71.

Wang, Y., Dong, L. (2024), Research on carbon peak prediction of various prefecture-level cities in Jiangsu Province based on factors influencing carbon emissions, *Sustainability*, **16 (16)**, 7105.

Xia, X., Liu, B., Wang, Q., *et al.* (2024), Analysis of carbon peak achievement at the provincial level in China: Construction of ensemble prediction models and Monte Carlo simulation, *Sustainable Production and Consumption*, **50**, 445–461.

Xu, G., Wang, W. (2020), China's energy consumption in construction and building sectors: An outlook to 2100, *Energy*, **195**, 117045.

Xue, L., Li, H., Xu, C., *et al.* (2022), Impacts of industrial structure adjustment, upgrade and coordination on energy efficiency: Empirical research based on the extended STIRPAT model, *Energy Strategy Reviews*, **43**, 100911.

Yang, L.H., Lei, Y.Q., Ye, F.F., *et al.* (2024), Forecasting carbon peaking in China using data-driven rule-base model: An in-depth analysis across regional and economic scenarios, *Journal of Cleaner Production*, **451**, 142053.

Yin, F., Bo, Z., Yu, L., *et al.* (2023), Prediction of carbon dioxide emissions in China using a novel grey model with multi-

parameter combination optimization, *Journal of Cleaner Production*, **404**, 136889.

York, R., Rosa, E.A., Dietz, T. (2003), STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts, *Ecological Economics*, **46 (3)**, 351–365.

Yu, X., Qu, H. (2013), The role of China's renewable powers against climate change during the 12th Five-Year and until 2020, *Renewable and Sustainable Energy Reviews*, **22**, 401–409.

Zhang, C., Luo, H. (2023), Research on carbon emission peak prediction and path of China's public buildings: Scenario analysis based on LEAP model, *Energy and Buildings*, **289**, 113053.

Zhang, M., Huang, X.J. (2012), Effects of industrial restructuring on carbon reduction: An analysis of Jiangsu Province, China, *Energy*, **44 (1)**, 515–526.