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Original Research

The Impact of Agricultural Industrial Agglomeration on Agricultural Carbon Emissions: Evidence from China

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Abstract

To aid the achievement of "dual carbon" targets and high-quality agricultural development, by analyzing data from 30 provinces in China from 2011 to 2021, this study offers insights into green and low-carbon development. Through the application of fixed-effect, mediation, and moderation effect models, it empirically examines the impact and mechanisms of agricultural-industrial agglomeration on carbon emissions. The findings indicate: (1) an Inverted U-shaped relationship between agricultural-industrial agglomeration and carbon emissions, with a positive slope at the agglomeration's minimum value and a negative slope at its maximum. (2) In heterogeneity analysis, the central and western, northern, major production, and major sales areas, as well as areas of high agglomeration, demonstrate a significant Inverted U-shaped relationship. (3) The progression of digital villages helps explain the complex, Inverted U-shaped link between agricultural-industrial concentration and carbon emissions, indirectly affecting the latter. (4) A substitution effect is present, wherein land use capability alters the overall impact of agricultural-industrial agglomeration on carbon emissions and adjusts the dynamic path of this impact with varying degrees of agglomeration. The study's conclusions provide meaningful implications for the government to optimize agricultural industry layouts for effective control of agricultural carbon emissions and the realization of green, sustainable development. Thus, this study suggests expediting the development of digital villages to enhance the carbon reduction efficiency of agricultural-industrial agglomeration.

Keywords: Agricultural industrial agglomeration, agricultural carbon emissions, inverted u-shape, digital rural development

Introduction

In recent years, the extensive use of high-energy-consuming resources such as coal has led to substantial emissions of carbon dioxide and other greenhouse

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gases, catalyzing global warming and numerous environmental issues. One of the main contributors to increased carbon emissions is inefficient energy use, making the enhancement of energy efficiency crucial for sustainable environmental development [1-3]. Since economic reforms began, China has experienced rapid economic growth accompanied by escalating resource and environmental challenges, characterized by high consumption and low efficiency [4]. As a significant source of greenhouse gas emissions, agriculture accounts for approximately 17% of China's total carbon emissions, a figure significantly higher than the global average for the agricultural sector [5]. Moreover, agricultural activities contribute to ecological damage through deforestation and soil degradation, exacerbating the greenhouse effect globally.

In response to the challenge of global climate change, President Xi delivered remarks at the United Nations General Assembly's 75th session, highlighting the importance of accelerating the development of green modes of development and lifestyles. He promised to advance China's own environmental commitments to hit a carbon emissions peak by 2030 and attain carbon neutrality by 2060. Later, more than 100 countries pledged at COP28 to double the rate of energy efficiency improvement by 2030 and emphasized the crucial role of renewable energy in driving energy transition, establishing it as the primary choice for achieving sustainable development. Additionally, China has also promised at the international level to expedite the transition to renewable energy sources and zero-emission technologies, striving for global net-zero emissions by 2050. Therefore, reducing emissions and enhancing carbon sequestration in agriculture are pivotal measures to achieve the dual carbon goals, with significant potential.

As the dividends of China's household contract responsibility system are gradually depleted, there is an urgent need for new organizational models to enhance agricultural efficiency. Agricultural industrial clusters, as an organizational innovation, are key to improving comprehensive agricultural capacities and productivity. Reducing fertilizer and pesticide use through economies of scale in agricultural production and industrial clusters effectively lowers the carbon footprint. Streamlining logistics and reducing transportation needs further diminish greenhouse gas emissions. Focused on innovation and sustainability, agricultural clusters harness renewable and waste-to-energy technologies to drive green economic development. They also facilitate the exchange of best practices in carbon management, aiding global efforts to mitigate climate change.

Driven by agricultural-industrial agglomeration, technological innovation has significantly advanced, optimizing agricultural production processes and contributing to low-carbon development goals. In 2023, China has particularly emphasized the application of "green low-carbon technology in agriculture" as an integral part of its national policy, highlighting the central role of industrial clusters in implementing the national green low-carbon development strategy. Through efficient and intensive operations, clusters do not only control agricultural carbon emissions effectively, but also alleviate the environmental impact of agricultural activities. Moreover, the development of industrial clusters drives the flow of agricultural production factors, especially capital and technology, into green innovation, steering these resources into carbon management and sustainable agricultural improvements. Thus, analyzing how agricultural-industrial agglomeration affects China's agricultural carbon emissions and revealing the underlying mechanisms is of vital practical significance for advancing China's sustainable green transformation and providing important theoretical and practical support for global climate change response strategies.

The potential contributions of this study are: First, while existing research on agricultural-industrial agglomeration has mainly focused on aspects such as high-quality agricultural economic growth and productivity, often examining linear relationships, studies linking agricultural-industrial agglomeration with carbon emissions are less common. This study bridges this gap by exploring the non-linear relationship between the two; Second, it employs quantitative research methods to empirically analyze the role and mechanisms of agricultural-industrial agglomeration in green agricultural development, filling a gap in current literature; Third, the study confirms that agricultural-industrial agglomeration indirectly reduces carbon emissions by enhancing the level of digital rural development. Fourth, a substitution effect is observed; the research reveals that land use capability not only changes the overall impact of agricultural-industrial agglomeration on carbon emissions but also adjusts the dynamic path of this impact as agglomeration levels vary, thus addressing a void in existing research.

Section two includes a literature review, research gaps, and limitations; section three presents theoretical analysis and research hypotheses; section four describes the research design, including methods, model settings, and data collection; section five discusses the empirical results and analyzes them; section six concludes and provides relevant recommendations.

Literature Review

Research on industrial agglomeration initially focused on its economic effects. Marshall was among the first to notice this phenomenon, proposing the "Industrial Districts Theory," which identified clusters of similar sectors within specific regions and explored the relationship between internal and external economies. Current studies analyze agglomeration effects from three perspectives: economic development, farmers' income, and sustainable development.

Agricultural industrial clusters originate from local natural resource endowments, such as geographic conditions, climate, and soil and water resources [6]. According to the findings of He et al. (2020), the clustering of China's agricultural industry might create a siphoning effect that could dampen the economic status of farmers in adjacent areas, potentially widening the gap in rural economic development [7]. Setyowati observed significant rural economic growth driven by cassava industry clusters in Indonesia [8]. Kim and Scorsone noted that while agglomeration can stimulate rural economic growth during agriculture's expansion phase, it may lead to unemployment during its decline [9, 10].

Agglomeration also affects labor migration and regional income disparities. Zhang et al. (2023) found that industrial clustering initially exacerbates income inequality, but beyond a certain threshold, the degree of inequality diminishes [11]. Ding demonstrated through spatial panel models that agglomeration has a direct and indirect positive impact on farmers' incomes [12].

There is an Inverted U-shaped relationship between economic growth and environmental pollution, according to the Environmental Kuznets Curve (EKC) [13]. Hosoe argued that agricultural agglomerations could have positive environmental effects by reducing pollution and carbon emissions [14]. Guo et al. (2020) emphasized that moderate agglomeration can achieve sustainable agriculture through economies of scale, but excessive agglomeration might result in crowding-out effects [15]. Xue et al. (2020) believed that moderate agglomeration enhances land management scale and resource sharing, thus advancing agricultural development [16]. Liu et al. (2017) found that the negative externality effects of industrial agglomeration in China's new normal are gradually weakening, with FDI and environmental regulations indirectly reducing pollution through industrial agglomeration [17].

The scholarly work on carbon emissions from farming is often grouped into three strands: assessing emission levels, policy-making for emission mitigation, and thorough investigation of the elements that drive emissions. First, significant studies focus on the calculation of agricultural carbon emissions. Streimikiene et al. (2021) highlighted that methane release during livestock digestion and rice production, along with waste treatment, and nitrous oxide from synthetic fertilizer application and additional agricultural methods, constitute major factors of agricultural carbon emissions in China [18]. He et al. (2016) used econometric models and kernel density analysis to discuss the structural characteristics, spatiotemporal evolution, and driving mechanisms of China's agricultural carbon emissions, noting a rising trend and regional specificity in recent years [19]. Wu et al. (2024) proposed a new agricultural carbon emission efficiency (ACEE) framework integrating indices related to water, energy, and food stress from a green development perspective [20]. Based on Yadav et al.'s (2021) findings, agricultural carbon emissions are closely related to food production, water resources, and energy [21].

The second group encompasses China's policy measures concerning agricultural carbon emissions. Ge (2023) reported China's introduction of specific policies targeted at reducing agricultural emissions. Key initiatives include the "Thirteenth Five-Year Plan" for environmental and ecological protection and the "Rural Revitalization Strategy," both aimed at promoting sustainable agricultural practices and reducing emissions [22]. García-García et al. (2020) speculated that the state of China's agricultural carbon emissions might shift with the evolution of policies, practices, and technology [23]. Du et al. (2023) explored the effects of China's 2018 sustainable agricultural development demonstration zones policy on agricultural carbon emissions reduction [24].

Finally, studies that delve into factors influencing carbon emissions. Li and Liu (2022)considered the impact of economic affluence on carbon emissions in the STIRPAT model, concluding that an increase in GDP per capita could lead to higher energy consumption and carbon emissions [25]. Wang et al. (2022) found that agricultural specialization leads to the overuse of chemical fertilizers, thus positively affecting carbon emissions [26]. Continual changes in the application of land, the overconsumption of resources, and substandard management of waste are all activities that result in the emission of carbon [27]. Moreover, factors such as urban-rural integrated development have been identified as influencing agricultural carbon emissions [28]. The trend of emissions with rising integration levels shows a cycle of initial decrease, subsequent increase, and final decrease. Zhang et al. (2022) in the context of sustainable agricultural development, observed a significant threshold effect between the agglomeration of agricultural industries and sustainable development [29]. Wang (2021) suggested that agglomerating agricultural industries can enhance the allocation of agricultural science and technology resources, promote innovation among micro entities, and increase the efficiency of fertilizers, while also supporting growth in food production [30].

Yet, inquiries into the consequences of agricultural industry agglomeration on carbon emissions remain at an early stage, with few studies existing, particularly concerning the mechanisms behind their Inverted U-shaped relationship. Therefore, this investigation works with panel data from 30 provinces in China, covering the years 2011 to 2021, to analyze the repercussions of agricultural-industrial agglomeration on the carbon emissions stemming from agriculture. With a particular emphasis on the digital evolution of the countryside, the study aims to unravel the core mechanisms and apply mediation and moderation effect analyses to explore the influencing factors on agricultural carbon emissions, endeavoring to supplement the existing research void.

However, there are some limitations to this study. Firstly, data availability is limited to the provincial level due to missing data from many prefectures. Second, this study only considered six major aspects of measuring agricultural carbon emissions, including pesticides, agricultural films, diesel fuel, fertilizer use, irrigation, and tillage. However, factors such as crop selection and cultivation methods as well as agricultural waste disposal may also affect agricultural carbon emissions and deserve further exploration. Thirdly, some studies have analyzed the impacts of energy policies, and industrialization on sustainable development and environmental quality [31-33]. However, this paper does not consider the impacts triggered by energy policies as well as industrialization in this context, which can be analyzed in future studies.

Theoretical Analysis and Hypotheses

Direct Effects of Agricultural-Industrial Agglomeration on Carbon Emissions

Fig. 1 is the logical framework for theoretical analysis. The relationship between agricultural-industrial agglomeration, economic development, and environmental protection is complex. In the early stages of agglomeration, economies of scale, increased resource efficiency, and accelerated technological innovation effectively reduce carbon emissions. However, as agglomeration intensifies, excessive resource use and environmental carrying capacity pressures may lead to increased carbon emissions, which forms an Inverted U-shaped relationship. According to a study by Liu et al. (2022) at the provincial scale, there is a nonlinear relationship between agricultural-industrial agglomeration and sustainable development [34]. Studies by Shen (2020) and Chen (2020) indicate that industrial agglomeration beyond a certain inflection point can reduce pollution emissions and create positive spatial spillover effects [35, 36]. The above findings suggest that the impact of agricultural-industrial agglomeration on environmental health is complex, and that early positive impacts may be overshadowed by later negative impacts. Therefore, it becomes crucial to assess the direct impact of agricultural-industrial agglomeration on carbon emissions, especially the Inverted U-shaped relationship, which not only helps to understand the complexity of the impact of industrial agglomeration on the environment but also provides a scientific basis for policy formulation. This can ensure that measures to control environmental pollution are combined with economic development to achieve sustainable growth. Based on the above understanding, this study proposes the following hypotheses:

H1: The impact of agricultural-industrial agglomeration on agricultural carbon emissions is not linear, but exhibits a nonlinear pattern.

The Intermediary Effect of Digital Rural Development Level

Agricultural-industrial agglomeration plays an important mediating role in promoting rural digitalization. The process and its outcomes generate a demand for digital villages. Agricultural agglomeration, as a special form of industrial agglomeration, necessitates extensive information exchange. The geographical proximity and business interactions of a cluster of enterprises and institutions [37] drive agglomeration effects through economies of scale, reduced transportation costs, and the synergistic movement of factors [38, 39]. The essence of any industrial agglomeration is the orderly flow of elements such as land, capital, and labor, which move within specific patterns and spatial-temporal scopes. To prevent disorder in agricultural factor flows and ensure alignment with agricultural development, operators must address information asymmetry. Therefore, agricultural agglomeration involves not only material exchange but also information flows, creating a demand for information on land size and quality, planting scale and crop types, agricultural inputs, labor sources, and wage levels.

The application of digital tools and technologies plays a crucial role in this process. With big data and artificial intelligence, it is possible to precisely assess and monitor farmland resources, scientifically plan plantings, intelligently manage inputs, and efficiently coordinate labor. This not only enhances the efficiency and benefits of agricultural production, but also significantly reduces resource wastage and environmental pollution. Moreover, informatization strengthens the connection between agricultural enterprises and markets, opening new sales channels and optimizing supply chain management. The application of digitalization in agricultural agglomeration also raises the overall level of rural development. E-commerce platforms facilitate market access for agricultural products and better sales prices; the use of smart farming machinery lightens manual labor and increases productivity; and IoT technologies make agricultural processes more transparent and traceable, enhancing product quality and safety.

Thus, agricultural agglomeration at both material and informational levels promotes the optimization of resources and industrial development, driving rural digitalization. The demand for and application of digitalization not only solves the problem of information asymmetry but also promotes the modernization and intelligent development of the agricultural industry chain.

Digital rural construction enhances agricultural production efficiency through information technology, deepens understanding of the agricultural industry chain and rural society, modernizes production methods and farmer skills, and fosters rural development and revitalization, while also serving as an intrinsic driver

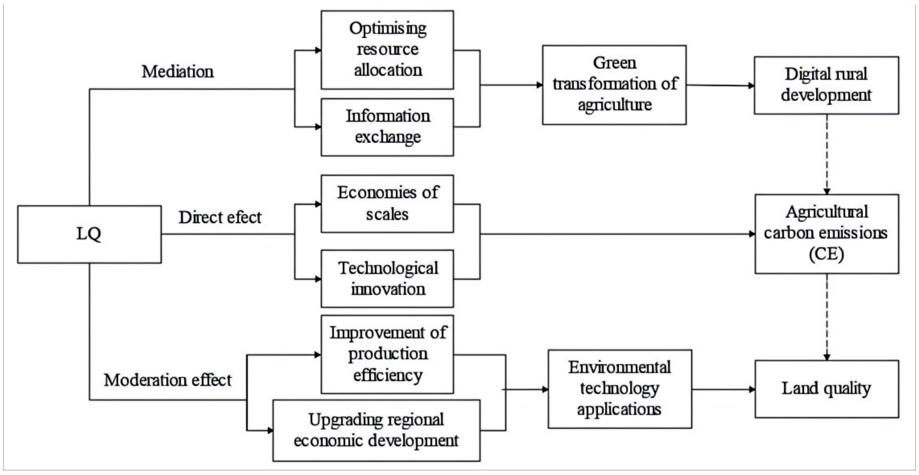

Fig. 1. Logical framework for theoretical analysis.

of carbon reduction in agriculture [40]. Agricultural producers use mobile communications devices and the internet to rapidly access knowledge of green agriculture, lowering information costs and overcoming technical barriers. As digital technology becomes more widespread and infrastructure improves, the agricultural production chain undergoes transformation and operational monitoring optimization, propelling a green shift in agriculture and reducing carbon emissions [41]. Based on these findings, the study proposes the following hypothesis:

H2: Agricultural-industrial agglomeration reduces agricultural carbon emissions by enhancing the development level of digital villages.

Analysis of the Moderating Effect

As modern agriculture develops and agricultural-industrial agglomeration deepens, agriculture's role as a major source of carbon emissions and its environmental impact attracts widespread attention. Agricultural-industrial agglomeration, a complex economic activity, not only boosts production efficiency and regional economic growth but also poses new environmental challenges. In this process, land quality becomes a key factor in moderating the relationship between agricultural-industrial agglomeration and carbon emissions. Utilizing national and provincial data, research by Lai (2016) and Chuai (2013) reveals the potential to increase carbon storage by optimizing land use structures, suggesting that appropriate policy measures can significantly reduce overall carbon emissions [42, 43]. High-quality land resources during the early stages of agricultural-industrial agglomeration help reduce carbon emissions through improved production efficiency and resource management, providing an initial buffer for carbon emission control. As agglomeration deepens, high-quality land continues to play a role, supporting the adoption of environmentally friendly technologies and the spread of sustainable agricultural practices, slowing the rate of carbon emission reduction. This implies that improving land quality can extend environmental benefits into the later stages of agglomeration, thereby adjusting the overall trend of agricultural carbon emissions. Therefore, the study posits the following hypothesis:

H3: Improving land quality helps reduce the growth of agricultural carbon emissions.

Research Design

Model Specification

Baseline Regression Model

This study employs a fixed effects model to test Hypothesis 1, as illustrated in Equation (1):

$$CE_{it} = \beta_0 + \beta_1 LQ_{it} + \beta_2 LQ^2{}_{it} + \beta_3\, control_{\,it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

Equation (1) represents the direct effect of agricultural-industrial agglomeration on agricultural carbon emissions. Here, i denotes the province or city, t represents the time period, CE_{it} stands for agricultural carbon emissions, LQ_{it} indicates agricultural-industrial agglomeration, and $LQ^2{}_{it}$ is the squared term of agricultural-industrial agglomeration. *Control* accounts for various control variables that could potentially affect the results. β_0 is the intercept term, while β_1 to β_3 are the regression coefficients corresponding to the respective variables. μ_i signifies the fixed effect for the province, γ_t denotes the fixed effect for the year, and ε_{it} is the random error term.

Mediation Models

To empirically examine the impact mechanism of agricultural-industrial agglomeration on agricultural

Table 1. Sources of agricultural carbon emissions and coefficients.

Carbon Source	Carbon Emission Coefficients	Sources
Pesticides	4.93 kg/kg	ORNL, USA
Agricultural films	5.18 kg/kg	IAREE, NAU
Irrigation	266.48 kg/hm^2	Ding et al.[41]
Diesel	0.59 kg/kg	IPCC2013
Fertilisers	0.89 kg/kg	ORNL, USA
Ploughing	312.60 kg/hm^2	CBT, CAU

carbon emissions, the following mediating model is established:

$$CE_{it} = \alpha_0 + \alpha_1 LQ_{it} + \alpha_2 LQ^2{}_{it} + \alpha_3\, control_{\,it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$$DC_{it} = \beta_0 + \beta_1 LQ_{it} + \beta_2 LQ^2{}_{it} + \beta_3\, control_{\,it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

$$CE_{it} = \delta_0 + \delta_l LQ_{it} + \delta_2 LQ^2{}_{it} + \delta_3\, control_{\,it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

DC_{it} stands for the mediating variable, which is the level of digital rural development. The coefficients are represented by α, β, and δ, while μ_i and γ_t signify the fixed effects for years and provinces, respectively. ε_{it} is the random error term.

Moderation Effects Model

This research develops a model to examine the moderating effect of land quality (Land) on the relationships under study.

$$CE_{it} = \lambda_0 + \lambda_1\, Land_{\,it} \times LQ_{it} + \lambda_2\, Land_{\,it} \times LQ^2{}_{it} + \lambda_3\, Land_{\,it} + \lambda_4\, control_{\,it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

To verify the Inverted U-shaped curve's moderating effect, this study multiplies the moderating variable with both the linear and quadratic terms of the independent variable (*LQ*) [44]. This allows us to assess the moderating impact on the curve's inflection point through the linear term, and on the steepness, shallowness, or the direction of opening or closing of the curve through the quadratic term.

Variable Selection

Dependent Variable: Total Carbon Emissions from Agriculture (*CE*). This research begins by estimating the carbon emissions from each input factor in agriculture. According to the IPCC calculating method, there are six main sources of agricultural carbon emissions: pesticides, agricultural film, irrigation, diesel, fertilizer, and farming [45]. The calculation formula is as follows:

$$CE = \sum S_{ijt} = \sum F_{ijt} Q_j \tag{6}$$

In equation (6), CE denotes the total carbon emissions, while S_{ijt} and F_{ijt} represent the carbon emissions and input quantities from the j-th carbon source in the i-th province (city) in year t. Q_j indicates the corresponding carbon emission coefficients for these sources. Specific details are provided in Table 1.

Independent variable: Agricultural Industry Agglomeration (LQ). This study chose the agricultural location entropy index to measure this indicator. The quotient is obtained by dividing the ratio of agricultural output value to GDP of a province (city) by the ratio of national agricultural output value to GDP. The larger the location entropy index, the higher the degree of agricultural industry agglomeration. The specific formula is as follows:

$$LQ_{ij} = (N_{ij}/M_{ij})/(N_i/M_j) \tag{7}$$

In equation (7), LQ is the level of agro-industrial agglomeration, T_{ij} represents the agricultural output of the i-th province (city), M_{ij} denotes the total production value of the i-th province (city), N_j is the national total agricultural output, and M_j is the national gross domestic product (GDP).

Mediating variable: (1) Level of Rural Digital Development (*DC*), measured by the ratio of rural broadband access to the rural population. A higher ratio suggests better development of digital villages.

Moderating variable: Land Quality (*Land*), assessed by the proportion of effective irrigated area to total crop sown area.

Control variables: (1) The intensity of financial inputs to agriculture (*Agrfi*) is measured using the ratio of agriculture, forestry, and water expenditures to total government expenditures. (2) Economic Development Level (*GDP*), measured by the per capita GDP of the region. (3) Per Capita Consumer Spending of Rural Residents (*Conru*). In assessing the scale of cropland management (*Lscale*), the ratio of the total area of cropland to the number of people in the agricultural labor force is used. (5) Disastered area ratio *(Disa)* is derived from the proportion of the affected area to the total sown area.

Data Source

In view of data availability and observability of research results, this study takes panel data from 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2011 to 2021. Among them, the data on agricultural carbon emissions come from the China Agricultural Yearbook and the China Rural

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CE	330	3.389	2.3	0.144	9.957
LQ	330	1.229	0.742	0.042	4.364
Agrfi	330	11.405	3.327	4.11	20.384
GDP	330	1.276	0.808	0.513	4.807
Conru	330	1.079	0.418	0.386	2.720
Lscale	330	7.650	4.142	2.088	29.196
Disa	330	3.504	3.652	0.02	18.96
DC	330	0.148	0.121	0.007	0.509
Land	330	0.433	0.172	0.172	1.233
Lp	330	4.085	2.201	1.167	13.557

Table 3. Variable comment table.

Variable	Full name of the variable	Variable Meaning
CE	Agricultural carbon emissions	Calculation of agricultural carbon emissions by region based on the ipcc land release coefficient
LQ	Agro-industrial agglomeration	The text uses locational entropy to represent
Agrfi	The intensity of financial inputs to agriculture	Using the ratio of agriculture, forestry and water expenditures to total government expenditures
GDP	Economic Development Level	Measured by the per capita GDP of the region
Conru	Per Capita Consumer Spending of Rural Residents	Per Capita Consumer Spending of Rural Residents
Lscale	The scale of cropland management	The ratio of the total area of cropland to the number of people in the agricultural labour force is used
Disa	Disastered area ratio	The proportion of the affected area to the total sown area.
DC	Level of Rural Digital Development	The ratio of rural broadband access to the rural population.
Land	Land Quality	Assessed by the proportion of effective irrigated area to total crop sown area.
Lp	Land productivity	Expressed as the ratio of gross agricultural output to the area sown to crops.

Statistics Yearbook; the data on agricultural-industrial agglomeration come from the National Bureau of Statistics, the China Statistical Yearbook, and the China Agricultural Statistical Yearbook; and the data involved in the mediating, moderating, and controlling variables come from the China Agricultural Statistical Yearbook, China Economic Network statistical database, the China Rural Business Management Statistics Annual Report, National Bureau of Statistics, China Provincial Statistical Yearbook, Wind database and EPS database. Descriptive statistics of all variables are shown in Table 2. Table 3 shows the full variable annotation table.

Empirical Results

Benchmark Regression

Table 4 presents the results of the baseline regression of this study, which examines the impact of agricultural-industrial agglomeration on agricultural carbon emissions. The original hypothesis was strongly rejected by the Hausman test, indicating that the fixed effects model should be used. The empirical results show that the coefficient of the linear term of agricultural industry agglomeration is significantly positive, while its squared term is significantly negative. The u-test identifies a turning point at 3.546 within the range of agricultural production agglomeration [0.042, 4.364]. At the minimum agglomeration value of 0.042, the curve's slope is positive at 0.679, whereas at the maximum value of 4.364, the slope is negative at

-0.159. These results confirm that the slope is positive at the minimum agglomeration level and negative at the maximum, aligning with the characteristics of an Inverted U-shaped curve [46]. These test outcomes support Hypothesis H1. This finding corroborates the Environmental Kuznets Curve (EKC) hypothesis, positing that environmental pollution, here represented by agricultural carbon emissions, initially increases with economic development (manifested through agricultural industry agglomeration), but eventually decreases following advancements in technology and the optimization of industrial structures. Specifically, in the initial stages, agricultural industry agglomeration leads to an increase in carbon emissions. However, as the degree of agglomeration intensifies, the effect on increasing carbon emissions weakens, eventually transitioning to a reduction in emissions. This may be attributed to the initial phase of agricultural agglomeration where increased production activities elevate energy consumption and carbon emissions; yet, as agglomeration effects deepen, technological advancements, efficiency improvements, and the adoption of cleaner energy sources reduce the energy consumption per unit of output, thereby lowering agricultural carbon emissions.

After considering the control variables, the direct positive relationship of agricultural industry concentration on agricultural carbon emissions remains unchanged, as does the negative effect of its quadratic term, which suggests that the Inverted U-shaped relationship of the main regression is still robust even after gradually adding other control variables. Moreover, agricultural fiscal input exhibits a consistently positive effect on carbon emissions in the baseline regression, potentially reflecting that increased fiscal input boosts agricultural production activities, indirectly fostering energy consumption and emissions. The level of economic development and the scale of farmland operation also have a significant positive impact on emissions, likely due to enhanced production efficiency associated with economic growth and scaled operations, albeit with a concurrent rise in energy demand. Per capita consumption expenditure by rural residents significantly reduces agricultural

Table 4. Benchmark regression result.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
LQ	0.666***	0.493***	0.630***	0.556***	0.673***	0.687***
	(0.162)	(0.139)	(0.156)	(0.162)	(0.171)	(0.164)
LQ^2	-0.070**	-0.059**	-0.076***	-0.063**	-0.096***	-0.097***
	(0.028)	(0.024)	(0.025)	(0.026)	(0.028)	(0.028)
Agrfi		0.065***	0.064***	0.058***	0.055***	0.052***
		(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
GDP			0.255**	0.376***	0.518***	0.522***
			(0.1051)	(0.122)	(0.155)	(0.152)
Conru				-0.434**	-0.378**	-0.398**
				(0.178)	(0.170)	(0.166)
Lscale					0.044***	0.044***
					(0.013)	(0.013)
Disa						0.011**
						(0.005)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
_cons	2.715***	2.164***	1.712***	2.163***	1.545***	1.542***
	(0.144)	(0.173)	(0.286)	(0.341)	(0.411)	(0.400)
N	330	330	330	330	330	330
F	20.565	23.035	17.239	14.192	12.370	10.882
R-Squared	0.093	0.199	0.216	0.234	0.267	0.280

Note: Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

Table 5. Heterogeneity test: Regional division.

	(1)	(2)	(3)	(4)
Variables	Eastern	Midwestern	Northern	Southern
LQ	0.392	0.260*	1.252***	0.310
	(0.568)	(0.139)	(0.319)	(0.349)
LQ^2	0.137	-0.048*	-0.183***	-0.017
	(0.173)	(0.025)	(0.047)	(0.096)
Control	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	0.820	3.594***	1.225*	2.935***
	(0.726)	(0.361)	(0.639)	(0.410)
N	121	209	165	165
R-Squared	0.356	0.355	0.418	0.145
F	4.885	12.383	7.267	3.191

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

carbon emissions, indirectly affecting emissions through improved living standards. On the other hand, an increase in the proportion of areas affected by disasters can also significantly increase carbon emissions, which illustrates the potential impact of natural disasters on agricultural production activities.

Heterogeneity Analysis

Test of Regional Heterogeneity

In this study, 30 provinces and cities in China are divided into two regional sub-samples of eastern and central-western regions, Beyond recognizing the regional development disparities, the study examines the dissimilar effects of agricultural-industrial agglomeration on agricultural carbon emissions in the northern and southern parts of China. The data, displayed in Table 5, suggests that the link between agricultural-industrial agglomeration and agricultural carbon emissions shows significant regional differences. Firstly, the eastern region does not show a significant linear relationship between agricultural-industrial agglomeration and agricultural carbon emissions, which may be due to the fact that the eastern region is more economically developed, has more modernized agricultural production methods, uses more advanced technologies, and has higher energy efficiency, and therefore an increase in agricultural-industrial agglomeration does not directly lead to a significant increase in agricultural carbon emissions. Additionally, the lack of significance in the squared term of agricultural-industrial agglomeration could mean that the eastern region's agglomeration hasn't arrived at a level that reduces agricultural carbon emissions. In the central and western regions, there's an inverted U-shape connection. At first, the agglomeration's coefficient is positive and significant at the 10% level, which relates to an increase in emissions. But with continued agglomeration, this effect reverses, as indicated by a significantly negative squared term at the 10% level, suggesting an eventual decrease in emissions potentially due to the central and western regions embracing better production techniques for energy saving and emission reduction in agricultural industry changes.

For the northern region, the analysis reveals that the agglomeration of the agricultural industry significantly boosts carbon emissions, with a positive coefficient at the 1% significance level. Moreover, the squared coefficient is significantly negative at the 1% level, indicating a clear inverted U-shaped trend. Initially, the vast farmland and concentrated agricultural activities in the north might have caused a rise in both production and carbon emissions due to agglomeration. But later, thanks to scaling and technological progress, this production began reducing carbon emissions per unit. Meanwhile, in the south, the effects of agricultural agglomeration on carbon emissions are less evident. This could be attributed to the region's moderate weather and diverse agricultural practices, which may dilute the agglomeration's impact on emissions.

Test of the Heterogeneity of Food Distribution

In this study, samples were categorized into three types based on the “National Medium and Long-term Plan for Food Security (2008–2020)”: areas primarily for grain production, main marketing regions, and

Table 6. Heterogeneity test: Food distribution.

	(1)	(2)	(3)
	Major production area	Main sales area	Production-sales balanced area
LQ	1.068***	1.357***	-1.076*
	(0.293)	(0.382)	(0.621)
LQ^2	-0.152***	-0.328***	0.335**
	(0.045)	(0.109)	(0.157)
Control	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
_cons	1.963**	0.863***	3.340***
	(0.813)	(0.236)	(0.785)
N	143	77	110
R-Squared	0.382	0.433	0.398
F	7.941	13.519	3.351

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

zones maintaining a balance between production and marketing. The outcomes of the regression analyses for these groups are shown in Table 6.

Analyses of the relationship between agro-industrial agglomeration and carbon emissions in China show that there are significant differences between different grain distributions. In major grain-producing areas, the relationship between agricultural industry agglomeration and carbon emissions shows a significant positive effect, while the squared term of agglomeration presents a significant negative effect, suggesting an Inverted U-shaped relationship. Initially, carbon emissions increase with agglomeration, but after reaching a certain level, the agglomeration effect reduces emissions by enhancing agricultural efficiency and technological progress. This suggests the potential for major grain-producing areas to transition towards more sustainable agricultural production through optimizing industry structures and technology levels. In major marketing areas, the positive impact of agricultural industry agglomeration on carbon emissions is more pronounced, and the threshold for its negative effect is higher, possibly due to rapid initial emission increases caused by high logistics and processing demands. When agglomeration reaches a critical point, it triggers technological advancements and efficiency improvements that contribute to a decrease in carbon emissions per unit of output. Conversely, in balanced production and marketing areas, agricultural industry agglomeration initially exerts a negative impact on carbon emissions. As agglomeration increases, this negative effect diminishes and ultimately turns positive. This suggests that balanced areas may already possess higher production efficiency and lower levels of carbon emissions, with further agglomeration leading to additional emissions.

Industrial Agglomeration of the Level of Heterogeneity Test

By using the median agglomeration level as a benchmark, this research differentiates between stronger and weaker agglomeration to examine their different effects on carbon emissions from agriculture. It turns out that the intensity of agricultural industry agglomeration has a marked impact on its carbon emissions. In less concentrated areas, the effect of agglomeration on carbon emissions appears to be minimal, with the squared term of agglomeration also showing an insignificant positive relationship. This may be because in regions with lower industrial agglomeration, the direct impact on carbon emissions is minimal, and increases in agglomeration do not significantly enhance production efficiency or prompt technological innovation to reduce emissions. Additionally, in low agglomeration areas, because of the relative lack of technology and information, the positive impact of agglomeration may not be sufficient to offset the carbon emissions from increased production. However, in areas where there is a significant agglomeration of the agricultural industry, there is initially a significant positive impact on carbon emissions, but this becomes negative as agglomeration increases, creating a clear inverted U-shaped curve. This suggests that with increasing agglomeration, initial carbon emissions may rise due to increased scale and production concentration. However, once agglomeration reaches a certain threshold, the effects of economies of scale and technological advancements can effectively

Table 7. Heterogeneity test: High and low levels of industrial agglomeration.

	(1)	(2)
Variable	Low industrial clustering	High industrial clustering
LQ	-0.992	0.709**
	(1.000)	(0.291)
LQ^2	0.774	-0.080*
	(0.588)	(0.048)
Control	YES	YES
Province FE	YES	YES
Year FE	YES	YES
_cons	1.601***	2.930***
	(0.548)	(0.744)
N	165	165
R-Squared	0.273	0.337
F	6.369	5.722

Note: Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

reduce carbon emissions per unit of output. In high agglomeration areas, due to the more concentrated resources and information, it is easier to achieve technological innovation and efficiency improvements, thus reducing carbon emissions through enhanced production efficiency at higher levels of agglomeration. The test results are shown in Table 7.

Influence Mechanism Test

In examining the relationship between the degree of agricultural agglomeration, rural digital progress, and agricultural carbon emissions, this study uses a mediated effects model, the results of which are presented in parts (1) to (3) of Table 8. Part (1) shows the main regression results consistent with the previous discussion. In part (2), a significant negative effect of agricultural agglomeration on rural digitization can be observed, while the square of the agglomeration term shows a significant positive effect. Viewing agricultural industry agglomeration as a resource input, suggests that as the degree of agglomeration increases, its negative effect on digital rural development may gradually diminish or even become positive. This could be due to the scale effects of moderate agglomeration, which fully utilizes resources and promotes the development of digital rural areas. In the analysis shown in part (3), we see that the digitization level of villages acts as an intermediary variable. For agricultural industry clusters, the initial impact on carbon emissions is strongly positive—confirmed at the 1% significance level. As the clusters grow, indicated by the negative coefficient of the squared term, this impact loses strength. This trend implies that the more advanced the digital framework of a village, the more it can affect the greenhouse gas output from agricultural practices, indirectly confirming the H2 hypothesis.

Moderation Effect Test

Table 9 presents the results of the moderation effect test in this study. By incorporating land quality as a moderating variable into the main effect of agricultural industry agglomeration on carbon emissions, land quality is multiplied by both the linear and squared terms of agglomeration to test its moderating role on the main effect. Findings indicate a significant positive moderation by land quality on the inverted U-shaped curve's main effect, and the moderation is also significant for the squared term, suggesting that this moderating variable influences both the shape and the direction of the curve's opening. Firstly, the interaction coefficient between land quality and the linear term of agricultural industry agglomeration is negative and remains significant at the 1% level, indicating that improved land quality can mitigate the initial positive impact of agricultural industry agglomeration on carbon emissions. This could be due to high-quality land supporting more efficient agricultural techniques and optimized resource management, thereby reducing carbon emissions from the outset. Secondly, the coefficient for the interaction between land quality and the squared term of agglomeration is positive and

Table 8. Influence mechanism test.

	(1)	(2)	(3)
VARIABLE	CE	DC	CE
LQ	0.687***	-0.155***	0.626***
	(0.164)	(0.047)	(0.158)
LQ^2	-0.097***	0.018*	-0.090***
	(0.028)	(0.009)	(0.027)
DC			-0.397*
			(0.204)
Control	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
_cons	1.542***	0.414***	1.707***
	(0.400)	(0.091)	(0.405)
N	330	330	330
R-Squared	0.280	0.166	0.286

Note: Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

Table 9. Moderating effects estimation.

	(1)	(2)
Variable	CE	CE
LQ	0.687***	1.627***
	(0.164)	(0.323)
LQ^2	-0.097***	-0.446***
	(0.028)	(0.124)
Land		0.477*
		(0.288)
LQ*Land		-2.230***
		(0.738)
LQ^2*Land		0.823***
		(0.274)
Control	YES	YES
Province FE	YES	YES
Year FE	YES	YES
_cons	1.542***	1.443***
	(0.400)	(0.445)
N	330	330
R-squared	0.280	0.330

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

significant at the 1% level. This suggests that at higher stages of agglomeration, enhanced land quality can slow down the decrease in carbon emissions, possibly because high-quality land allows for wider application of positive environmental technologies and sustainable practices within the agglomeration effect, thus controlling and reducing carbon emissions effectively in later stages of agglomeration. These findings lend support to hypothesis H3.

The results underscore that land quality not only alters the overall impact of agricultural industry agglomeration on carbon emissions but also adjusts the dynamic path of this impact as the degree of agglomeration changes. Therefore, improving land quality, particularly through effective land management and continuous improvement of its productive capacity, can be considered a policy tool to optimize the environmental benefits of agricultural industry agglomeration and achieve sustainable agricultural production.

Sensibility Analysis

Replace the Explanatory Variable

Considering the potential lag effect of agricultural industry agglomeration on carbon emissions, this study conducts regression analyses with one-period and two-period lags for agglomeration and its squared term to ensure accuracy in the test results. In the data in columns (1) and (2) of Table 10, the correlation coefficient of the first-order lagged term is 0.667 and that of its squared term is -0.092, which both show significant effects. The lagged term positively affects the results, while the squared term negatively affects them. The second-order lag term with a coefficient of 0.639 and its squared term with a coefficient of -0.090 also show significant positive and negative effects, respectively. This confirms Hypothesis 1.

Add Control Variables

Additional control variables are introduced to mitigate bias from omitted variables: by incorporating land productivity (*Lp*) as a new control variable, The findings from column (3) of Table 10 indicate that the coefficient for the primary term of agricultural industry agglomeration is significantly positive at 0.636, and the coefficient for the squared term is significantly negative at -0.092, further confirming the robustness of the baseline regression results.

Exclusion of Specific Areas

In order to accurately assess the impact of agro-industrial agglomeration on carbon emissions, four cities with special administrative divisions, namely Beijing, Tianjin, Shanghai and Chongqing, are excluded from this study. The data in column (4) of Table 10 show that the linear term coefficient of agricultural industry density is 0.731, a significant positive correlation, while the squared term coefficient is -0.101, a significant negative correlation, which further confirms our basic conclusion.

Removing Interference from Extreme Values

The study also addresses the influence of outliers by truncating 1% of the tail from all variables in the baseline regression. After truncation, the analysis results, as shown in column (5) of Table 10, reveal a significant positive coefficient for the primary term at 0.600 and a negative coefficient for the squared term at -0.071, thereby further validating the robustness of the baseline regression.

Overall, these robustness checks consistently support the conclusion of an inverted U-shaped relationship between agricultural industry agglomeration and carbon emissions.

Table 10. Robustness test results.

	(1)	(2)	(3)	(4)	(5)
VARIABLE	CE	CE	CE	CE	CE
L.LQ	0.667***				
	(0.182)				
L.LQ²	-0.092***				
	(0.032)				
L2.LQ		0.639***			
		(0.191)			
L2.LQ²		-0.090**			
		(0.035)			
LQ			0.636***	0.731***	0.600***
			(0.165)	(0.196)	(0.166)
LQ²			-0.092***	-0.101***	-0.071**
			(0.029)	(0.032)	(0.028)
Lp			0.024*		
			(0.012)		
Control	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
_cons	1.717***	2.037***	1.513***	1.717***	1.721***
	(0.409)	(0.405)	(0.410)	(0.571)	(0.424)
N	300	270	330	286	330
R-squared	0.259	0.231	0.286	0.317	0.273
F	7.601	5.741	9.509	11.610	10.754

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Endogeneity Test

Endogeneity issues primarily arise from three areas: omitted variable bias, measurement error in data, and reverse causality. To mitigate the impact of omitted variable bias, this study incorporates a comprehensive set of factors influencing agricultural carbon emissions, thereby addressing potential endogeneity concerns to an extent. However, to counteract endogeneity arising from other sources, an instrumental variable (IV) approach is employed. The IV chosen is the lagged term of agricultural industry agglomeration and its squared term, with the Two-Stage Least Squares (2SLS) method applied for model validation. The IV tests indicate significant positive correlations between agricultural industry agglomeration and its squared term with their instruments at the 1% level. The second-stage regression yields a Kleibergen-Paap rk LM statistic of 55.951 (P-value = 0.000) and a Cragg-Donald Wald F statistic of 205.553, well above the threshold of 10, confirming the IV's validity and the model's identifiability. The second-stage IV regression results demonstrate a significant positive coefficient for agricultural industry agglomeration and a significant negative coefficient for its squared term at the 1% level, reaffirming a U-shaped impact on agricultural carbon emissions. This evidence supports the existence of a U-curve linking agricultural industry agglomeration to carbon emissions, even after accounting for endogeneity.

Considering the inertia of changes in agricultural carbon emissions, namely that the historical level of development may affect the current effect, a dynamic panel model incorporating the lagged term of agricultural carbon emissions is developed based on Equation (1). This addition aims to alleviate the impact of potential omitted variables and reduce model specification errors. The endogeneity concern related to the lagged term is addressed using the System GMM approach. The non-existence of autocorrelation as proven by AR(1) and AR(2) tests and the validity of all

Table 11. Endogeneity test.

	Firststage		Secondstage	SYS-GMM
Variable	LQ	LQ^2	CE	CE
L.LQ	0.839^{***}			
	(0.051)			
$L.LQ^2$		0.939^{***}		
		(0.051)		
L.CE				1.114^{***}
				(0.073)
LQ			0.872^{***}	1.069^{*}
			(0.220)	(0.554)
LQ^2			-0.115^{***}	-0.150^{*}
			(0.035)	(0.088)
Cragg-Donald Wald F statistic			205.553	
Kleibergen-Paap rk Wald F statistic			139.255	
Kleibergen-Paap rk LM statistic			55.951^{***}	
AR(1)				0.024
AR(2)				0.536
Hansen				0.856
Control	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	0.246	-0.165	-2.245^{***}	-2.607^{***}
	(0.172)	(0.621)	(0.670)	(0.836)
N	300	300	300	300
R-squared	0.788	0.826	0.994	/

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

instruments as confirmed by the Hansen test establish the appropriateness of the model and analytical approach. The relationship between the effects of agricultural-industrial agglomeration and carbon emissions is consistent with the original regression results, indicating that the effect of endogeneity is small, which enhances the reliability of the model. The endogeneity test results are shown in Table 11.

Conclusions

This study explores the dynamic impact of agricultural-industrial agglomeration on agricultural carbon emissions through the panel data of 30 provinces in China from 2011 to 2021. The results of the study are summarized as follows: (1) The impact of agricultural-industrial agglomeration on agricultural carbon emissions shows a significant inverted U-shape rather than a linear pattern, and the impact is more obvious in the central-western and northern regions. The analysis of food distribution shows that the inverted U-shaped influence is significant in the main production and marketing areas, and the inverted U-shaped pattern is significant in the areas with balanced production and marketing. Under the high and low levels of industrial agglomeration, the agglomeration of high agglomeration areas also shows a significant inverted U-shaped relationship. (2) Agricultural-industrial agglomeration plays a role in reducing agricultural carbon emissions by influencing the digital development of rural areas. (3) The found substitution effects suggest that better land quality helps to mitigate the growth of agricultural carbon emissions. (4) Various robustness tests strengthen the reliability of these findings.

Based on the above conclusions, this study makes the following recommendations. On the one hand, the government should set up a special fund to support scientific research projects related to low-carbon agriculture, especially in nitrogen fertilizer management, soil carbon sequestration, and water-saving irrigation technology. By introducing international advanced technologies and experiences, agricultural productivity can be effectively improved and carbon emissions per unit of output can be reduced, thus promoting the green transformation and sustainable development of agriculture. On the other hand, the government should promote agricultural informatization and establish a nationwide agricultural big data platform. At the same time, it should help farmers purchase and use digital agricultural equipment, and conduct regular training on digital agriculture to improve their knowledge and application of new technologies. Optimizing resource allocation and improving management accuracy through digital technology will reduce agricultural carbon emissions. This is similar to the research viewpoint of some scholars [47]. Finally, the key is to fundamentally improve land productivity. The government should promote conservation tillage and crop rotation systems to enhance soil fertility while supporting the research, development, and application of organic farming and bio-fertilizers to reduce reliance on chemical fertilizers. Additionally, demonstration farms should be set up to promote efficient and eco-friendly agricultural models to increase agricultural production and income at a lower environmental cost.

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Conflicts of Interest

The authors declare no conflict of interest.

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