PREDICTION OF CARBON EMISSION FROM CULTIVATION IN EASTERN CHINA UNTIL 2035 BASED ON ANALYSIS OF CARBON EMISSION FROM 1998 TO 2018 BY STIRPAT MODEL

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Abstract. It is widely acknowledged that greenhouse gases (GHG) like carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) play a key role in the development of global climate change. 17% of China's GHG came from the agricultural industry. For China's future development, it is essential to investigate low-carbon emission paths in planting fields, as one of the key components of agriculture. In this study, the IPCC method was used to estimate the total carbon emission from cultivation in Eastern China. The Tapio decoupling model was used to study the relationship between economic growth and carbon emission. An extended STIRPAT stimulus model was established to predict the carbon emission of the planting industry in East China with three development paths. The results show that carbon emission in East China has shown a fluctuating downward trend with a peak in 1999, which has strong decoupling characteristics with economic growth. Adjusting agricultural structure and raising the mechanization rate can remarkably reduce agricultural carbon emission. Compared to 2020, carbon emission in 2035 will decrease by 12.50%, 13.68%, and 14.32% with Baseline, Low-carbon, and Enhanced Low-carbon scenarios, respectively. Effective measures such as optimizing planting structure by adjusting rice area, promoting intensive mechanization, and improving fertilizer use efficiency can reduce carbon emission actively.
Keywords: *GHG, driving factors, decoupling model, low-carbon, enhanced low-carbon*

Introduction

The issue of global warming was first raised and identified several decades ago. In recent years, global warming has caused the deterioration of human living environment more seriously, so it has attracted remarkably wide attention around the world. The greenhouse gases produced by human activities are the leading cause of the greenhouse effect and are a significant challenge to the sustainable development of human society (Edenhofer et al., 2014). As the largest carbon emitter in the world, China's agricultural production activities produce a higher proportion of carbon than that of any other country (Huang et al., 2019; Ye et al., 2021). China announced in 2020 that China would strive to peak CO_2 emission by 2030 and carbon neutrality by 2060. Introducing the dual carbon target is a bold strategic choice for China and an unavoidable need to achieve green transformation and sustainable development.

Greenhouse gases from activities in the agricultural field have become an important integral part of the greenhouse effect (Anthony et al., 2021). It is estimated that 13.5% of global GHG and 53% of global non-CO_2 emission come from agriculture in the

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world (Charkovska et al., 2019). Planting field, as one of the major agricultural parts in China, accounted for about 48.41% of the total agricultural carbon emission (Min et al., 2012). Therefore, China's dual carbon targets will be impossible to reach without significant reductions in GHG emission from the planting field (Wollenberg et al., 2016). Eastern China, which includes six provinces (Shandong, Jiangsu, Zhejiang, Anhui, Fujian, and Jiangxi, as well as Shanghai), is an essential agricultural production base in China. According to China's National Bureau of Statistics, the total carbon emission from the planting industry in East China ranked first with 99.17 million t CO_{2e} in 2018, accounting for 25.43% of the total carbon emission of the planting industry in China. Its input of high-carbon production materials such as chemical fertilizers, pesticides, farming films, and herbicides is the highest in China. The ratio of fertilizer, pesticide and agricultural film use to the total used in China were 23.78%, 31.05% and 27.92%, respectively (National Bureau of Statistics of China, 2014), with nitrogen fertilizers applied 134 kg/hm^2, about 1.8 times that of developed countries (Xu et al., 2021). There is vast potential for carbon emission reduction in East China, as it is the fastest region with economic development and technological innovation in China. Therefore, it is of great theoretical and practical significance for formulating reasonable and effective policies and measures for agricultural carbon emission reduction by knowing the carbon emission situation, understanding the driving factors affecting agricultural carbon emission, and forecasting the trend of carbon emission in the future in Eastern China, as the forefront of green low-carbon transformation and development in China.

Research on assessment and prediction models of carbon emission has become a hot topic. Some scholars in recent years have established the link between carbon emission and economic, policy and demographic factors by Kaya equation (Gui et al., 2021; Zhang et al., 2013), and calculated the contribution value of influencing factors to carbon emission by using Logarithmic Mean Divisia Index (LMDI) method (Tan et al., 2013). He et al. (2013) decomposed the change of agricultural carbon emission into four factors with LMDI method and showed that the economic effect is the most significant driving factor for agricultural carbon emission increasing. Also some experts (Wang et al., 2022; Pata et al., 2021; Parajuli et al., 2019) analyzed the impact of economic development and technological progress on carbon emission with Environmental Kuznets curve model (EKC) and decoupling model. Li et al. (2018) used prediction models such as grey model (GM) and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to build an index system with population size, per capita GDP, mechanization level, production efficiency and industrial structure to analyze driving factors affecting carbon emission and forecast the carbon emission in agriculture system in Hunan Province. Tong et al. (2015) used the IPCC method combined with the GM prediction model to predict carbon emission in China. Niu et al. (2022) based on the STIRPAT model and ridge regression analysis constructed and forecasted carbon emission in Zhejiang Province in China. These approaches have enriched the study of influencing factors, but there are still some problems and limitations. The LMDI model can effectively identify the driver factors of carbon emission, but drivers need long-term time series data (Xiong et al., 2016; Tian et al., 2016). The EKC model and the decoupling model mainly examine the impact of specific factors, which cannot be conducive to the macro-regulation of all elements. The GM prediction model only allowed short-term predictions of carbon emission without considering changes in the influencing factors. There are also many limits to the

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STIRPAT model for multiple linear regression analysis (Nosheen et al., 2020). For example, when the selected independent variables are multi-correlated, it is impossible to build a model using ordinary least square regression. However, the STIRPAT model can identify a broader range of influences, which is the biggest advantage of forecast software. Most previous studies are focused on only simulated scenarios of technical measures or from an economic perspective, but lacked comprehensive simulation combining multiple perspectives of economy, population and technology.

Therefore, with the quantitative study of carbon emission in planting field in Eastern China, in this paper we expanded two driving factors (planting industry structure and mechanical efficiency level), which changed quickly in recent years, set up extending STIRPAT simulation model to forecast carbon reduction potential with three kinds of scenarios in Eastern China, and put forward appropriate and scientific carbon reduction strategies in China. This study is of utmost importance considering the strong desire of Chinese government to pursue the goal of carbon peak in 2030 and neutrality in 2060.

Materials and methods

The map of Eastern China is shown in *Figure 1*. The study area includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi and Shandong Provinces. According to the data of the National Bureau of Statistics in China, in 2018 Eastern China accounted for 38.21% of the total gross domestic product (GDP), 29.90% of the total population and 24.89% of the total food production in China, as one of the fastest-growing economic regions in China. Multiple Cropping in Eastern China is three times a year due to a subtropical and tropical monsoon climate with rice, cotton, hemp, oilseed rape, sugar cane and tea dominating. The plains and hills of the middle and lower reaches of the Yangtze River have a typical warm and humid climate, with intensive farming and extensive water areas.

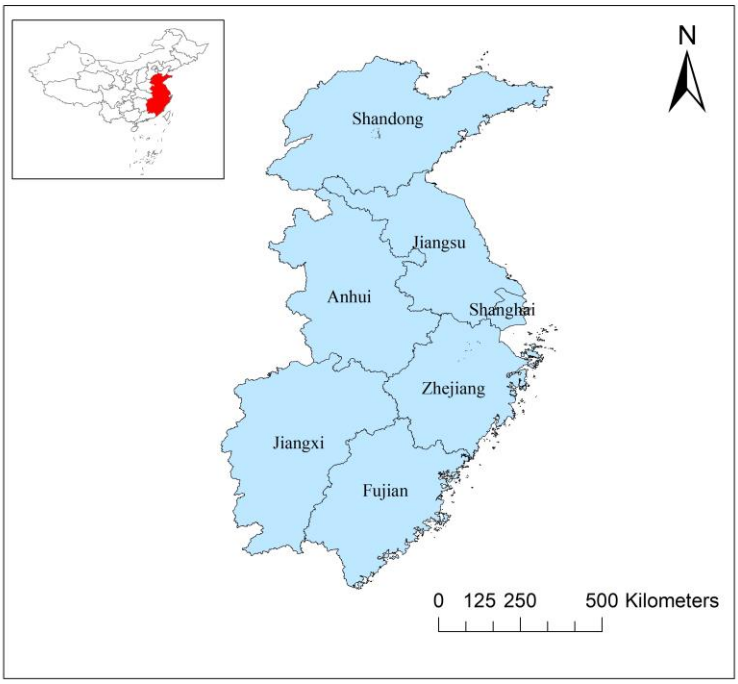

Figure 1. *Study area*

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Carbon emission estimation methods

Greenhouse gas emission from China’s planting fields consists of three main components: carbon dioxide emission from planting activities, methane emission from rice cultivation, and nitrous oxide emission from nitrogen fertilizer and straw returning to the fields.

Methodology for calculating CO_2 emission

$$E_{CO_2} = \sum E_i = \sum T_i \times \varepsilon_i \tag{Eq.1}$$

E_{CO2} is the total CO_2 emission from planting cultivation (t); i is the carbon emission from carbon source category in the cropping sector; T_i is the quantity of each carbon source (kg or ha); i is the carbon emission coefficient (kg c/kg or kg c/ha) (Hu et al., 2023).

Methane emission calculation method

$$E_{CH_4} = \sum EF_{Rice} \times A_{Rice} \tag{Eq.2}$$

E_{CH4} is CH_4 emission from rice fields (t); EF_{Rice} is the CH_4 emission coefficient of the subtype of rice (including early paddy, late paddy and seasonal paddy), (kg/ha) (Hu et al., 2023); A_{Rice} is the annual area of rice sown in each province (10^3 ha).

Calculation method for nitrous oxide emission

$$E_{N_2O} = (N_{Fertilizer} + N_{Straw}) \times EF_{Direct} \tag{Eq.3}$$

E_{N2O} is emission of nitrous oxide from planting field (t); $N_{Fertilizer}$ is the amount of nitrogen fertilizer applied to planting field (t); N_{Straw} is nitrogen quantity of straw return (above ground and below ground) (t); EF_{Direct} is emission coefficient of nitrous oxide from planting field (Gan et al., 2020).

$$N_{Straw} = \sum_{i=1}^{n} (M_i/L_i - M_i) \times \beta_i \times K_i + M_i/L_i \times \alpha_i \times K_i \tag{Eq.4}$$

N_{Straw} is nitrogen quantity of straw return (t); M_i is the yield of each crop; L_i is the economic coefficient of each crop; β is the straw return rate of the i crop; K_i is the nitrogen content of the straw of each crop; α is the root-shoot ratio of the i crop (Gan et al., 2020).

Methodology for estimating GHG emission from plantations

$$E_{Total} = E_{CO_2} \times 1 + E_{CH_4} \times 25 + E_{N_2O} \times 298 \tag{Eq.5}$$

E_{Total} is total greenhouse gas emission (tCO_{2e}); E_{CO2} is total CO_2 emission (t); E_{CH4} is total CH_4 emission (t); E_{N2O} is total N_2O emission (t); CH_4 and N_2O emission were converted to CO_2 equivalents by 1 t CH_4 = 25 t CO_2 and 1 t N_2O = 298 t CO_2. (Wgiii et al., 2007).

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Estimation method of GHG intensity

$$EI = E_{Total}/CA \quad \text{(Eq.6)}$$

EI is carbon emission intensity (t/ha); E_{Total} is greenhouse gas emission (t); CA is the actual sown area (ha) in each province.

Decoupling analysis with Tapio model

Tapio model, was further proposed based on OECD model, is currently used for decoupling elasticity studies, which can better reflect the sensitivity of changes in carbon emission to economic growth.

$$e = \frac{\Delta C/C}{\Delta GDP/GDP} \quad \text{(Eq.7)}$$

e is the decoupling elasticity coefficient of carbon emission in planting field from planting GDP growth; $\Delta C/C$ is the ratio of the change of planting carbon emission to the total carbon emission in this region; $\Delta GDP/GDP$ is the ratio of the change of plantation GDP to the GDP in the region.

STIRPAT model

Ehrlich et al. (1971) proposed the IPAT model with decomposing all environmental influences into three categories: population size, economy and technology. Based on this, in this paper we used the extended STIRPAT model to analyze the influences on planting carbon emission, which can identify more effects and quantitatively evaluate the drivers of various environmental pressures.

Basic form of the STIRPAT model

$$I = aPbAcTde \quad \text{(Eq.8)}$$

The standard STIRPAT model is a non-linear multivariate equation. Population, economic development and technology are considered as important driving factors in carbon emission in planting fields. However, the above factors are limited and lack high precision. In addition, China is still a developing country. The adjustment of agricultural structure and the increase of mechanization level will have an important impact on carbon emission. So the STIRPAT model in this paper is extended not only to analyze the impact of population, economic development and technology, but also to consider the impact of changes in the planting structure and the level of mechanization on carbon emission in recent years. The ratio of irrigated area to sown area reflects planting structure changes, and the ratio of diesel usage in planting machinery to the sown area reflects agricultural machinery efficiency. Furthermore, regression analysis was conducted using ridge regression to overcome the problem of multi-collinearity.

$$\ln I = \ln a + b\ln P + c\ln W + d\ln T + f\ln K + g\ln H + \ln e \quad \text{(Eq.9)}$$

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I indicates the total carbon emission from plantations in Eastern China (tCO_{2e}); P is the number of people employed in agriculture in Eastern China (10,000 people); W is the agricultural economic level, the ratio of total agricultural output to rural population (Yuan/person); T is planting production efficiency, that is carbon emission intensity of planting industry (tCO_{2e}/ha); K is the structure of the planting industry, the ratio of irrigated area to sown area (%); H is planting machinery efficiency, the ratio of diesel use in planting machinery to a own area (t/ha); in *Equation 9*, b, c, d, f and g are elasticity coefficients, representing the changes in b%, c%, d%, f% and g% every time P, W, T, K, and H are changed by 1%.

Data

The data in this paper about fertilizer, pesticide, agricultural film, diesel, irrigated area, and so on in the STRIPAT model required for measuring carbon dioxide emission from the planting sector in Eastern China are available from the National Bureau of Statistics Yearbook in China (1998-2018).

Results and analysis

Carbon emission in East China

Emission analysis of CO_2, CH_4 and N_2O

The total GHG emission in East China from 1998 to 2018 are shown in *Figure 2*, which showed a fluctuating downward trend, reaching a peak of 126.4 $MtCO_{2e}$ in 1999, and the rate of decline accelerated year by year during the period 2010-2018 (S1). Among them, CO_2 emission showed a fluctuating trend (*Fig. 3*) with a significant downward trend after reaching a peak of 28.9 $MtCO_{2e}$ in 2013. During this period, the Ministry of Agriculture in China put forward the policy of controlling the total amount of agricultural water and the pollution of agricultural water environment, reducing the use of chemical fertilizers and pesticides, converting livestock and poultry manure, agricultural film and crop straw to comprehensive recycling and harmless treatment. The implementation of this program has effectively reduced the use of agricultural materials, and led to a reduction in carbon emission from the cultivation sector. Methane emission also has shown a downward trend due to the shift in rice cultivation patterns from double to single-season rice cultivation in the region in recent years. Nitrous oxide emission is divided into two phases, the first one has an upward trend with reaching a peak of 126,400 tons in 2014 resulted from excessive use of nitrogen fertilizers. The second stage was from 2015 to 2018, nitrous oxide emission showed a decreasing trend due to the continuous updating of technology and fertilizer control effectively while ensuring yield.

Source analysis of GHG

The source share of GHG emission from the plantation sector in East China in 1998 and 2018 is shown in *Figures 4* and *5*, in which the most significant impact on GHG is methane, accounting for 51.95% and 46.06% respectively, followed by nitrous oxide and carbon dioxide. Among all the factors affecting carbon emission, there are two prominent characteristics: Firstly, carbon emission from single-season rice planting increased from 23.21% to 29.51% in East China due to the shift from double cropping

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to single cropping rice in recent years; Secondly, the proportion of nitrogen fertilizer increased compared with 1998, it is still a prominent factor affecting carbon emission although the nitrogen fertilizer has been gradually controlled in China in recent years.

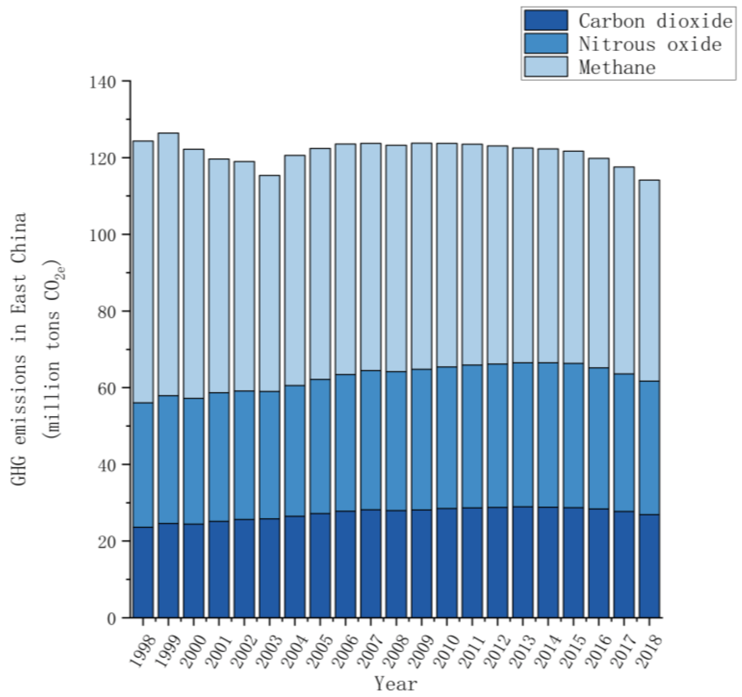

Figure 2. *Total GHG from planting field in East China from 1998 to 2018*

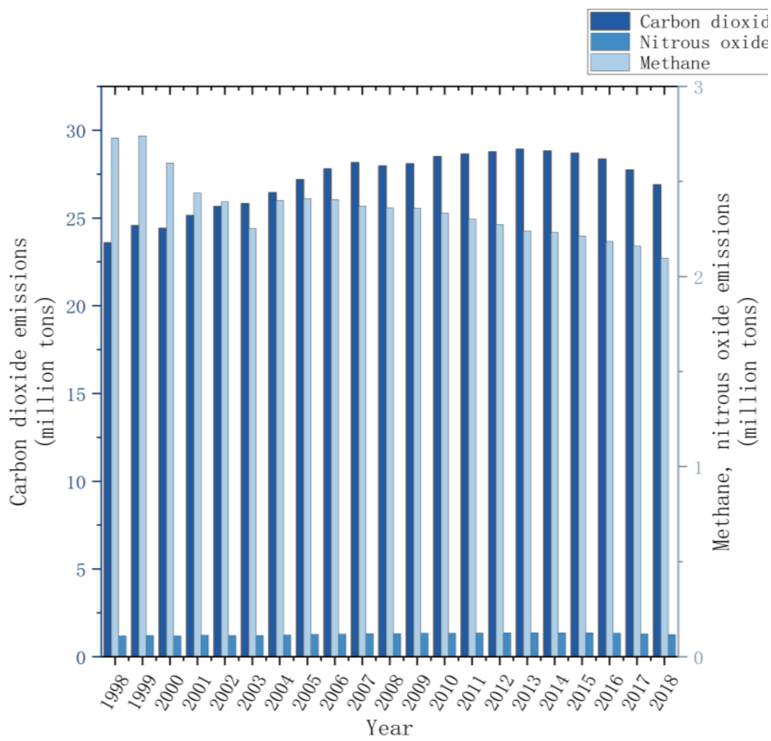

Figure 3. *Emission of CO_2, CH_4 and N_2O in East China from 1998 to 2018*

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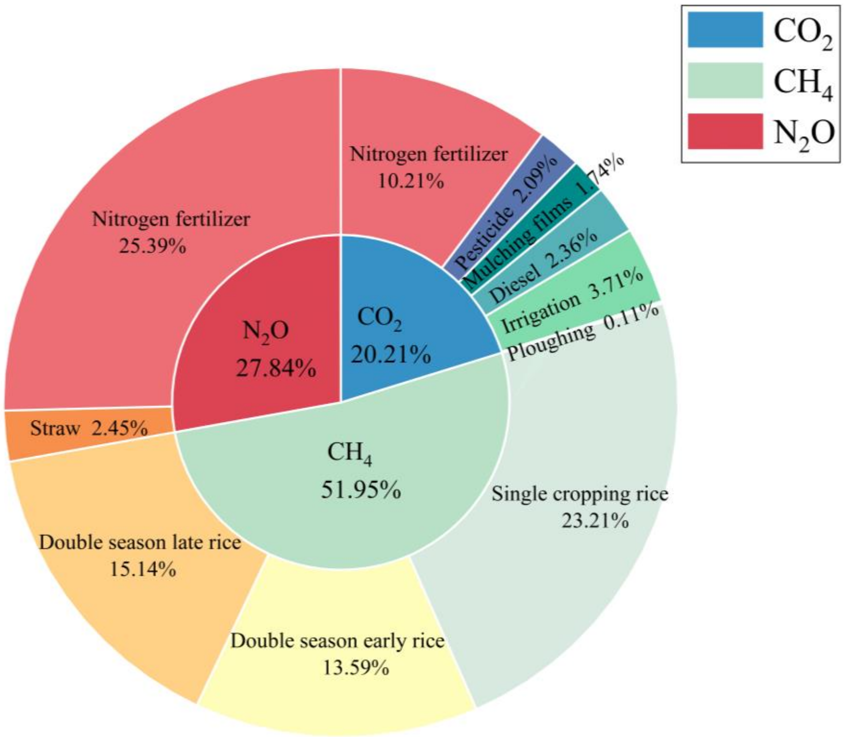

Figure 4. *Source proportion of GHG in East China in 1998*

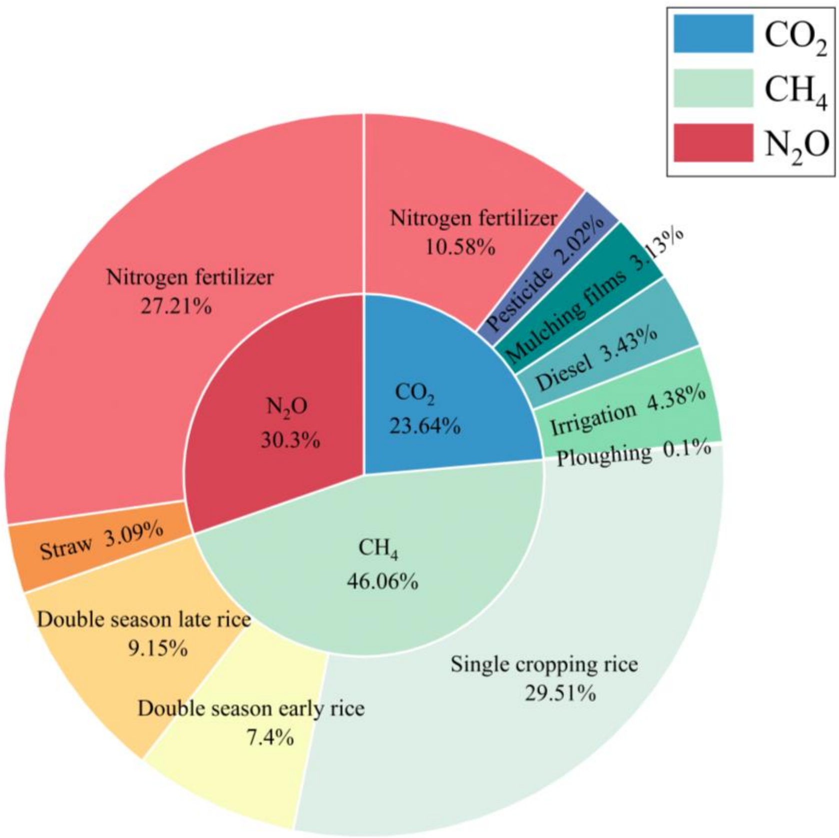

Figure 5. *Source proportion of GHG in East China in 2018*

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GHG emission intensity

The average carbon emission intensity in plantation sector in Eastern China in 2018 was 2.7 t/hm^2. The provinces from the strongest to weakest emission intensity in Eastern China are Fujian Province, Zhejiang Province, Shanghai City, Jiangsu Province, Jiangxi Province, Anhui Province, and Shandong Province, with 5.57 t/hm^2, 3.93 t/hm^2, 3.77 t/hm^2, 3.33 t/hm^2, 3.10 t/hm^2, 2.72 t/hm^2, and 1.40 t/hm^2, respectively.

Decoupling characteristics analysis

The temporal changes of decoupling characteristics in Eastern China are shown in *Table 1*. The decoupling characteristics between carbon emission and economic growth in China during 1998-2018 are mainly strong decoupling. In general, the gross agricultural product in Eastern China shows an overall growth trend, and most of the decoupling elasticity index is less than 1, which means that the development speed of the economy in Eastern China is faster than the growth rate of carbon emission. Eastern China has achieved remarkable carbon emission reduction in the planting industry in recent years, the decoupling process is divided into three stages. The first stage was from 1998 to 2003, which showed a strong decoupling stage. As the primary stage of China's agricultural economic development, the carbon emission were reduced due to the decrease in rice planting area. From 2004 to 2009, it showed a weak decoupling with an average annual growth of 1.19% in carbon emission, as well as 11.8% growth in total agricultural GDP. At the same time, with the improvement of agricultural technology, the vigorous promotion of recycling agriculture, and the continuous adjustment of planting structure, the growth rate of carbon emission in Eastern China was effectively curbed, and the total agricultural output achieved relatively rapid growth. The third stage was a strong decoupling stage, which showed a decreasing trend in carbon emission from 123.7 $MtCO_{2e}$ in 2010 to 114.1 $MtCO_{2e}$ in 2018 with an average annual reduction rate of 0.89%. In contrast, the total agricultural output has increased rapidly, from 122.68 billion dollars in 2010 to 207.97 billion dollars with an average annual growth rate of 6.9%. Previous environment deterioration has driven governments to strengthen environmental protection and to restrict the excessive use of pesticides and fertilizers. Guided by the concept of "resource-saving and environment-friendly", the government in Eastern China has introduced a series of policies to encourage the development of green, high-efficiency, and low-carbon agriculture, such as water and fertilizer integration, soil formula fertilization and pesticide biological control.

Regression analysis of STIRPAT model

Correlation test

Based on multiple linear regression analysis by SPSS software, the results were (*Table 2*) shown that there was a strong correlation among the four variables K, P, W and H. And by examining the variance inflation factor (VIF) (*Table A2* in the *Appendix*), we found only the VIF of lnT was less than 10, and the VIF of lnK reached 148.981 with severe multicollinearity among the variables. Therefore, it needs use a ridge regression model to overcome the problem of multicollinearity among the independent variables for regression analysis.

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Table 1. *Decoupling effect in Eastern China from 1998 to 2018*

Year	Environmental stress (ΔC/C)	Economic growth (ΔG/G)	Decoupling elastic (e)	Decoupling characteristics
1998-1999	0.016848495	0.045216206	0.372620721	Weak decoupling
1999-2000	-0.033549394	0.002921534	-11.48348564	Strong decoupling
2000-2001	-0.020420482	0.045868985	-0.445191488	Strong decoupling
2001-2002	-0.005660767	0.020808579	-0.272040052	Strong decoupling
2002-2003	-0.030472577	-0.024470886	1.245258448	Recessionary decoupling
2003-2004	0.045116359	0.217763095	0.207180925	Weak decoupling
2004-2005	0.015143095	0.051993615	0.291249121	Weak decoupling
2005-2006	0.009504262	0.096784693	0.098200057	Weak decoupling
2006-2007	0.001245523	0.109881949	0.011335097	Weak decoupling
2007-2008	-0.0039731	0.114272943	-0.034768515	Strong decoupling
2008-2009	0.004730283	0.093713352	0.050476082	Weak decoupling
2009-2010	-0.000637864	0.14941476	-0.004269081	Strong decoupling
2010-2011	-0.001904794	0.101515499	-0.018763576	Strong decoupling
2011-2012	-0.003682891	0.072781627	-0.050601927	Strong decoupling
2012-2013	-0.004095886	0.089669843	-0.04567741	Strong decoupling
2013-2014	-0.001874009	0.056724331	-0.033037132	Strong decoupling
2014-2015	-0.005138931	0.056474268	-0.090995973	Strong decoupling
2015-2016	-0.015330072	0.000961492	-15.94404575	Strong decoupling
2016-2017	-0.01860614	0.024961853	-0.745382957	Strong decoupling
2017-2018	-0.029321017	0.03126792	-0.937734783	Strong decoupling

Table 2. *Correlation results*

	lnK	lnP	lnT	lnW	lnH
lnK	1	0.948	0.111	-0.952	-0.958
lnP	0.948	1	-0.073	-0.86	-0.935
lnT	0.111	-0.073	1	-0.131	-0.208
lnW	-0.952	-0.86	-0.131	1	0.844
lnH	-0.958	-0.935	-0.208	0.844	1

Analysis of ridge regression results

In the ridge regression analysis, screening independent variables and determining k were first carried out (Kennard et al., 1970). The output of the pre-data period showed that when k is 0.124, the ridge regression coefficients all tended to be stable with R^2 equal to 0.844 (*Table A3*). Therefore, the equation of the formula based on the ridge regression is as follows:

$$\ln I = 6.886 + 0.166 \times \ln P + 0.012 \times \ln W + 0.532 \times \ln T - 0.101 \times \ln H - 0.167 \times \ln K \quad \text{(Eq.10)}$$

The data measured by the model were compared with the actual carbon emission (*Fig. 6; Table A5*). It can be seen that the absolute error between the model prediction and the actual carbon emission is 0.660% on average, indicating that the constructed

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prediction model has some empirical significance. Elasticity coefficients of P, W, T, H, and K were 0.166, 0.012, 0.532, -0.101, and -0.167, respectively.

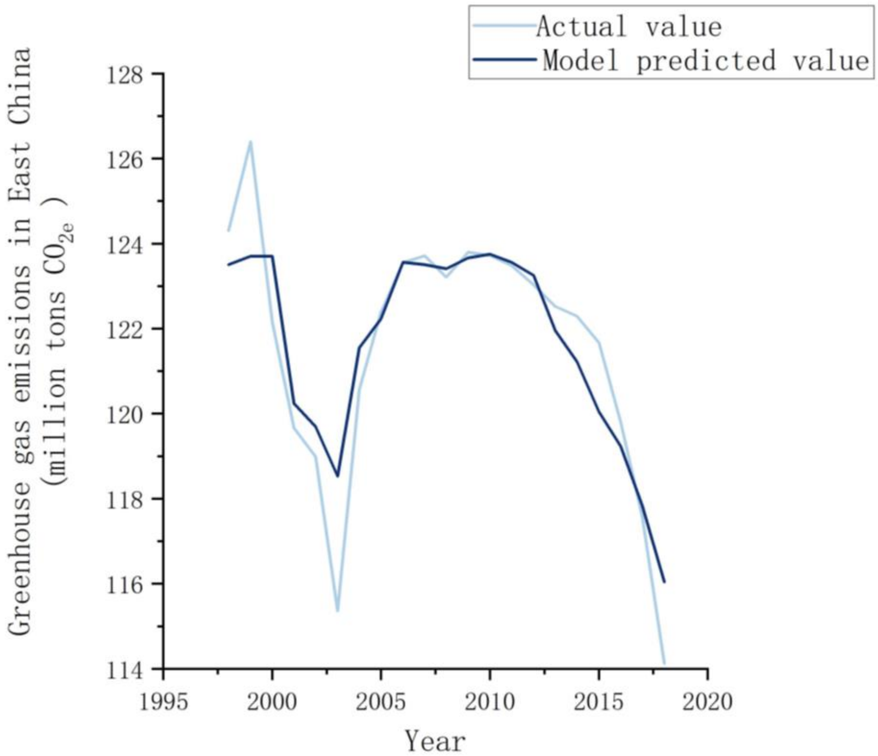

Figure 6. *Model validation in Eastern China from 1998 to 2018*

According to the final regression equation of carbon emission in Eastern China, the regression coefficients of independent variables are sorted to illustrate the degree of influence of each explanatory variable on carbon emission. Among them, P, W and T have a significant positive influence on carbon emission. H and K were negatively correlated with carbon emission, and the negative influence of K was remarkable. When T, P, W, K and H change by 1%, the total carbon emission change by 0.532%, 0.166%, 0.012%, -0.167% and -0.101%, respectively. Therefore, it is of great significance to reduce carbon emission in East China by adjusting the industrial structure and improving the mechanical efficiency (*Table 3*).

Table 3. *Ridge estimation results*

Variables	B	SE(B)	Beta	T	Sig
lnP	.16594590	.07123364	.23662417	2.33	0.034**
lnW	.01165943	.00574095	.22776239	2.031	0.060*
lnT	.53245790	.09075464	.70852031	5.867	0.000***
lnH	-.10064524	.01837026	-.58575499	-5.479	0.000***
lnK	-.16725758	.02227199	-.47254922	-7.51	0.000***
Constant	6.88640908	.64861288	.00000000	10.632	0.000***

B represents regression coefficient; SE(B) means standard error; Beta means standardization coefficient; T means Test results of regression coefficient t; Sig means significance level
***, ** and * represent the significance level of 1%, 5% and 10% respectively

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Carbon emission trend forecasting

Scenario simulation parameter setting

In order to forecast carbon emission in Eastern China comprehensively, in this paper it was set up three carbon emission scenarios (*Table 4*) by considering driving factors related to economic and social development and emission reduction. Baseline scenario predicts changes in carbon emission according to current policy documents on climate change and energy in China with conventional development rate in the number of people employed in agriculture, GDP per agricultural worker, agricultural production efficiency, agricultural machinery efficiency, and agricultural structure. Low-carbon scenario is strengthened to achieve certain breakthroughs in agricultural productivity, agricultural machinery efficiency, and agricultural structure based on the baseline scenario. Enhanced Low-carbon scenario further strengthens carbon reduction by actively control measures to improve agricultural production efficiency, agricultural machinery efficiency and agricultural structure based on the low-carbon scenario.

Table 4. *Growth parameter setting in East China under different development scenarios*

Scenario	Year	Growth rate setting (%)				
		Number of people employed in agriculture	**Agricultural GDP per capita**	**Agricultural productivity efficiency**	**Agricultural machinery efficiency level**	**Structure of agricultural industry**
The baseline scenario	2021-2025	-0.0128	0.0550	-0.0067	0.0040	0.0180
	2025-2030	-0.0134	0.0578	-0.0060	0.0044	0.0189
	2030-2035	-0.0141	0.0606	-0.0053	0.0048	0.0198
The low carbon scenario	2021-2025	-0.0150	0.0550	-0.0070	0.0050	0.0183
	2025-2030	-0.0158	0.0578	-0.0063	0.0055	0.0192
	2030-2035	-0.0165	0.0606	-0.0056	0.0061	0.0202
Enhancing the low-carbon scenario	2021-2025	-0.0198	0.0550	-0.0074	0.0070	0.0187
	2025-2030	-0.0206	0.0578	-0.0067	0.0073	0.0195
	2030-2035	-0.0214	0.0606	-0.0060	0.0076	0.0203

According to the China Rural Development Report 2020, projections indicate that the number of people employed in agriculture will maintain a downward trend in the future. Average annual growth rate from 2008 to 2018 was -1.28%, therefore we set growth rates of -1.28%, -1.50%, and -1.98%, respectively for the Baseline, Low carbon and Enhanced Low-carbon models for 2021-2025 with decreasing at a rate of 5% every 5 years. Average annual growth rate of agricultural GDP per capita is 5.5% of income per capita based on the target of the “Fourteenth Five-Year Plan in China” and “Outline of the 2035 Vision in China”, three kinds of scenarios are synchronized to achieve low carbon development. The data of FAO shows that China’s agricultural carbon emission intensity has a decreasing trend from 1978 to 2018. Combining the changes in carbon emission intensity in the last 10 years, we set the growth rates of -0.67%, -0.7%, and -0.74% for the baseline model, Low carbon, and Enhanced Low-carbon from 2021 to 2025, respectively, with decreasing at a rate of 10% every 5 years in this paper. The National Agricultural Mechanisation Development Statistical Bulletin in China indicates that comprehensive mechanization rate for crop cultivation and harvesting increased obviously in recent years. So combined with average annual change rate in mechanical efficiency by 0.4% over the past 10 years, we set the growth rates of the Baseline, Low carbon and Enhanced Low-carbon in 2021-2025 at 0.4%, 0.5%, and

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0.7% respectively, with increasing at a rate of 10% every 5 years. Similarly, the average growth rates of agricultural structure in East China at 1.8%, 1.83%, and 1.98% were set for Baseline, Low carbon and Enhanced Low-carbon in 2021-2025, respectively, with increasing at a rate of 5% every 5 years.

Forecast of carbon emission trend in East China during 2020-2035

Based on the three scenarios, the STIRPAT model was used to fit carbon emission in the planting field in East China, and the carbon emission trends are shown in *Figure 7*. The results show that carbon emission will be 100.9 $MtCO_{2e}$ in 2035 with the Baseline Scenario, and decrease 12.50% than that in 2000; in the Low Carbon Scenario, carbon emission will be 99.5 $MtCO_{2e}$, a decrease of 13.68% compared to 2000, and will decrease 1.4 $MtCO_{2e}$ compared to the Baseline Scenario; in Enhance Low Carbon Scenario, it is estimated that by 2035, carbon emission will be 97.4 $MtCO_{2e}$, a reduction of 14.32% compared to 2000. Compared to the Baseline and Low Carbon Scenario, it will be decreased by 3.43% and 2.08%, respectively. This shows that under the Low Carbon Scenario development model, there is great potential to reduce carbon emission from agriculture in East China.

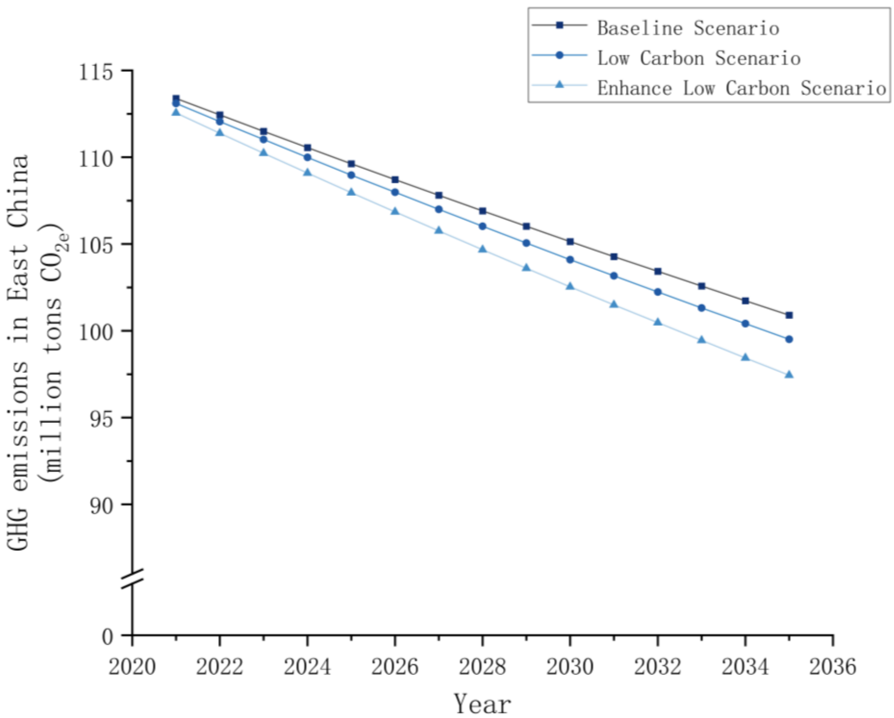

Figure 7. *Forecast map of planting carbon emission in East China*

Discussion

We found in this paper that carbon emission in the planting field in East China have reached a peak and shown a decreasing trend. Zhu et al. (2022) also resulted that China’s total agricultural carbon emission had a seismic downward trend from 2013 to 2017, and the increasing Thiel index indicated that China is in economic transition, and the government began to emphasize agricultural technology innovation and environmental protection. Based on the Stirpat and GM model, Li et al. (2018) analyzed

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the driving factors and predicted the trend of agricultural carbon emission in Nanjing. The results showed that the agricultural carbon emission in Nanjing showed a downward trend, which was similar to our results in this paper. and also indicated that the adjustment of agricultural structure and the implementation of green agricultural production mode could effectively reduce carbon emission. Western Europe reduced agricultural carbon emission mainly due to the adoption of friendly climate and environmental policies. So it is necessary for China to actively explore emission reduction paths and control carbon emission (Liu et al., 2013).

We found that fertilizer application accounted for 37.79% of carbon emission in this paper. Existing studies also showed that fertilizer application is the most important carbon emission source in China’s planting field (Cao et al., 2016; Reay et al., 2012). Carbon emission can be reduced by improving quality and controlling quantity, such as selecting suitable Slow-release fertilizer and precision fertilization. Meanwhile, the CH_4 emission from rice cultivation was mostly underestimated or ignored by previous studies. The greenhouse effect caused by CH_4 emission was found to be as high as 46.06% in our study. Optimal rice planting is one of the important measures to control and reduce carbon emission. Yang et al. (2012) pointed out that water-saving irrigation is an optimal irrigation method to improve water use efficiency and reduce carbon emission. Suresh et al. (2020) also point out that micro-irrigation technology can effectively solve the problem of water scarcity and greenhouse gas emission. Therefore, choosing the appropriate irrigation method according to local condition is a long-term solution to developing low-carbon agriculture. As the world’s largest producer of rice, China should also pay attention to such non-CO_2 greenhouse gas emission and fully consider them in the estimation of carbon emission (Wang et al., 2023).

The model in this paper predicts that carbon emission in the planting field in Eastern China will still achieve a steady decrease from 2020 to 2035. In Low-carbon and Enhance Low-carbon scenarios, the trend of reducing carbon emission is significantly remarkable. With rapid economic and technological development, agricultural structure adjustment and agricultural machinery efficiency will be changed rapidly and will determine the speed and efficiency of carbon reduction in Eastern China. It is necessary by actively adjusting the planting structure, expanding new and good food varieties and improving the yield and quality of products to reduce carbon emission on the basis of meeting food security (Liu et al., 2010; Minami et al., 1994).

Promoting intelligent and mechanized production is a significant and available way to rapidly improve productivity. The shift from manual labor to mechanization reduces the number of people employed in agriculture. The results in our paper found that improving agricultural machinery efficiency and promoting the popularization of agricultural machinery can significantly reduce carbon emission reduction. Xie et al. (2011) also pointed out that application of large medium-sized intelligent machinery is an important vehicle for carbon emission reduction in agriculture. China is actively implementing a digital economy to improve efficiency in agriculture with a networked and digital management model, which will ultimately reduce carbon emission by improving efficiency in agriculture.

Conclusion

The carbon emission in East China from 1998 to 2018 were analyzed by IPCC method. The results showed that carbon emission in the planting field had fluctuating

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downward trend at a peak of 126.4 $MtCO_{2e}$ in 1999. Correlation between carbon emission and its economic growth was mainly strong decoupling, adjusting the planting structure and increasing the mechanization rate can significantly reduce carbon emission by the STIRPAT prediction model. The results of the scenario simulation analysis in Eastern China showed that the carbon emission was reduced by 12.50%, 13.68% and 14.32% with the Baseline Scenario, Low Carbon Scenario and Enhanced Low Carbon Scenario in 2035, respectively, compared with that in 2000. Eastern China has enormous potential for reducing agricultural carbon emissions, and future reductions in agricultural emissions will hasten China’s progress toward its goal of being carbon neutral.

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APPENDIX

Table A1. *Variation of GHG emission in East China*

Year	GHG	Growth rate %	CO_2	Growth rate %	CH_4	Growth rate %	N_2O	Growth rate %
1998	12430.43		2358.78		272.89		10.90	
1999	12639.86	1.68	2457.40	4.18	274.00	0.41	11.18	2.56
2000	12215.80	-3.35	2441.58	-0.64	259.76	-5.20	11.01	-1.57
2001	11966.35	-2.04	2514.43	2.98	243.88	-6.11	11.26	2.28
2002	11898.61	-0.57	2565.18	2.02	239.34	-1.86	11.24	-0.15
2003	11536.03	-3.05	2582.32	0.67	225.31	-5.86	11.14	-0.87
2004	12056.49	4.51	2644.52	2.41	240.02	6.53	11.45	2.73
2005	12239.07	1.51	2718.53	2.80	240.98	0.40	11.73	2.48
2006	12355.39	0.95	2780.56	2.28	240.45	-0.22	11.96	1.93
2007	12370.78	0.12	2816.43	1.29	237.04	-1.42	12.18	1.82
2008	12321.63	-0.40	2796.40	-0.71	236.09	-0.40	12.16	-0.15
2009	12379.91	0.47	2810.19	0.49	235.91	-0.07	12.32	1.35
2010	12372.02	-0.06	2850.12	1.42	233.31	-1.10	12.38	0.47
2011	12348.45	-0.19	2864.75	0.51	230.29	-1.29	12.50	1.01
2012	12302.97	-0.37	2877.04	0.43	227.35	-1.28	12.56	0.42
2013	12252.58	-0.41	2892.45	0.54	224.04	-1.45	12.61	0.45
2014	12229.62	-0.19	2882.61	-0.34	223.17	-0.39	12.64	0.23
2015	12166.77	-0.51	2869.91	-0.44	221.29	-0.84	12.63	-0.08
2016	11980.26	-1.53	2835.93	-1.18	218.46	-1.28	12.36	-2.17
2017	11757.35	-1.86	2773.32	-2.21	216.00	-1.13	12.03	-2.68
2018	11412.61	-2.93	2689.91	-3.01	209.61	-2.96	11.69	-2.84

Table A2. *Ordinary least squares estimation results*

Model	Unstandardized coefficients		Standardized	t	Sig	Correlations			Collinearity statistics	
	B	Std. error	Beta			Zero-order	Partial	Part	Tolerance	VIF
Constant	12.437	1.679		7.409	0.000					
lnP	-0.286	0.177	-0.407	-1.610	0.128	0.492	-0.384	-0.081	0.040	25.242
lnW	0.076	0.016	1.486	4.639	0.000	-0.232	0.768	0.234	0.025	40.446
lnT	0.797	0.073	1.060	10.919	0.000	0.420	0.942	0.550	0.269	3.716
lnH	-0.021	0.072	-0.122	-0.290	0.776	-0.203	-0.075	-0.015	0.014	70.165
lnK	-0.793	0.218	-2.242	-3.647	0.002	-0.463	-0.686	-0.184	0.007	148.981

B means regression coefficient; Std.Error means Standard error of the system; Beta means standardization coefficient; t means regression coefficient; Sig means significance level; Zero order means Degree of bivariate linear correlation; Partial means analysis of square variance; VIF means variance expansion coefficient
R^2 = 0.962, F-statistic = 75.867, Sig.F = 0

Table A3. *Model summary*

Model	Mult R	R square	Adj RSqu	SE
1	.9189413207	.8444531508	.7926042011	.0115191590

Mult R means correlation coefficient R; R means square goodness of fit; Adj RSqu means measurement factor of correction; SE means standard error

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Table A4. *ANOVA*

Model	df	ss	MS	F value	Sig F
Regress	5.000	.011	.002	16.28679376	.00001355
Residual	15.000	.002	.000		

df means degrees of freedom; ss means sum of squares from mean deviation; MS means mean square; F means value statistic; Sig F means significance level

Table A5. *Comparison of predicted and actual carbon emission in East China*

Year	Actual carbon emission	Model predicted value	Deviation	Error than (%)
1998	12430.42919	12345.80846	-84.62072863	-0.680754681
1999	12639.86322	12365.23491	-274.6283075	-2.172715817
2000	12215.80347	12143.33821	-72.46525918	-0.593209111
2001	11966.35087	12018.9891	52.63823413	0.439885431
2002	11898.61215	11964.05154	65.43938653	0.549974953
2003	11536.03077	11847.17317	311.142404	2.697135698
2004	12056.49448	12149.89969	93.40521395	0.774729455
2005	12239.06712	12217.78184	-21.28527904	-0.173912593
2006	12355.39043	12350.44456	-4.945869363	-0.040030053
2007	12370.77935	12345.74697	-25.03237865	-0.202350862
2008	12321.629	12336.68363	15.0546328	0.12218054
2009	12379.91379	12362.00936	-17.90442698	-0.144624812
2010	12372.01709	12371.85831	-0.158776784	-0.001283354
2011	12348.45095	12352.87188	4.420928353	0.035801481
2012	12302.97295	12322.44878	19.47583499	0.15830186
2013	12252.58138	12192.75261	-59.82876904	-0.488295219
2014	12229.61993	12120.87492	-108.7450108	-0.889193707
2015	12166.77275	12003.14976	-163.6229852	-1.344834728
2016	11980.25525	11922.42019	-57.83506407	-0.482753187
2017	11757.34895	11782.34369	24.99474492	0.212588272
2018	11412.61152	11603.86853	191.2570062	1.6758391

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