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Original Research

Will Limiting Agricultural Carbon Emissions Affect China's Agricultural Economy? Panel Data from 31 Provinces in China

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Abstract

The purpose of this paper is to analyze the impact of agricultural carbon emissions on China's agricultural economic development, which is of great significance to the modernization of China's agricultural sector. Based on the panel data of 31 provinces in China from 2019 to 2022, this paper selected 10 carbon emission-related indicators and comprehensively adopted a pooled regression model, a fixed effect model, and a random effect model to evaluate the impact. It also passes the Hausman test and Tobit model stability test. The results show that limiting agricultural carbon emissions in China has a significant impact on agricultural economic development; the total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF) have a significant positive impact on the output of agricultural economy (OAE), while cultivated land (CA) has no significant impact. Chinese agriculture is currently on the left side of the inverted "U" shape of the environmental Kuznets curve. Therefore, there is a need for more research and development of agricultural biotechnology and agricultural policy support to strengthen farmers' knowledge of how to reduce carbon emissions using the above indicators, which can promote agricultural economic growth and achieve high-quality agricultural development in China.

Keywords: China's agriculture, Carbon emissions, Agricultural economy

Introduction

With the emergence of the global greenhouse effect and extreme climate, the issue of "carbon emission" has attracted worldwide attention. In 1992, more than 150 countries in the world jointly signed the United Nations Framework Convention on Climate Change (UNFCCC), which put forward a framework international convention to address global warming with the control of carbon dioxide emissions for the first time. China not only has a large population but is also the world's factory, consuming a large amount of fossil energy every year. Limiting

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carbon emissions will have a negative impact on China's traditional economic development model, but to maintain the world's ecological environment, China has taken the initiative to reduce carbon emissions. In 2021, the State Council of China issued the Action Plan for Peaking Carbon Emissions Before 2030, which has achieved a steady decline in national carbon emissions each year.

Reducing agricultural carbon emissions is also an important part of China's efforts to achieve carbon peaking and carbon neutrality. However, agricultural development faces the dual dilemma of green low-carbon transformation and high-quality development of the agricultural economy. In 2022, the per capita disposable income of China's rural residents was only 20,133 yuan, and China's agricultural economy is characterized by a large population and low per capita income. China's agriculture plays two important roles. One role is to produce agricultural products to ensure that farmers have food to eat, are not hungry, and maintain the basic life of farmers. The development of agriculture is also conducive to maintaining national and social stability. On the other hand, agriculture is the main source of income for farmers, especially for the majority of farmers who are poorly educated and have few job opportunities. Agricultural income is their lifeline and the main source of income for them to send their children to school and support elderly people. Agricultural development concerns the livelihoods of the vast majority of Chinese farmers, and limiting agricultural carbon emissions is also the most difficult task. Therefore, this work has important practical significance for China's agricultural economic development, ecological protection and policy formulation. At the same time, this study provides a reference for the United Nations carbon emission policy to consider the actual difficulties of Chinese farmers.

The impact of carbon emissions on agricultural development is a hot topic worldwide, and relevant research results have focused mainly on the following three aspects.

First, the existing research has focused on agro-ecological efficiency. The concept of ecological efficiency was first proposed by German scholars Schaltegger and Sturm in 1990 [1]. In 2003, the concept of "agricultural sustainable development" was incorporated into the scope of agricultural policy formulation. Agenda 2000 requires all EU Member States to comply with minimum environmental standards and promote ecological efficiency and ecological equity [2]. Life cycle assessment and data envelopment analysis are important methods for evaluating eco-efficiency [3]. In the evaluation of eco-efficiency performance at the agricultural sector level in EU countries, it was found that 10 countries had good ecological effects and 18 countries had poor ecological effects [4]. Greenhouse gas emissions from agricultural output, the labor force, agricultural acreage, and nitrogen, phosphorus, and potassium fertilizers increased significantly in 24 selected EU member states [5]. Agriculture is the second largest source of greenhouse gas emissions, with agricultural soils accounting for a major share [6]. There is a conflict between industrial agriculture and sustainable agriculture, and small farms are difficult to choose [7]. The Dutch agricultural sector has the highest ammonia emissions per hectare of farmland, nitrogen and phosphorus surpluses, and pesticide use in the EU [8]. Polish farms, under pressure from greenhouse gas emissions, were able to reduce conventional inputs by almost a quarter without reducing production [9]. China's agricultural ecological efficiency has steadily improved. With land, machinery, labor, fertilizer, pesticides, and agricultural film as input variables and economic output and agricultural carbon emissions as output variables, the ultraefficient SBM model is adopted, and the results show that agricultural ecological efficiency in China has a stable and fluctuating trend of growth [10]. Technological progress, agricultural infrastructure and human capital improvement contributed positively to the growth of agricultural production efficiency [11]. Economic complexity affects the ecological footprint and leads to environmental degradation [12].

Second, the existing research has focused on the measurement and method of agricultural carbon emissions. Agricultural carbon emissions are affected by many factors. Scholars from various countries have attempted to measure carbon emissions from multiple perspectives, but their conclusions are inconsistent in terms of sample selection, estimation methods and calculation results. Carbon cycle analysis can measure carbon emissions from energy use and primary fuels, electricity, fertilizers, lime, pesticides, irrigation, seed production and agricultural machinery [13]. Land use, input and soil management, good agricultural management and organic farming practices contribute to reducing carbon emissions [14]. Soil microbes are a critical ecological parameter in the ecosystem's C cycle [15]. The crop production index and livestock production index have different impacts on carbon emissions [16]. The propensity score matching method revealed that agricultural production has an effect on reducing agricultural carbon emissions [17]. Energy carbon emission efficiency in rural China is on the rise, and technological change can reduce carbon emissions [18]. The income structure of national and rural residents changes China's agricultural CO_2 emissions [19]. The exponential method, nuclear density analysis and convergence analysis can be used to quantitatively analyze the influence of the animal husbandry structure on carbon emissions [20]. Carbon emissions in the Asia-Pacific region and China have also become popular research topics. The SBM-bad model of the factor analysis system was used to calculate the agroecological output of each province separately [21]. Carbon emission rights can improve the total factor productivity of agricultural enterprises and promote green innovation [22]. An increase in agricultural land area in Nepal triggered increased CO_2 emissions [23]. Both agricultural carbon emissions and carbon emission intensity showed a downward trend in Zhejiang Province [24]. According to MK trend analysis, Monte Carlo simulation, and other methods, China's provincial carbon peak-shifting echelons can be divided into five carbon-peak-shifting echelons: basic realization, early realization, early realization, on-time realization, and possibly delayed realization [25]. Economic growth and renewable energy can predict CO_2 emission levels in the MINT economies [26]. Green technology innovations and renewable energy help limit carbon emissions [27].

Third, other studies have focused on the impact of agricultural carbon emissions on the economy. Academics have also found a strong link between agricultural carbon emissions and economic growth. Through the study of the environmental Kuznets curve (EKC) hypothesis in Brazil, Russia, India, China, and South Africa, it has been found that agricultural activities and energy use affect the environment [28]. In the European Union, the relationship between economic performance and CO_2 emissions has attracted the interest of the scientific community and has become a priority in the Common Agricultural Policy, where there is a cointegration relationship between agricultural carbon equivalent and per capita income in the agricultural sector of EU countries [29]. There is a cointegration relationship between economic growth and carbon emission intensity caused by chemical fertilizer, pesticides, agricultural film, agricultural diesel, and the five carbon sources of agriculture [30]. An increase in agricultural carbon emission intensity in China will reduce the level of agricultural trade and the overall development level of the agricultural economy [31]. Agricultural industrial upgrading and rural electricity consumption are significantly positively correlated with agricultural carbon emissions [32]. Economic growth, energy use, agricultural productivity, and forest area in Kazakhstan have dynamic effects on carbon dioxide (CO_2) emissions [33]. There is heterogeneous dynamic causality among the intensity of energy use, land agglomeration, and carbon dioxide emissions [34]. An increase in forest area leads to a decrease in carbon emissions [35]. In Peru, economic growth, renewable energy use, and agricultural land expansion have an impact on CO_2 emissions, and increasing renewable energy use can reduce CO_2 emissions [36]. There is a relationship between agricultural production, economic growth, and CO_2 emissions in Pakistan, which decreases as barley and sorghum production increases [37]. The development of the regional digital economy has reduced agricultural carbon emissions significantly [38]. Encouraging agricultural science and technology research and innovation can promote the green and low-carbon development of agriculture [39]. The implementation of policies for high-standard farmland construction has a continuous inhibitory effect on agricultural carbon emissions [40]. The contribution rate of agricultural science and technology progress and total agricultural output value have an impact on carbon emissions [41]. Agricultural mechanization can reduce carbon emissions of the major grain production areas [42]. Both agricultural carbon emissions and agricultural carbon intensity conform to the inverted U-shape assumed by the EKC [43]. Provincial demonstration policies for clean energy have an impact on carbon emissions [44]. A reduction in carbon emission intensity will promote high-quality economic development [45]. Agricultural economic growth and net agricultural carbon emissions can also be decoupled [46]. There is a decoupling state between agricultural carbon emissions and agricultural economic growth in the Hotan area [47]. There is a bidirectional causality between agricultural productivity and renewable energy consumption [48]. The impact of GDP growth escalates the ratio of CO_2. China's agricultural carbon emissions show an inverted U-shaped trend, but the overall growth rate shows a gradual declining trend [49].

In summary, existing studies have elaborated on the concept, measurement methods, influence, existing problems, and possible solutions of eco-efficiency related to agricultural carbon emissions, which provides a basis for subsequent studies of the impact of carbon emissions on the agricultural economy. However, there is a lack of systematic discussion about agricultural carbon emissions and China's agricultural economic growth. In the critical period of China's agricultural upgrading, it is of great theoretical and practical significance to discuss the impact of agricultural carbon emissions on agricultural economic development. This paper uses the environmental Kuznets curve theory to carry out an empirical study on the effect of agricultural carbon emissions on China's agricultural economic development.

Materials and Methods

The EKC Theory and Research Hypotheses

For the first time, American economists Grossman and Krueger conducted an empirical study on the relationship between environmental quality and per capita income and noted that pollution increases with increasing per capita GDP at low income levels but decreases with increasing GDP at high income levels. Panayotou first elaborated on the environmental Kuznets curve (EKC) in 1993, revealing the inverse U-shaped relationship between environmental quality and income. China's agricultural development is still in the initial stage, agricultural production and planting depend on farmers, and the agricultural production mode is relatively rough. Carbon emissions are gaseous substances produced in agricultural production, and carbon dioxide will cause greenhouse effects, which will have adverse effects on the natural environment and social and economic activities. Modern agricultural production needs to consume electrical energy, fertilizer, agricultural plastic film, and arable land resources, and agricultural machinery and equipment need to be invested in these materials. According to the environmental Kuznets function theory and literature review, in the initial stage of agricultural development, the amount of input and consumption of materials is proportional to the agricultural carbon emissions generated, and the inputs of electrical energy, fertilizer, agricultural plastic film, cultivated land resources and agricultural machinery and equipment also affect agricultural economic output. Controlling carbon emissions may indirectly affect agricultural economic output. Therefore, combining the environmental Kuznets

curve and the characteristics of the current stage of Chinese agriculture, the following hypothesis is given:
H_1: China's agricultural carbon emissions positively affect its agricultural economic growth.

Based on the above research, an index system of agricultural carbon emissions affecting agricultural economic development was selected and constructed. Why not calculate agricultural emissions on this basis, and use this carbon calculation to extrapolate the causal relationship with the agricultural economy? This is mainly based on this consideration. First, although there are rough calculation standards for carbon emissions of each influencing factor at home and abroad, the data are not uniform, and the calculated carbon emissions results will be controversial and affect the causal judgment of agricultural economic growth. Second, this paper mainly focuses on determining the positive or negative effects of carbon emission factors on agricultural economic growth and does not require a clear calculation of its impact coefficient. Therefore, the selection of influencing factors of carbon emissions as factors affecting agricultural economic growth can satisfy the inference conditions and can be set as intermediate variables without calculating specific data on agricultural carbon emissions.

Data and Sample Information

This paper takes the agricultural carbon emission index and agricultural economic output of 31 provinces in China from 2019–2022 as examples to analyze the impact of the agricultural carbon emission index on China's agricultural economic development through panel data. According to the above summary and theoretical research, this paper selected 10 indicators, namely, the Output of Agriculture Economic (OAE), Cultivated Land (CA), Total Power of Agricultural Machinery (TPAM), Rural Electricity Consumption (REC), Amount of Agricultural Chemical Fertilizer Applied (AACF), Amount of Plastic Film used in Agriculture (APF), Number of Biogas Projects (NBP), Reservoir Capacity (RC), Waterlogging Control Area (WCA), and Soil Erosion Control Area (SECA), in addition to the year and province. A total of 1488 samples were selected. The data were selected from the 2020-2023 edition of the China Rural Statistical

Table 1. Indicator description

Property of variable	Variable name	Variable code	Variable unit	Variable definition
Dependent variable	The Output of Agriculture Economic (The Abbreviation is "OAE", the same below.)	Y	Billion Yuan	Agriculture, forestry, animal husbandry and fishery The total value of all products and supporting service activities for agricultural, forestry, animal husbandry, and fishery production activities
Independent variable	Cultivated Area ("CA")	X_1	Km^2	The area sown or transplanted in which crops are harvested during the year. All crops harvested in the current year, whether sown in the current year or the previous year, are counted as planted area.
	Total Power of Agricultural Machinery("TPAM")	X_2	GW	The sum of the rated power of all agricultural machinery power. It includes machinery and equipment for planting, animal husbandry, fishery, primary processing of agricultural products, agricultural transportation and farmland capital construction.
	Rural Electricity Consumption("REC")	X_3	GW	In a year, the total annual electricity consumption of rural production and living after deducting the electricity consumption of state-owned industry, transportation, infrastructure, and other units in rural areas
	Amount of Agricultural Chemical Fertilizer applied("AACF")	X_4	Million kg	The number of fertilizers actually used in agricultural production during the year, including nitrogen, phosphate, potash, and compound fertilizers. The amount of fertilizer application should be calculated according to the conversion amount.
	The Amount of Plastic Film used in agriculture("APF")	X_5	Million kg	It refers to the amount of various plastic films used in the agricultural production process for breeding seedlings and crop growth to prevent cold, heat preservation, and moisture
Control variable	Number of Biogas Projects("NBP")	X_6	Units	Number of projects using anaerobic digestion technology to treat organic waste (water) and produce biogas
	Reservoir Capacity("RC")	X_7	Billion m^3	The volume of water contained under the normal water level, that is, the storage capacity under the flood level is the total storage capacity.
	Waterlogging Control Area("WCA")	X_8	Km^2	The waterlogging area can be controlled by water conservancy projects such as dam and pumping dam so that the waterlogging area can be exempted from flooding
	Soil Erosion Control Area("SECA")	X_9	Km^2	Soil and water conservation measures shall be taken in areas with soil erosion, so that the amount of soil loss reaches or is below the allowable amount of soil loss

Yearbook published by the Rural Socioeconomic Survey Department of the National Bureau of Statistics of China. The data are collected by the National Bureau of Statistics price survey, which collects and sorts the basic statistical information of rural social and economic development and is more comprehensive, objective, and accurate. However, it is unbalanced panel data due to the presence of missing values. For missing data in sample data, this paper adopts the interpolation method.

Among the 10 variables selected in addition to the year and province, this paper takes the output of the agricultural economy (OAE) as the dependent variable, and the total output values of agriculture, forestry, animal husbandry, and fishery (OAFAF) are chosen as representative variables.

Independent variables are the main influencing factors of carbon emissions in China's agricultural economy, including cultivated land (CA), total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF). The control variables are the number of biogas projects (NBP), the reservoir capacity (RC), the waterlogging control area (WCA), and the soil erosion control area (SECA). The specific indicators are defined below (Table 1).

In Table 1, for the statistical analysis of the sample data, the sample data are from 2019-2022. For the provincial data, the sequence number is 1-31. The maximum and minimum values, average values and standard deviations of the Output of Agriculture Economic (OAE), the Cultivated land (CA), the Total Power of Agricultural Machinery (TPAM), Rural Electricity Consumption (REC), the Amount of Agricultural Chemical Fertilizer applied (AACF), the Amount of Plastic Film used in agriculture (APF), the Number of Biogas Projects (NBP), the Reservoir Capacity (RC), the Waterlogging Control Area (WCA), and Soil Erosion Control Area (SECA) are as follows (Table 2):

In Table 2, the Output of Agriculture Economic (OAE) is taken as an example. The province with the largest Output of Agriculture Economic (OAE) was 121.307 billion yuan, while the province with the smallest Output (OAE) was 21.28 billion yuan. Other indicators are not enumerated. China's agricultural economy and agricultural carbon emissions are very different among provinces, mainly due to the uneven distribution of agricultural resources and the uneven development of the agricultural economy in China. China has municipalities directly under the control of the central government, and the level of these municipalities is the same as the administrative level of provinces, but their economic activities are mainly urban economic activities, basically less basic farmland and cultivated land, farmers have been transformed into citizens, agricultural production activities are less common, and statistics are often conducted to collect data on the nonagricultural economy, so the statistical indicators of agricultural economic components are low.

According to the statistical analysis of the above sample data, the index of each indicator has a large gap, and the units are inconsistent. To further study the correlation and causality between the indicators of the sample data, the data need to be processed in the early stage. Therefore, the logarithm of economic data is processed in this paper to eliminate the impact of the dimensions between the original data and variables, as well as the changes between the values. The basic formula of the model is Formula 1:

$$Y_{ij} = \ln X_{ij} (i = 2019 \sim 2022, j = 1 \sim 31) \tag{1}$$

In Formula 1, X_{ij} represents an indicator in a province in a given year; X represents indicators such as "OAE", "CA", "TPAM", "REC", "AACF", "APF", "NBP", "RC", "WCA", and "SECA". i represents the year from 2019 to 2022. j represents provinces, from 1 to 31, and includes all 31 provinces or municipalities in China. Y_{ij} represents the value of the natural logarithm of X_{ij}. The data processing procedure is shown in Table 3.

In Table 3, taking the Output of Agriculture Economic (OAE) as an example, the province with the largest

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
year	124			2019	2022
province	124			1	31
OAE (Y)	124	455.508	304.859	21.28	1213.07
CA (x_1)	124	41171.903	36084.213	248.00	171954.0
TPAM (x_2)	124	34.422	28.856	1.002	115.305
REC (x_3)	124	24506.121	33332.026	250.00	201100
AACF (x_4)	124	168.752	133.743	2.80	666.70
APF (x_5)	124	768.251	647.147	14.92	2790.0
NBP (x_6)	124	2867.593	3896.75	8.00	23011.0
RC (x_7)	124	30.806	29.445	1.20	126.40
WCA (x_8)	124	7892.488	11380.98	1.10	45263
SECA (x_9)	124	47741.919	37552.981	1.50	166787

Output of Agriculture Economic (OAE) in X_1 is 121.307 billion yuan, and the logarithm is 7.101. The province with the smallest value (OAE) is 21.28 billion yuan, and the logarithm is 3.058. The gap between the original data is relatively large, but after logarithms are taken, they are all close. To ensure that the value is positive after taking the natural logarithm, a value greater than 1 is given for the original data below 1.

Research Methods

Pooled Regression Model

To study the relationships among cultivated land (CA), the total power of agricultural machinery (TPAM), rural electricity consumption (REC), the amount of agricultural chemical fertilizer applied (AACF), the

Table 3. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
year	124			2019.0	2022.0
province	124			1.000	31.000
OAE (lny)	124	5.710	1.122	3.058	7.101
CA ($\ln x_1$)	124	10.082	1.298	5.513	12.055
TPAM ($\ln x_2$)	124	3.060	1.163	.002	4.748
REC ($\ln x_3$)	124	9.415	1.322	5.521	12.212
AACF ($\ln x_4$)	124	4.586	1.339	1.03	6.502
APF ($\ln x_5$)	124	6.204	1.114	2.703	7.934
NBP ($\ln x_6$)	124	6.798	1.927	2.079	10.044
RC ($\ln x_7$)	124	2.909	1.145	0.182	4.839
WCA ($\ln x_8$)	124	7.224	2.745	0.095	10.720
SECA ($\ln x_9$)	124	10.059	2.103	0.405	12.024

Table 4. The description of the MLS regression results

	(1)	(2)	(3)	(4)	(5)
VARIABLES	y	y	y	y	y
CA ($\ln x_1$)	-0.112*	0.063	0.040	0.044	0.057
	(-1.67)	(1.16)	(0.83)	(0.89)	(1.10)
TPAM ($\ln x_2$)	0.417***	0.214***	0.169***	0.162***	0.173***
	(5.39)	(3.40)	(3.00)	(2.78)	(2.89)
REC ($\ln x_3$)	0.177***	0.146***	0.142***	0.139***	0.153***
	(4.37)	(4.69)	(5.16)	(4.87)	(4.61)
AACF ($\ln x_4$)	0.332***	0.249***	0.278***	0.276***	0.271***
	(4.83)	(4.70)	(5.90)	(5.78)	(5.63)
APF ($\ln x_5$)	0.121**	0.085**	0.085**	0.087**	0.077*
	(2.19)	(2.01)	(2.29)	(2.31)	(1.95)
NBP ($\ln x_6$)		0.149***	0.122***	0.123***	0.120***
		(9.27)	(8.09)	(7.96)	(7.53)
RC ($\ln x_7$)			0.118***	0.118***	0.126***
			(5.79)	(5.72)	(5.52)
WCA ($\ln x_8$)				0.004	-0.002
				(0.43)	(-0.17)
SECA ($\ln x_9$)					-0.013
					(-0.84)
Constant	1.636***	0.361	0.475	0.456	0.412
	(2.80)	(0.78)	(1.15)	(1.09)	(0.98)
Observations	124	124	124	124	124
R-squared	0.937	0.963	0.972	0.972	0.972

*t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

''indicates that there is at least a 90% chance that the event will occur. '**'indicates that there is at least a 95% chance that the event will occur, and '***'indicates that there is at least a 99% chance that the event will occur. The same as below.*

amount of plastic film used in agriculture (APF) and the total output of the agricultural economy (OAE) in each region, the location and time variables were first ignored, and the whole sample data were regarded as a cross-sectional database for pooled regression. The OLS multiple regression function is as follows:

$$Y = \beta_0 + \sum_{i=2019}^{2022} \beta_j X_{ij} + \varepsilon \quad (2)$$

In Formula 2, Y represents the Output of Agriculture Economic (OAE), and X_{ij} are agricultural carbon emissions indicators, such as cultivated land (CA), total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF) in the ith year. β_j are the contribution rates of these factors, respectively, and ε is the error term.

According to existing studies, the emission coefficients of agricultural carbon emission sources are as follows: fertilizer, 0.896 kg/kg (West and Marland, 2002); pesticide, 4.934 kg/kg; agricultural film, 5.180 kg/kg; agricultural irrigation, 20.476 kg/ha; and agricultural farming, 312.600 kg/ha [1]. Therefore, the annual carbon emissions of Hunan's agriculture can be preliminarily calculated. These emission coefficients are all positive, and the total carbon emissions are directly proportional to the above influencing factors. Carbon emissions increase with the growth of various indicators. This paper mainly focuses on the impact of carbon emission factors on agricultural economic development and conducts multiple linear regression on the above factors. Through multivariate least squares regression (mixed estimation), the results of multiple regression are as follows (Table 4).

Table 4 shows that in Model y (1), the causal relationships between the relevant influencing factors of agricultural carbon emissions (cultivated land (CA), total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF)) are significant. Among them, TPAM, REC, AACF and APF had positive impacts, and the total power of agricultural machinery (TPAM) had a greater positive impact, with an impact coefficient of 0.417, followed by the amount of agricultural chemical fertilizer applied (AACF), with an impact coefficient of 0.332. However, cultivated land (CA) has a negative impact on the Output of Agriculture Economic (OAE), and the complex impact coefficient is mainly because China has a large population and little land, and agricultural production does not increase as cultivated land increases. In contrast, due to the expansion of urbanization, cultivated land is shrinking, but the total agricultural economy is constantly growing.

In y (2), y (3), y (4) and y (5), cultivated land (CA) has no significant impact on the Output of Agriculture Economic (OAE), but in addition, the Total Power of Agricultural Machinery (TPAM), Rural Electricity Consumption (REC), the Amount of Agricultural Chemical Fertilizer Applied (AACF), and the Amount of Plastic Film used in Agriculture (APF) still have a positive impact on the Output of Agriculture Economic (OAE). Cultivated land (CA), the total power of agricultural machinery (TPAM), the amount of agricultural chemical fertilizer applied (AACF), and the amount of plastic film used in agriculture (APF) have significant effects on carbon emissions and agricultural economic development. The original Hypotheses H_1 are accepted.

According to the endogeneity test, after the mixed regression of the sample data, the F value is 4.51, and the P value is 0.005. Through the endogeneity test, it can be shown that the key variables of the model are not correlated with the error term.

Fixed Effect Model (FE) and Random Effects Model (RE)

To further analyze the influence of carbon emission factors such as cultivated land (CA), total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF) on the output of agricultural economy (OAE), fixed effects and random effects were analyzed.

Table 5. Descriptions of the FE regression results

OAE (lny)	Coef.	St. Err.	t value	p value	[95% Conf	Interval]	Sig
CA ($\ln x_1$)	-0.028	0.078	-0.360	0.721	-0.182	0.127	
TPAM ($\ln x_2$)	0.566	0.118	4.810	0.001	0.332	0.800	***
REC ($\ln x_3$)	0.068	0.028	2.490	0.015	0.014	0.123	**
AACF ($\ln x_4$)	-0.784	0.137	-5.710	0.001	-1.057	-0.511	***
APF ($\ln x_5$)	-0.078	0.135	-0.580	0.566	-0.345	0.190	
Constant	7.691	1.326	5.800	0.001	5.056	10.326	***
Mean dependent var	5.710		SD dependent var		1.122		
R-squared	0.500		Number of obs		124		
F test	17.607		Prob > F		0.000		
Akaike crit. (AIC)	-313.486		Bayesian crit. (BIC)		-296.564		

**** p<0.01, ** p<0.05, * p<0.1*

Fixed effects take into account both individual traits and essential error distinctions, but their individual traits are "fixed". In general, the model formula (sample formula) of the fixed effect is shown in Formula 3 below.

$$Y_{it} = X'_{it}\beta + Z'_i\delta + u_i + \varepsilon_{it}(i = 2019 \sim 2022) \quad (3)$$

In Formula 3, X'_{it} represents an individual index. i represents different individuals, and t represents different points in time. β represents the individual correlation coefficient. Z'_i represents individual fixed effects in which factors unique to the firm that do not change over time affect the explanatory variables and the explained variables, and δ represents the correlation coefficient of individual fixed effects. Here, u_i is the individual error term, ε_i is the essential error term, and ε_i is related to an explanatory variable, so the OLS regression results are inconsistent. The method of model transformation was proposed to solve the problem of eliminating the individual effect u_i.

Given individual i, average the time on both sides of the equation:

$$\overline{Y}_i = \overline{X}'_i\beta + Z'_i\delta + u_i + \overline{\varepsilon}_i(i = 2019 \sim 2022) \quad (4)$$

In Formula 4, the variable has the same meaning as in Formula 3. In addition, $\overline{X}'_i$ and Z'_i represent the average and , respectively. The average Equation (4) is subtracted from the original Equation (3) to obtain the deviation form (5).

$$Y_{it} - \overline{Y}_i = (X'_{it} - \overline{X}'_i)\beta + (\varepsilon_{it} - \overline{\varepsilon}_i) \quad (5)$$

The fixed effect simulation results are as follows (Table 5).

According to the fixed effect regression results, the total power of agricultural machinery (TPAM), rural electricity consumption (REC), and amount of agricultural chemical fertilizer applied (AACF) had positive impacts on the output of agricultural economy (OAE), and the total power of agricultural machinery (TPAM) had the largest influence coefficient (0.566), while the cultivated land (CA) and amount of plastic film used in agriculture (APF) had no significant impact on the output of agricultural economy (OAE).

Random effects also take into account individual traits and essential error distinctions, but their individual traits are "random." In general, the model formula (sample formula) for random effects is shown as follows (Formula 6):

$$Y_{it} = X'_{it}\beta + Z'_i\delta + u_i + \varepsilon_{it} \quad \text{v} \quad (6)$$

In Formula 6, the variable has the same meaning as in Formula 3, but individual effects u_i are not correlated with the explanatory variables; it is random. The OLS results were consistent. Since the perturbation term consists of $(u_i + \varepsilon_{it})$ and is not spherical, OLS is not the most efficient. In the two cases of whether it is equal to s, the variance exists as follows (Formula 7 and Formula 8). When $t \neq s$,

$$Cov(u_i + \varepsilon_{it}, u_i + \varepsilon_{is}) = Cov(u_i, u_i) + Cov(u_i, \varepsilon_{is}) + Cov(\varepsilon_{it}, u_i) + Cov(\varepsilon_{it}, \varepsilon_{is}) \quad (7)$$

When $t = s$,

$$VAR(u_i + \varepsilon_{it}) = \sigma_u^2 + \sigma_\varepsilon^2 \quad (8)$$

The random effect results of the model are as follows (Table 6).

In Table 6, through the above random effects, it can be seen that the total power of agricultural machinery (TPAM), rural electricity consumption (REC) and the amount of plastic film used in agriculture (APF) have positive impacts on the output of agricultural economy (OAE), and the total power of agricultural machinery (TPAM) influence coefficient is the largest, at 0.566. Cultivated land (CA) and the amount of agricultural chemical fertilizer applied (AACF) had no significant impact on the output of agricultural economy (OAE).

According to the Hausman test, the P value is close to 0, and both the fixed and random effects of this model are significant, which passes the Hausman test.

Table 6. The description of the RE regression results

OAE (lny)	Coef.	St.Err.	t value	p value	[95% Conf	Interval]	Sig
CA (lnx_1)	-0.025	0.071	-0.350	0.725	-0.164	0.114	
TPAM (lnx_2)	0.628	0.098	6.430	0.001	0.437	0.819	***
REC (lnx_3)	0.128	0.029	4.380	0.001	0.071	0.186	***
AACF (lnx_4)	-0.010	0.091	-0.110	0.910	-0.188	0.168	
APF (lnx_5)	0.225	0.094	2.390	0.017	0.041	0.409	**
Constant	1.484	0.580	2.560	0.010	0.347	2.620	**
Mean dependent var	5.710		SD dependent var		1.122		
Overall r-squared	0.911		Number of obs		124		
Chi-square	320.385		Prob > chi2		0.000		
R-squared within	0.296		R-squared between		0.915		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results and Discussion

Regression Results Analysis

Through the mixed multiple regression and endogenous tests above, it was found that the main influencing factors of agricultural carbon emissions in China (cultivated land (CA), total power of agricultural machinery (TPAM), rural electricity consumption (REC), amount of agricultural chemical fertilizer applied (AACF), and amount of plastic film used in agriculture (APF)) had significant causal relationships with the output of agricultural economy (OAE), and the effects on the output of agricultural economy (OAE) were all positive. After increasing the control variables (such as the number of biogas projects (NBP), reservoir capacity (RC), waterlogging control area (WCA), and soil erosion control area (SECA)), the causal relationships between the main factors affecting agricultural carbon emissions in China and the total output of agricultural economy (OAE) are still significant, and the missing variables are controlled through an endogeneity test. In the process of Fixed Effect and Random Effect analysis, it is found that the influence factors of the two are slightly different. In the Fixed Effect, the Total Power of Agricultural Machinery (TPAM), Rural Electricity Consumption (REC), and the Amount of Agricultural Chemical Fertilizer Applied (AACF) had a positive impact on the Output of Agriculture Economic (OAE), while the influence of cultivated land (CA) and the amount of plastic film used in agriculture (APF) was not significant. In terms of the random effect, the total power of agricultural machinery (TPAM), rural electricity consumption (REC) and amount of plastic film used in agriculture (APF) have a positive impact on the output of agricultural economy (OAE), while cultivated land (CA) and the amount of agricultural chemical fertilizer applied (AACF) have no significant impact on the output of agricultural economy (OAE). These causal analyses indicate that the influence of agricultural carbon emissions on agricultural economic development in China is not significant in the cultivated land situation in each region, and the influence of limiting carbon emissions by controlling cultivated land is of little significance. Therefore, according to the research above, three main conclusions can be drawn: (1) Carbon emission measurement indicators such as the total power of agricultural machinery (TPAM), rural electricity consumption (REC), the amount of agricultural chemical fertilizer applied (AACF), and the amount of plastic film used in agriculture (APF) positively affect the development of China's agricultural economy. The greater the input of these indicators is, the greater the carbon emissions, and the greater the agricultural economic growth. (2) The carbon emission index of cultivated land in all regions has no significant impact on China's agricultural economy. It is difficult to limit carbon emissions by controlling cultivated land because the Chinese government has issued strict policies on farmland protection, and the elasticity of this index has not decreased. (3) The relationship between China's agricultural carbon emissions and agricultural economic development is still on the left side of the inverted "U" shape of the environmental Kuznets curve, with increasing carbon emissions and increasing agricultural economic development. Since agricultural carbon emissions affect the development of China's agricultural economy and affect China's food security, the Chinese government should actively explore new ways to promote agricultural economic development without increasing carbon emissions.

Robustness Test Analysis

The influence of the carbon emission index on agricultural economic development also needs to be tested for robustness. Since the Output of Agriculture

Table 7. Descriptions of the Tobit regression results

OAE (lny)	Coef.	St.Err.	t value	p value	[95% Conf	Interval]	Sig
CA ($\ln x_1$)	0.057	0.050	1.150	0.254	-0.042	0.156	
TPAM ($\ln x_2$)	0.173	0.057	3.020	0.003	0.059	0.287	***
REC ($\ln x_3$)	0.153	0.032	4.810	0.001	0.090	0.216	***
AACF ($\ln x_4$)	0.271	0.046	5.880	0.001	0.180	0.362	***
APF ($\ln x_5$)	0.077	0.038	2.030	0.044	0.002	0.151	**
NBP ($\ln x_6$)	0.12	0.015	7.850	0.001	0.090	0.150	***
RC ($\ln x_7$)	0.126	0.022	5.760	0.001	0.083	0.169	***
WCA ($\ln x_8$)	-0.002	0.011	-0.170	0.863	-0.024	0.020	
SECA ($\ln x_9$)	-0.013	0.015	-0.880	0.381	-0.044	0.017	
Constant	0.412	0.403	1.020	0.308	-0.385	1.210	
var	0.035	0.004	0.001	0.001	0.027	0.045	
Mean dependent var	5.710		SD dependent var		1.122		
Pseudo r-squared	1.166		Number of obs		124		
Chi-square	442.673		Prob > chi2		0.000		
Akaike crit. (AIC)	-41.132		Bayesian crit. (BIC)		-10.109		

**** p<0.01, ** p<0.05, * p<0.1*

Economic (OAE) is always greater than or equal to 0, the dependent variable is roughly continuously distributed over positive values. Therefore, the limited dependent variable regression model (Tobit) is selected to analyze the influence of carbon emission factors on agricultural economic growth income. The basic form of the model is as follows (Formulas 9 and 10):

$$Y_i = X_i'\gamma + \varepsilon, \varepsilon_i \sim N(0, \sigma^2) \quad \text{(Formula 9)}$$

In Formula 9, Y_i is the dependent variable, that is, the i influencing factor of carbon emissions. X_i' is the explanatory variable, that is, the influencing factor affecting the i carbon emission, γ is the regression coefficient, ε_i is the random error, and the perturbation term ε_i follows the normal distribution with mean 0 and variance σ^2.

$$Y = \begin{cases} \alpha(y_i^* \le \alpha) \\ y_i^*(\alpha \prec y_i^* \prec \beta) \\ \beta(\beta \le y_i^*) \end{cases} \quad \text{(Formula 10)}$$

In Formula 10, y_i is the dependent variable, that is, the i influencing factor of carbon emissions. represents the right intercept point, α represents the left intercept point, where α represents the maximum and β represents the minimum of China's agricultural economic growth level. Through Tobit regression, the regression results are as follows (Table 7):

Through the Tobit regression analysis of China's agricultural economic growth by influencing factors of carbon emission, the causal relationship between the Total Power of Agricultural Machinery (TPAM), Rural Electricity Consumption (REC), the Amount of Agricultural Chemical Fertilizer applied (AACF), the Amount of Plastic Film used in agriculture (APF) and Output of Agriculture Economic (OAE) was significant. Among them, the TPAM, REC, AACF and APF have positive effects on the OAE, while the influence of Cultivated land (CA) on the OAE is not significant. Among the control variables, the Number of Biogas Projects (NBP) and the Reservoir Capacity (RC) have significant and positive effects on the OAE, while the Waterlogging Control Area (WCA), and Soil Erosion Control Area (SECA) have no significant effects on the OAE. In general, the Tobit regression basically confirmed that the influencing factors of carbon emissions had a positive impact on China's agricultural economic growth, and the original Hypotheses H_1 were valid.

Conclusions

China's agricultural carbon emissions and agricultural economic development are the subject of heated discussion. China is a large country with a large population and large agriculture area, and the control of agricultural carbon emissions has a significant impact on the development of China's agricultural economy. Based on the panel data of 31 provinces in China from 2019 to 2022, this paper selects a series of carbon emission correlation indicators and measurement model methods to study and discuss whether the influencing factors of China's agricultural carbon emissions affect the development of China's agricultural economy. Carbon emission indicators such as the total power of agricultural machinery (TPAM), rural electricity consumption (REC), and amount of agricultural chemical fertilizer applied (AACF) have a significant positive impact on the development of China's agricultural economy. The greater the carbon emissions of these indicators are, the faster the growth of China's agricultural economy. However, the impact of agricultural use is not significant, and it is difficult to limit carbon emissions by controlling cultivated land (CA). Moreover, to protect China's food security, the Chinese government has introduced strict cultivated land protection policies. At present, the relationship between China's agricultural carbon emissions and agricultural economic development is still on the left side of the inverted "U" shape of the environmental Kuznets curve when carbon emissions increase and agricultural economic development also increases. The research findings will be utilized in various aspects of agricultural production, such as the application of agricultural fertilizers, power for agricultural machinery, energy consumption, agricultural production techniques, recycling of agricultural film waste, soil quality improvement, and so forth. At present, China's agricultural economy is still in the primary stage of agricultural development. While controlling carbon emission indicators (TPAM, REC, AACF, APF, etc.), the government should actively explore other development methods, such as agricultural biotechnology research and development, agricultural policy support and strengthening farmers' vocational education, to continuously reduce the cost of agricultural production. Improving the scientific and technological level of agriculture and the quality level of farmers will not only increase carbon emissions but also promote agricultural economic growth and achieve high-quality agricultural development in China. This paper emphasizes the development of an agricultural economy through new technologies under the control of agricultural carbon emissions rather than encouraging agricultural development to decouple from carbon emissions because of carbon emission limits.

Policy Recommendations

The Chinese government is advised to develop a series of policies to support agricultural carbon emissions, including providing low-carbon education for farmers, offering incentives for agricultural carbon emissions reduction, and subsidizing agricultural carbon sinks. On one hand, the government should actively promote the policy of low-carbon agricultural production and provide farmers with education on the importance of low-carbon agriculture. On the other hand, the government should provide subsidies to operators who adopt low-carbon agricultural production methods, such as using organic fertilizers, agricultural machinery and equipment, agricultural film, electricity, etc. The government should also subsidize product prices and encourage banks to offer flexible credit policies for low-carbon agriculture. With these policies in place, China's low-carbon agriculture will continue to develop and achieve high-quality development goals.

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Conflict of interest

The authors declare no conflicts of interest.

References

1. YIN K., WANG R.S., ZHOU C.B., LIANG J. Review of eco-efficiency accounting method and its applications. Acta Ecologica Sinica, **32** (11), 3595, **2012**.
2. PREDA M.C., CHIRCULESCU R.E. Integrating sustainable development policies in creating an agricultural cooperative. political sciences, Law, Finance, Economics and Tourism Conference Proceedings, **5**, 377, **2016**.
3. ANGULO-MEZA L., GONZÁLEZ-ARAYA M., IRIARTE A., REBOLLEDO-LEIVA R., DE MELLO J.C.S. A multiobjective DEA model to assess the eco-efficiency of agricultural practices within the CF plus DEA method. Computers and Electronics in Agriculture, **161** (S1), 151, **2019**.
4. RYBACZEWSKA-BLAZEJOWSKA M., GIERULSKI W. Eco-efficiency evaluation of agricultural production in the EU-28. Sustainability, **10** (12), 4544, **2018**.
5. STANISZEWSKI J. Attempting to measure sustainable intensification of agriculture in countries of the European Union. Journal of Environmental Protection and Ecology, **19** (2), 949, **2018**.
6. GANCONE A., PUBULE J., ROSA M., BLUMBERGA D. Evaluation of agriculture eco-efficiency in Latvia. International Scientific Conference - environmental and Climate Technologies, **128**, 309, **2017**.
7. CZYZEWSKI B., MATUSZCZAK A., GRZELAK A., GUTH M., MAJCHRZAK A. Environmental sustainable value in agriculture revisited: How does common agricultural policy contribute to eco-efficiency? Sustainability Science, **16** (1), 137, **2021**.
8. VAN GRINSVEN H.J.M., VAN EERDT M.M., WESTHOEK H., KRUITWAGEN S. Benchmarking Eco-efficiency and footprints of dutch agriculture in european context and implications for policies for climate and environment. Frontiers in Sustainable Food Systems, **3**, 13, **2019**.
9. GOLAS M., SULEWSKI P., WAS A., KLOCZKO-GAJEWSKA A., POGODZINSKA K. On the way to sustainable agriculture-eco-efficiency of Polish commercial farms. Agriculture-Basel, **10** (10), 438, **2020**.
10. CHI M.J., GUO Q.Y., MI L.C., WANG G.F., SONG W.M. Spatial Distribution of Agricultural Eco-efficiency and agriculture high-quality development in China. Land, **11** (5), 722, **2022**.
11. YANG H., WANG X.X., BIN P. Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. Journal of Cleaner Production, **334**, 130193, **2022**.
12. KHAN S., WANG Y.H., CHANDIO A.A. How does economic complexity affect ecological footprint in G7 economies: the role of renewable and non-renewable energy consumptions and testing EKC hypothesis. Environmental Science and Pollution Research, **29** (31), 47647, **2022**.
13. WEST T.O., MARLAND G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the United States. Agriculture Ecosystems & Environment, **91** (1-3), 217, **2002**.
14. MOHAMAD R.S., VERRASTRO V., AL BITAR L., ROMA R., MORETTI M., AL CHAMI Z. Effect of different agricultural practices on carbon emission and carbon stock in organic and conventional olive systems. Soil Research, **54** (2), 173, **2016**.
15. ADINGO S., YU J.R., LIU X.L., LI X.D., JING S., XIAONG Z. Variation of soil microbial carbon use efficiency (CUE) and its influence mechanism in the context of global environmental change: a review. Peerj, **9**, e12131, **2021**.
16. APPIAH K., DU J.G., POKU J. Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies. Environmental Science and Pollution Research, **25** (25), 24764, **2018**.
17. SUN X.Y., GUANG S.Y., CAO J.J., ZHU F.Y., LIU J.X., SRIBOONCHITTA S. Effect of agricultural production trusteeship on agricultural carbon emission reduction. Agriculture-Basel, **13** (7), 1457, **2023**.
18. TIAN Y., WANG R., YIN M.H., ZHANG H.J. Study on the measurement and Influencing factors of rural energy carbon emission efficiency in China: Evidence Using the Provincial Panel Data. Agriculture-Basel, **13** (2), 441, **2023**.
19. CHEN J.D., CHENG S.L., SONG M.L. Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2005 to 2013. Renewable & Sustainable Energy Reviews, **94**, 748, **2018**.
20. SHI R.B., IRFAN M., LIU G.L., YANG X.D., SU X.F. Analysis of the impact of livestock structure on carbon emissions of animal husbandry: A sustainable way to improving public health and green environment. Frontiers in Public Health, **10**, 835210, **2022**.
21. AKBAR U., LI Q.L., AKMAL M.A., SHAKIB M., IQBAL W. Nexus between agro-ecological efficiency and carbon emission transfer: evidence from China. Environmental Science and Pollution Research, **28** (15), 18995, **2021**.
22. HUA J.G., ZHU D., JIA Y.F. Research on the policy effect and mechanism of carbon emission trading on the total factor productivity of agricultural enterprises. International Journal of Environmental Research and Public Health, **19** (13), 102045, **2022**.
23. REHMAN A., MA H.Y., KHAN M.K., KHAN S.U., MURSHED M., AHMAD F., MAHMOOD H. The asymmetric effects of crops productivity, agricultural land utilization, and fertilizer consumption on carbon emissions: revisiting the carbonization-agricultural activity nexus in Nepal. Environmental Science and Pollution Research, **29** (26), 39827, **2022**.
24. LI J.J., LI S.W., LIU Q., DING J.L. Agricultural carbon emission efficiency evaluation and influencing factors in Zhejiang province, China. Frontiers in Environmental Science, **10**, 1005251, **2022**.
25. SIBO WANG G.Z., XIAOMING DOU. Tiered division of peak carbon emissions and differentiated emission paths among provinces in China. WuHan University Journal (Philosophy & Social Science), **76** (03), 136, **2023**.

26. DU L., JIANG H., ADEBAYO T.S., AWOSUSI A.A., RAZZAQ A. Asymmetric effects of high-tech industry and renewable energy on consumption-based carbon emissions in MINT countries. Renewable Energy, **196**, 1269, **2022**.
27. HABIBA U., XINBANG C.,ANWAR A. Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions? Renewable Energy, **193**, 1082, **2022**.
28. BALSALOBRE-LORENTE D., DRIHA O.M., BEKUN F.V., OSUNDINA O.A. Do agricultural activities induce carbon emissions? The BRICS experience. Environmental Science and Pollution Research, **26** (24), 25218, **2019**.
29. ZAFEIRIOU E., MALLIDIS I., GALANOPOULOS K., ARABATZIS G. Greenhouse gas emissions and economic performance in EU agriculture: An empirical study in a non-linear framework. Sustainability, **10** (11), 3837, **2018**.
30. LONG D.J., TANG L. The impact of socio-economic institutional change on agricultural carbon dioxide emission reduction in China. Plos One, **16** (5), e0251816, **2021**.
31. ZANG D.G., HU Z.J., YANG Y.Q., HE S.Y. Research on the relationship between agricultural carbon emission intensity, agricultural economic development and agricultural trade in China. Sustainability, **14** (18), 11694, **2022**.
32. LIU Y.Q., GAO Y. Measurement and impactor analysis of agricultural carbon emission performance in Changjiang economic corridor. Alexandria Engineering Journal, **61** (1), 873, **2022**.
33. PRASTIYO S.E., IRHAM, HARDYASTUTI S., JAMHARI. How agriculture, manufacture, and urbanization induced carbon emission? The case of Indonesia. Environmental Science and Pollution Research, **27** (33), 42092, **2020**.
34. AHMAD M., LI H., ANSER M.K., REHMAN A., FAREED Z., YAN Q.Y., JABEEN G. Are the intensity of energy use, land agglomeration, CO_2 emissions, and economic progress dynamically interlinked across development levels? Energy & Environment, **32** (4), 690, **2021**.
35. KOONDHAR M.A., SHAHBAZ M., OZTURK I., RANDHAWA A.A., KONG R. Revisiting the relationship between carbon emission, renewable energy consumption, forestry, and agricultural financial development for China. Environmental Science and Pollution Research, **28** (33), 45459, **2021**.
36. RAIHAN A., TUSPEKOVA A. The nexus between economic growth, renewable energy use, agricultural land expansion, and carbon emissions: New insights from Peru. Energy Nexus, **6**, 100067, **2022**.
37. ALI S., LI G., YING L., ISHAQ M., SHAH T. The relationship between carbon dioxide emissions, economic growth and agricultural production in Pakistan: An Autoregressive distributed lag analysis. Energies, **12** (24), 4644, **2019**.
38. CHEN Z. W.,TANG C. Impact of digital economy development on agricultural carbon emissions and its temporal and spatial effects. Science and Technology Management Research, **43** (12),137, **2023**.
39. LIU Z., ZHANG X.X., WEI W.G. The impact of rural digital economic development on agricultural carbon emissions: Based on the panel data of 29 provinces in China. Journal of Jiangsu University (Social Sciences Edition), **25** (03), 20, **2023**.
40. XIONG F.X., ZHAO X.L., GUO Z.Y., ZHU S.B. Research on the effects of rural land consolidation on agricultural carbon emissions: a quasi-natural experiment based on the high-standard farmland construction policy. Chinese Journal of Eco-Agriculture, **31** (12), 2022, **2023**.
41. JIE LI C.X., YE YAN. Study on the relationship between science and technology expenditure, agricultural gross output value and agricultural carbon emission in Inner Mongolia. Scientific Management Research, **37** (04), 131, **2019**.
42. QING H., JUNBIAO J., HU Z. The impact of agricultural mechanization on agricultural carbon emission: An empirical study from major grain-producing areas. Statistics and decision, **39** (01), 88, **2023**.
43. BIAO GAO J.F., XIAOLING LU,YUBO LI. Evolution relationship between agricultural carbon emissions and economic growth and its reduction potential. Journal of Arid Land Resources and Environmen, **31** (01), 13, **2017**.
44. CHEN Y.Z.J.L.H. The impact of clean energy demonstration provincial policies on carbon emissions and economic development levels in Pilot areas: Verification based on Multi-phase PSM-DID. Soft Science, **38** (1), 53, **2024**.
45. HAILONG CHEN Y.L. Spatial effect analysis of the influence of carbon emission intensity on high-quality economic developmen. Statistics & Decision, **38** (23), 117, **2022**.
46. YU Z., MAO S. Analysis of the decoupling of China's agricultural net carbon emissions from its economic growth. China population, Resources and Environment, **32** (11), 30, **2022**.
47. XIONG C.H., YANG D.G., HUO J.W., ZHAO Y.N. The relationship between agricultural carbon emissions and agricultural economic growth and policy recommendations of a low-carbon agriculture economy. Polish Journal of Environmental Studies, **25** (5), 2187, **2016**.
48. CHOPRA R., MAGAZZINO C., SHAH M.I., SHARMA G.D., RAO A., SHAHZAD U. The role of renewable energy and natural resources for sustainable agriculture in ASEAN countries: Do carbon emissions and deforestation affect agriculture productivity? Resources Policy, **76**, 102578, **2022**.
49. LIU D.D., ZHU X.Y., WANG Y.F. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. Journal of Cleaner Production, **278**, 123692, **2021**.