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Mechanisms Through Which the Digital Economy Influences Agricultural Carbon Emissions

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Abstract

Against the backdrop of the "dual carbon" goals and the green transformation of agriculture, it is of great significance to explore the impact and mechanisms through which the digital economy influences agricultural carbon emissions, thereby promoting low-carbon and sustainable agricultural development. Based on panel data from 30 Chinese provinces covering the period 2011–2024, this study empirically examines the impact of the digital economy on agricultural carbon emissions and its underlying mechanisms by constructing a two-way fixed-effects model. The empirical results show that the digital economy significantly reduces agricultural carbon emissions, a conclusion that holds after a series of robustness tests. Mediating mechanism analysis reveals that reductions in energy intensity and the optimized allocation of agricultural machinery act as mediators. Furthermore, the impact exhibits regional heterogeneity, being more pronounced in northwestern China and in areas with high agricultural carbon emissions. Based on these findings, relevant policy recommendations are proposed in terms of institutional design, system development, and policy guidance.

Keywords

Digital economy; Agricultural carbon emissions; Energy intensity.

1. Introduction

Global climate change governance has entered a new phase. Agriculture is not only the sector most directly affected by climate change but also a major source of greenhouse gas emissions; its low-carbon transition is of fundamental and overarching importance to achieving the "dual carbon" goals. The 2025 Central Economic Work Conference proposed "coordinately advancing carbon reduction, pollution control, green development, and economic growth, and accelerating the comprehensive green transformation of economic and social development," while also calling for "actively utilizing digital and green technologies to transform and upgrade traditional industries." The 2025 Central Rural Work Conference further emphasized "developing new quality productive forces in agriculture in accordance with local conditions" and "strengthening research and development of key core agricultural technologies and the efficient transformation and application of scientific and technological achievements."

Leveraging its ability to reshape the flow of information, capital, and materials, the digital economy is deeply penetrating the entire agricultural production chain, and this technological-economic transformation also provides an endogenous driving force for reducing agricultural carbon emissions. The "15th Five-Year Plan for Accelerating the Modernization of Agriculture and Rural Areas" issued by the State Council explicitly calls for accelerating the innovation and application of digital technologies and outlines major projects and initiatives such as "AI+" agriculture. The penetration of digital technology into agriculture systematically reshapes traditional methods of factor allocation and production decision-making logic, and this reshaping inevitably translates into changes in carbon emissions through specific economic

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mechanisms. In terms of its impact, the digital economy can optimize the structure of factor inputs by reducing information asymmetry between agricultural producers and the market; improve resource utilization efficiency in key areas such as water and fertilizer management through the Internet of Things (IoT) and intelligent decision-making systems; and reduce energy consumption in storage and transportation by shortening the distribution chain for agricultural products through digital supply chains.

Therefore, a systematic analysis of the impact and mechanisms through which the digital economy affects agricultural carbon emissions is of great value for understanding the intrinsic logic of technology-enabled low-carbon agricultural development and for informing the formulation of targeted policies across different regions.

2. Literature Review

2.1. Research on the Digital Economy

At the theoretical level, Goldfarb and Tucker (2019) established a foundational analytical framework for the digital economy, identifying the reduction of market transaction costs by digital technologies as the underlying logic of its operation [1]. Gong Lixin et al. (2024) reviewed Chinese domestic theoretical research and clarified that the digital economy is a new economic model in which data serves as the core means of production [2]. Xu Wenbin and Cheng Enfu (2026) expanded the theoretical boundaries from a political economy perspective, analyzing how data, computing power, and algorithms collectively constitute the production system of the digital economy [3]. Hou Meiyue et al. (2024), drawing on the theory of new quality productive forces, elucidated the intrinsic logic by which the digital economy reshapes traditional production paradigms [4].

In terms of indicator measurement, Li Yanru et al. (2023) constructed a comprehensive provincial-level digital economy index, with an indicator system covering three core dimensions: digital infrastructure, digital industries, and digital inclusion [5]. Yang Chuanming et al. (2024) optimized the measurement scheme at the prefecture-level city scale, refined the weights of sub-dimensions, and improved the accuracy of quantifying the digital economy in small and medium-sized regions [6]. Chen (2025) employed a combination of principal component analysis and the entropy method to calculate a cross-national digital economy index, establishing a unified measurement standard that allows for horizontal comparisons [7]. Wang Xinliang et al. (2026) incorporated the digital labor factor into the measurement system, thereby refining the existing index-construction framework [8].

Regarding growth transmission mechanisms, Cai et al. (2024) empirically demonstrated that the digital economy continuously enhances regional total factor productivity through technological innovation [9]. Chao Xiaojing and Wang Chenwei (2023) systematically summarized various mediating pathways through which the digital economy drives aggregate growth [10]. Li Tao (2026) used city-level panel data to verify the mediating role of human capital accumulation in the growth effects of the digital economy [11]. Jiao Yong et al. (2024) confirmed that the digital economy unleashes innovative momentum through three channels: technology, markets, and management [12]. Li et al. (2026) empirically demonstrated that the digital economy optimizes the efficiency of regional factor allocation, thereby strengthening the foundation for long-term growth [13].

2.2. Research on Agricultural Carbon Emissions

Regarding measurement systems, Hou Na et al. (2025) established a comprehensive agricultural emissions inventory and pointed out that the use of uniform emission factors leads to measurement biases [14]. Xiu Shengzhi et al. (2025) refined the carbon footprint calculation standards for grain crops, thereby distinguishing the carbon emission structures of agricultural

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inputs across different crops [15]. Yang Xiaojie and Wang Meng (2025) focused on the perspective of land transfer to refine calculation methods, quantifying the additional carbon emissions caused by fragmented farmland [16]. Liu Wenchao et al. (2025) used ecological farms as case studies to calculate carbon emissions from integrated crop-livestock systems [17]. At the international level, Smith et al. (2024) optimized a localized modeling approach for nitrous oxide emissions from farmland [18]. Gao et al. (2025) developed a framework for accounting for agricultural carbon emissions across the entire supply chain [19].

Regarding spatiotemporal characteristics and regional differentiation, Chen Yi and Dai Xiaowen (2025) estimated carbon emissions from crop production in China's major grain-producing regions and found that production and carbon emissions in these regions have long been in a state of weak decoupling [20]. Zhao Qichen et al. (2023) conducted a spatial econometric analysis based on county-level data and concluded that agricultural carbon emissions exhibit distinct patterns of spatial concentration [21]. Zheng Lanqin et al. (2026) examined the effectiveness of emission reductions driven by agricultural productivity on a regional basis and demonstrated that emission reduction potential is realized more slowly in regions dominated by a single industry [22]. Dai Mengting et al. (2025) used a threshold model to compare regional differences in emission reductions enabled by digitalization [23]. In the international literature, Liu et al. (2024) compared the spatial patterns of carbon emissions across different global agricultural regions and found that carbon emission intensity in paddy fields was significantly higher than in dryland areas [24]. Brown et al. (2025) used long-time-series data to analyze the phased evolution of agricultural carbon emissions [25].

2.3. Research on the Impact of the Digital Economy on Agricultural Carbon Emissions

The existing literature, both domestic and international, confirms that the digital economy exerts a significant mitigating effect on agricultural carbon emissions. Chen Weihong et al. (2024) employed provincial-level panel regression analysis and found that the digital economy can effectively reduce both the total volume and emission intensity of carbon emissions from crop cultivation [26]. Shi Wei (2024) used a two-way fixed-effects model to empirically demonstrate that increased digitalization directly reduces the scale of agricultural carbon emissions [27]. He et al. (2024) conducted a cross-national study using the STIRPAT model and verified that rural digital development has a significant mitigating effect on agricultural carbon emissions; the more developed the regional digital infrastructure, the more pronounced the emission reduction effect [28]. Chen and Li (2024) focused on the digital transformation of agriculture and confirmed that such transformation can sustainably lower agricultural carbon emission levels [29].

Existing research has identified multiple mediating pathways through which the digital economy influences agricultural carbon emissions, all of which have been empirically validated using econometric models. Liu Ruiqi et al. (2025) confirmed that large-scale farming serves as a key mediating channel; digital service platforms can facilitate the transfer of contiguous farmland, and large-scale agricultural production models effectively curb the extensive use of chemical fertilizers and energy for agricultural machinery, thereby achieving carbon reduction and efficiency gains in agriculture [30]. Shi Changliang (2025) verified the mediating role of green technological innovation, demonstrating that Internet of Things (IoT) and smart water and fertilizer systems—implemented via digital platforms—can reduce carbon emissions at the agricultural production stage through precision farming models [31]. Zhong et al. (2026) further refined the mediating mechanism of technological progress, showing that digital production factors can accelerate the promotion and application of low-carbon agricultural machinery and ecological cultivation techniques, thereby achieving carbon emission reductions through agricultural technology upgrades [32]. Xie Tingting et al. (2026) proposed a mediating

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channel through industrial integration, noting that digital production and marketing platforms effectively extend the agricultural industrial chain and reduce carbon emissions across the entire agricultural value chain [33].

2.4. Literature Review

The existing literature, both domestic and international, has formed a relatively comprehensive research framework, laying a solid theoretical and empirical foundation for this study. At the basic research level, the academic community has clarified the core concepts, measurement systems, and growth transmission mechanisms of the digital economy. Meanwhile, research on agricultural carbon emissions has yielded substantial results in areas such as accounting systems, spatiotemporal evolution, and regional differentiation, refining agricultural carbon measurement standards and distribution patterns across multiple scenarios and scales. In interdisciplinary research, existing studies have generally confirmed that the digital economy exerts a significant mitigating effect on agricultural carbon emissions. They have also validated multiple core mediating pathways—such as economies of scale and technological innovation—and clarified the fundamental relationship and operational logic between the two. However, existing research still has certain shortcomings and limitations. Most studies focus on the independent validation of single emission reduction pathways, with insufficient research on the synergistic effects of multiple mediating mechanisms or comparative analyses of different mediating pathways. Furthermore, discussions on the heterogeneous emission reduction mechanisms across different regions and agricultural production scenarios still need to be deepened.

Given the gaps in existing research, this study on the impact of the digital economy on agricultural carbon emissions holds significant theoretical and practical significance. On a theoretical level, this study systematically integrates the theoretical logic underlying how the digital economy contributes to carbon emission reductions in agriculture, analyzes the synergy mechanisms among various mediating pathways, and further enriches the interdisciplinary research framework on the digital economy and low-carbon agricultural development. From a practical perspective, the current green and low-carbon transformation of agriculture is a critical component of rural revitalization and the implementation of the “dual carbon” goals. By thoroughly investigating the mitigating effects of the digital economy on agricultural carbon emissions and the underlying mediating mechanisms, this study can accurately identify the emission reduction potential of digital agriculture under different scenarios. It provides empirical evidence and targeted strategies to help localities leverage digital technologies to optimize agricultural production models, improve the allocation of agricultural production factors, and promote the coordinated development of agricultural scale expansion and greening, thereby supporting low-carbon transformation and high-quality development in the agricultural sector.

3. Theoretical Analysis and Research Hypotheses

3.1. Direct Mechanism of the Digital Economy’s Impact on Agricultural Carbon Emissions

Supported by the theory of induced technological innovation—whose core tenet is that changes in the relative prices of factors of production drive the supply of adaptive technologies—digital technology can alter the cost structure of agricultural factor inputs, thereby directly influencing agricultural carbon emissions. Digital tools such as digital platforms, smart agricultural machinery, and IoT monitoring reduce the costs arising from the inefficient use of high-carbon inputs such as land, chemical fertilizers, and fuel. Traditional agriculture relies on experience-based, extensive fertilization and indiscriminate operations by fuel-powered machinery,

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resulting in redundant factor inputs and directly leading to excessive greenhouse gas emissions. By collecting real-time data on soil moisture and crop nutrient requirements, digital technologies can precisely match fertilizer application rates, thereby reducing nitrous oxide generated by fertilizer decomposition; they can also intelligently schedule agricultural machinery routes to shorten idle travel time, lowering carbon dioxide emissions from diesel combustion. At the same time, digital monitoring systems can manage livestock manure treatment processes in real time, preventing the uncontrolled accumulation and fermentation of manure that releases methane. From the logic of induced technological innovation, digital technology raises the marginal cost of high-carbon inputs, prompting farmers to spontaneously reduce redundant high-carbon inputs and achieve emission reductions without the need for external constraints. Based on this, the following hypothesis is proposed:

H1: The development of the digital economy can reduce agricultural carbon emissions.

3.2. Indirect Mechanisms Through Which the Digital Economy Affects Agricultural Carbon Emissions

Based on the theory of energy factor efficiency optimization, the digital economy achieves precise matching of factors throughout the entire agricultural production process through digital sensing, precise control, and intelligent scheduling mechanisms. It can dynamically adjust energy inputs according to crop growth needs and operational scenarios, thereby reducing ineffective and redundant fossil fuel consumption and curbing energy waste in agriculture at the input stage. At the same time, digital technologies enhance agricultural production efficiency and the value added along the industrial chain, thereby expanding the scale of agricultural economic output and improving the marginal efficiency of energy inputs. The combined effect of slowing energy input growth and sustained increases in agricultural output value significantly reduces agricultural energy intensity and optimizes the agricultural energy structure. Ultimately, by improving the inefficient allocation of energy and reducing redundant consumption of high-carbon energy sources, the digital economy effectively curbs agricultural carbon emissions.

From the perspective of optimizing factor allocation, the development of the digital economy has effectively resolved the challenges of misallocation of agricultural machinery and diseconomies of scale by restructuring the logic of agricultural factor allocation. Digital technology has broken down spatiotemporal information barriers in the supply and demand of agricultural machinery, separated ownership from usage rights, and driven the transition of agricultural machinery power resources from fragmented, farmer-owned configurations to a highly efficient model of intensive and shared allocation through socialized services. Empowered by digital technology, farmers no longer need to purchase high-powered agricultural machinery to maintain excess machinery capacity to meet agricultural production needs. This has significantly reduced agricultural production’s reliance on privately owned agricultural machinery, effectively reduced redundant machinery power reserves, and—given a relatively stable rural resident population—significantly lowered the regional per capita allocation of mechanical power. Therefore, we propose the following hypothesis:

H2: The digital economy reduces agricultural carbon emissions through reductions in energy intensity and the optimized allocation of mechanical power.

3.3. Heterogeneity in the Impact of the Digital Economy on Agricultural Carbon Emissions

Significant disparities exist across Chinese regions in terms of agricultural development foundations and digital infrastructure, leading to a heterogeneous effect of the digital economy on agricultural carbon emissions. In practical terms, marked differences in agricultural resource endowments, farming and livestock management models, and stages of low-carbon

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development directly lead to significant disparities in the efficiency of implementing and adapting digital agricultural technologies. In regions with high levels of agricultural modernization and a high proportion of large-scale, intensive farming and livestock operations, the integration of agricultural supply chains with digital technologies is well-established, allowing for faster adoption of practices such as precision fertilization, smart agricultural machinery, and digital monitoring and control of carbon emissions. In contrast, regions dominated by traditional, extensive farming and livestock operations have limited coverage of digital transformation, offering significant marginal emission reduction potential through investments in digital carbon reduction technologies. In regions with relatively low baseline agricultural carbon emissions, low-carbon farming practices have long been in place, and the marginal carbon reduction potential of digital technology continues to shrink; in regions with high agricultural carbon emissions, where excessive use of agricultural inputs is a prominent issue, the carbon reduction achieved by optimizing production processes through digital means is more substantial. Furthermore, regions with well-developed digital infrastructure and comprehensive agricultural support policies can provide both channels for the flow of production factors and supportive incentive systems for the low-carbon transition of digital agriculture, thereby further widening regional disparities in the emission reduction effects of the digital economy on agriculture. Based on this, the following hypothesis is proposed:

H3: The impact of the digital economy on agricultural carbon emissions is heterogeneous.

4. Variable Selection and Model Construction

4.1. Variable Selection

4.1.1. Dependent Variable

Agricultural carbon emissions are selected as the dependent variable. Agricultural carbon emissions are defined as the direct or indirect greenhouse gas emissions generated during agricultural production due to the consumption of various inputs. Based on existing studies, these inputs encompass chemical fertilizers, pesticides, agricultural plastic film, diesel, tillage, and agricultural irrigation. Following the approach of Huang Weihua et al. (2023), agricultural carbon emissions are estimated using the IPCC carbon emission factor method [34].

$$y = \Sigma y_i = \Sigma T_i \times \partial_i \tag{1}$$

Let y denote the total agricultural carbon emissions, and let y_i denote the carbon emissions from the i-th type of agricultural carbon emission source. Further, let T_i denote the input of the i-th source, and let ∂_i denote the carbon emission coefficient for the i-th source. The coefficients for various agricultural carbon emission sources are primarily derived from data published by authoritative institutions.

Table 1. Agricultural Carbon Emission Sources and Their Coefficients

Carbon Source	Carbon emission factor	Reference Sources
Fertilizer	0.8956 kg/kg	Oak Ridge National Laboratory, USA
Pesticides	4.9341 kg/kg	Oak Ridge National Laboratory, USA
Agricultural film	5.18 kg/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
Diesel	0.5927 kg/kg	IPCC (Intergovernmental Panel on Climate Change)
Tilling	312.6 kg/hm^2	College of Biology and Technology, China Agricultural University

ISSN: 2710-0170

Agricultural irrigation	25 kg/hm^2	Duan Hua et al. (2011) [35]

4.1.2. Explanatory Variable

This study selects the development level of the digital economy as the core explanatory variable. Following Zhao Tao et al. (2021) [36], this variable is calculated using the entropy method based on a comprehensive indicator system comprising five indicators.

Table 2. Indicators for the Comprehensive Level of Digital Economy Development

First-Level Indicators	Second-Level Indicators	Tertiary Indicators
Comprehensive Digital Economy Index	Internet Penetration Rate	Number of Internet Users per 100 People
	Number of Internet-Related Employees	Percentage of Employees in Computer Services and Software
	Internet-Related Output	Total telecommunications services per capita
	Number of mobile Internet users	Number of mobile phone subscribers per 100 people
	Development of Digital Inclusive Finance	China Digital Inclusive Finance Index

4.1.3. Mechanism Variables

Energy intensity (Es) is measured as the ratio of energy consumption to regional gross domestic product. Mechanical power per capita (Mpc) is measured as the ratio of total mechanical power to the rural population.

4.1.4. Control Variables

Taking into comprehensive consideration factors that may influence the results, this paper selects the following five variables as control variables:

Rural residents' income level (Rdi): measured as the total per capita disposable income of rural residents.

Urbanization rate (Urban): measured as the ratio of the urban population to the permanent resident population at year-end.

Fiscal support for agriculture (Fsp): calculated as local government expenditure on agriculture, forestry, and water affairs divided by local government general budget expenditure.

Average years of education in rural areas (Rays): calculated by multiplying the population in each educational category—elementary school, junior high school, senior high school (including vocational high school), and college or higher—by the corresponding years of education (6, 9, 12, and 16 years, respectively), summing these products, and then dividing by the total population aged 6 and older.

Agricultural industrial agglomeration (Aic): measured as the ratio of the province's primary sector GDP as a share of its total GDP to the national primary sector's share of total GDP.

The specific variable definitions are shown in Table 3.

ISSN: 2710-0170

Table 3. Variable Definitions

Variable Type	Variable Name	Symbol	Variable Definition
DependentVariable	Agricultural Carbon Emissions	Y	Estimated
Explanatoryvariables	Level of the digital economy	X	Calculated using the entropy method
Mediatingvariable	Energy intensity	Es	Energy Consumption/GDP
	Mechanical Power Allocation	Mpc	Total Mechanical Power / Rural Population
Control variables	Rural Residents' Income Level	Rdi	Log of per capita disposable income of rural residents
	Urbanization rate	Urban	Urban Population / Permanent Resident Population at Year-End
	Level of Fiscal Support for Agriculture	Fsp	Local government expenditures on agriculture, forestry, and water affairs / Local government general budget expenditures
	Average Years of Education in Rural Areas	Rays	(Population by educational attainment × Sum of corresponding school years) / Total population aged 6 and older
	Agricultural Industry Clustering	Aic	(Province's primary sector share of GDP) / (National primary sector share of GDP)

4.2. Model Specification

4.2.1. Benchmark Regression Model

To test H1, and based on the theoretical analysis in the preceding section, the following two-way fixed-effects model (controlling for both individual and time fixed effects) is specified:

$$y_{it} = \alpha_0 + \alpha_1 x_{it} + \alpha_2 Controls_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{2}$$

Where, y_{it} represents the agricultural carbon emissions of province i in year t; x_{it} represents the development level of the digital economy in province i in year t; $Controls_{it}$ denotes the vector of control variables; μ_i and λ_t denote the individual fixed effect and the time fixed effect, respectively; and ε_{it} is the random error term.

4.2.2. Mediating Effect Model

To test H2, the following mediating effect models are constructed based on Model (1), following the stepwise procedure proposed by Wen et al. (2014) [37]:

$$M_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 Controls_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{3}$$

$$y_{it} = \varphi_0 + \varphi_1 x_{it} + \varphi_2 M_{it} + \varphi_3 Controls_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{4}$$

Where, M_{it} is the mediating variable (energy intensity or mechanical power per capita) for province i in year t; x_{it} denotes the development level of the digital economy; and y_{it} denotes agricultural carbon emissions. Equation (2) tests the effect of the digital economy on the mediating variable, while Equation (3) estimates the joint effects of the digital economy and the mediating variable on agricultural carbon emissions. The testing procedure is as follows: after

ISSN: 2710-0170

confirming the significance of the total effect in the baseline model (1), we estimate Equation (2) and Equation (3) sequentially. A mediating effect is considered to exist if the coefficient aa in Equation (2) and the coefficient b in Equation (3) are both statistically significant, following the criteria of Wen et al. (2014).

4.3. Data Sources and Descriptive Statistics

This paper uses panel data from 30 provinces (autonomous regions and municipalities) in China from 2011 to 2024 as the research sample (excluding Tibet, Hong Kong, Macao, and Taiwan). The data were sourced from the China Statistical Yearbook, provincial statistical yearbooks, the Guotai-An database, and the China Research Data Service Platform (CNRDS). In addition, missing data for some regions were imputed using linear interpolation.

Table 4 presents the descriptive statistics for the variables.

Table 4. Descriptive Statistics of Variables

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
y	420	5.251	1.059	2.457	6.769
x	420	0.243	0.183	0.053	1
Rdi	420	9.532	0.454	8.361	10.729
Urban	420	0.606	0.118	0.344	0.898
Fsp	420	11.34	3.43	3.87	20.937
Rays	420	7.881	0.649	5.878	10.416
AIC	420	1.233	0.675	0.027	3.286
Es	420	0.717	0.421	0.154	2.189
Mpc	420	1.937	1.173	0.349	7.809

5. Empirical Analysis

5.1. Baseline Regression

The Hausman test yielded a p-value of < 0.0000, indicating that fixed effects are the preferred choice. To account for individual and time heterogeneity and to improve the model's explanatory and predictive power, this study employs a two-way fixed effects model. The specific results are shown in Table 5.

Model (1) in Table 5 is the baseline regression, incorporating only the core explanatory variable—the development level of the digital economy (x). The regression results show that the coefficient of x is -3.147 and is statistically significant at the 1% level, providing preliminary evidence of a negative relationship between the digital economy and agricultural carbon emissions. Model (2) adds provincial and year fixed effects to Model (1); Model (3) incorporates relevant control variables; and Model (4) includes both two-way fixed effects and the full set of control variables. In Model (4), the coefficient of x is -0.750 and is statistically significant at the 1% level.

Overall, from Model (1) to Model (4), the coefficient of the core explanatory variable (x) gradually adjusted from -3.147 to -0.750. Although the magnitude varied across specifications, the coefficient remained consistently negative and statistically significant at the 1% level, indicating that the digital economy has a significant mitigating effect on agricultural carbon emissions. Hypothesis H1 is thus confirmed.

ISSN: 2710-0170

Table5. Benchmark Regression Results

Variables	Y			
	Model (1)	Model (2)	Model (3)	Model (4)
x	-3.147***	-0.457***	-2.611***	-0.750***
	(-13.221)	(-2.330)	(-6.739)	(-5.258)
a			0.866***	0.767***
			(6.219)	(3.397)
b			-6.921***	1.692***
			(-8.743)	(5.352)
c			-0.044**	0.013***
			(-2.327)	(3.186)
d			0.513***	-0.090***
			(4.462)	(-3.882)
e			-0.021	0.055*
			(-0.180)	(1.710)
_cons	6.015***	5.362***	-1.700	-2.407
	(83.235)	(115.933)	(-1.256)	(-1.179)
Adj-R^2	0.293	0.992	0.449	0.995
N	420	420	420	420
Fixed vintage	No	Yes	No	Yes
Fixed by province	No	Yes	No	Yes

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; values in parentheses are robust standard errors; the same applies below.

5.2. Mediation Analysis

Focusing on the core question of how the digital economy mitigates agricultural carbon emissions, we employed the stepwise mediation testing procedure to explore the underlying mechanisms. The specific results are presented in Table 6.

5.2.1. Mediation by Energy Intensity

Columns 2–3 of Table 6 show that the digital economy has a significant negative effect on energy intensity, while energy intensity has a significant positive effect on agricultural carbon emissions. This indicates that the digital economy can reduce agricultural energy intensity, thereby optimizing the regional agricultural energy structure. First, precision digital farming and IoT-based intelligent management reduce energy waste in agricultural production, while rural e-commerce and digitalized industrial chains enhance the value added of agricultural products, thereby expanding agricultural economic output while lowering energy consumption per unit of agricultural output. Second, county-level digital energy dispatch and online environmental supervision systems accelerate the adoption of clean energy sources such as solar power and biogas in agricultural settings, reducing the use of high-carbon fossil fuels like diesel and coal, and continuously lowering energy intensity indicators.

5.2.2. Mediation by Mechanical Power per Capita

Columns 4–5 of Table 6 show that the digital economy has a significant negative effect on mechanical power per capita, while mechanical power per capita has a significant positive effect on agricultural carbon emissions. This indicates that the digital economy reduces agricultural carbon emissions by lowering the regional per capita allocation of mechanical

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power. On the one hand, digital rural platforms establish online agricultural machinery rental and cross-regional operation scheduling systems. Farmers no longer need to own heavy agricultural machinery to complete cultivation tasks, which significantly reduces the demand for household purchases of agricultural machinery. Given a relatively stable rural population, the per capita total power of agricultural machinery decreases. On the other hand, lightweight digital technologies—such as precision farming and drone-based crop protection—replace traditional high-power agricultural practices like deep plowing with heavy plows, thereby reducing the demand for high-power fuel-powered agricultural machinery. At the same time, if a region blindly expands its fleet of heavy agricultural machinery, it will revert to an extensive agricultural production model characterized by high fuel consumption, and the resulting increase in fuel consumption will directly drive up agricultural carbon emissions.

Table 6. Regression Results for Mediating Effects

AnalysisofRegression Variables	Energy Intensity Test		Test of Machinery Power Configuration	
	Es	Y	Mpc	Y
X	-0.493***	-0.696***	-2.651***	-0.485***
	(-4.311)	(-4.836)	(-3.523)	(-4.276)
Es		0.109**		
		(2.131)		
Mpc				0.100***
				(10.169)
_cons	9.123***	-3.400	11.695	-3.574**
	(3.959)	(-1.608)	(0.930)	(-2.393)
Control variables	Yes	Yes	Yes	Yes
Year and provincefixed	Yes	Yes	Yes	Yes
N	420	420	420	420
Adj-R^2	0.953	0.995	0.890	0.996

5.3. Robustness Tests

5.3.1. Alternative Measure of Core Explanatory Variable

The original indicator system was re-measured after replacing its variable composition. Changing the calculation method for the explanatory variable can mitigate potential measurement errors in the original indicators and the randomness in weight setting. Six relevant variables—electronic information manufacturing, telecommunications services, Internet penetration rate, software services, digital information, and e-commerce—were selected, and the index was recalculated using the entropy method. The regression results show that the coefficient of the new explanatory variable (x) is -1.940, with a sign consistent with the baseline estimate, the statistical significance unchanged, and the magnitude comparable. This indicates that the conclusions of the baseline regression do not depend on the calculation method of a single variable system and are therefore robust.

5.3.2. Excluding Municipalities Directly under the Central Government

Given that the four major municipalities (Beijing, Tianjin, Shanghai, and Chongqing) possess more comprehensive digital infrastructure and more preferential digital support policies for agriculture, their pace of agricultural digital transformation and agricultural production models differ from those of other provinces. Sample heterogeneity may introduce bias into the

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estimates of the core variables. To eliminate the interference caused by this special sample, this study excludes the four municipalities and re-estimates the model. The test results indicate that the coefficient of the digital economy variable remains significantly negative at the 1% level. This suggests that the special characteristics of the municipalities do not distort the underlying relationship between the digital economy and agricultural carbon emissions; the mitigating effect of the digital economy on agricultural carbon emissions is equally applicable across ordinary provinces nationwide, further validating the robustness and reliability of the baseline regression conclusions.

5.3.3. Sample Truncation Test

The sample truncation test involves re-estimating the model while keeping the regression specification unchanged but adjusting the range of sample observations. After truncation, the coefficient of the digital economy variable is -0.820, which remains statistically significant at the 1% level. The estimated coefficients of the core explanatory variable all remain significantly negative, further validating the stability of the model results and indicating that the study's conclusions are not affected by fluctuations in sample size.

Table 7. Results of theRobustness Tests

Variable	(1) Replacement of the core dependent variable	(2) Exclude municipalities directly under the central government	(3) Data Truncation
X	-1.940** (-2.18)	-0.3863*** (-2.91)	
X_winsor			-0.820*** (-6.02)
_cons	-0.550 (-0.25)	1.530 (0.82)	-2.594 (-1.29)
Sample Size	420	364	420
Adj-R^2	0.994	0.994	0.995
Control	Yes	Yes	Yes
Province and	Yes	Yes	Yes

Across all three robustness tests, the coefficient of the core explanatory variable remained negative and statistically significant at the 1% level. Furthermore, all models controlled for covariates, year fixed effects, and province fixed effects, with R^2 values consistently at a high level. In summary, the mitigating effect of the digital economy on agricultural carbon emissions, as discussed above, demonstrates good robustness.

5.4. Endogeneity Test

To address potential endogeneity arising from reverse causality, we used the first-order lag of the explanatory variable (L.x) as an instrumental variable and conducted estimation via two-stage least squares (2SLS). The Kleibergen-Paap LM statistic was 14.416, with a p-value of 0.0001, rejecting the null hypothesis at the 1% significance level and indicating that the model does not suffer from under-identification. The Wald F-statistic was 760.636, far exceeding the critical value of 16.38, indicating that weak instruments are not a concern. The regression results show that, after controlling for endogeneity, the negative impact of the digital economy on agricultural carbon emissions remains robust, further corroborating the reliability of the baseline conclusions. Endogeneity does not materially alter the research findings.

ISSN: 2710-0170

Table 8. Results of the Endogeneity Test

Variables	(1) Stage 1	(2) Stage 2
L.x	0.861*** (26.30)	
x		-0.799** (-2.51)
Observed values	390	390
Control variables	Yes	Yes
Fixed Year	Yes	Yes
Fixed by province	Yes	Yes
R-squared	0.690	0.780
LM statistic	14.416 [0.0001]	
Wald F-statistic	760.636{16.38}	

Note: Values in ( ) are t-values; values in [ ] are the corresponding p-values for the LM statistic; values in { } are the Stock-Yogo weak instrumental variable critical values at the 10% significance level.

5.5. Heterogeneity Analysis

Building on the validated robustness test results, and taking into account differences in geographical location and level of economic development across provinces, we further analyze the heterogeneous effects of the digital economy on agricultural carbon emissions.

5.5.1. Regional Heterogeneity

In Chinese academic research, the Hu Huanyong Line serves as a key comprehensive demarcation line distinguishing China's natural ecological foundations, patterns of human development, and levels of regional economic development; there are significant differences in agricultural production conditions and the endowment of development factors on either side of the line. Based on this, this paper uses the Hu Huanyong Line as a criterion to divide the 30 provincial samples into the Southeast and Northwest regions and conducts a test of regional heterogeneity. The results of the subregional regression analysis indicate that the development of the digital economy has a significant negative effect on agricultural carbon emissions in both regions, but the magnitude of this reduction exhibits distinct regional variations; the coefficients of the core explanatory variable in both subsamples are statistically significant.

The results show that the regression coefficient for the digital economy in the Southeast region is -0.533, while the corresponding coefficient for the Northwest region is -0.780. A comparison reveals that the mitigating effect of the digital economy on agricultural carbon emissions is stronger in the Northwest region. This regional disparity stems from the following factors: the Southeast region began agricultural modernization earlier and has a mature digital support system; it had already completed large-scale agricultural emission reduction upgrades using digital technology in the early stages, and the marginal potential for further emission reductions through the digital economy is gradually narrowing. In contrast, the Northwest has a higher proportion of traditional, extensive agriculture and historically low penetration rates of digital agricultural technologies. With the implementation of digital agricultural equipment and smart management models, the emission reduction potential of digital technologies—which optimize agricultural input use, reduce agricultural energy consumption, and standardize cultivation and breeding processes—can be fully realized. Consequently, the carbon emission reductions resulting from the same increment in digital economic development are significantly higher in the Northwest than in the Southeast.

ISSN: 2710-0170

5.5.2. Heterogeneity in Carbon Emission Levels

The mitigating effect of the digital economy on agricultural carbon emissions varies with the baseline level of agricultural carbon emissions in each area. To accurately identify the patterns of this heterogeneity, this study uses the median value of the dependent variable—agricultural carbon emissions—as the grouping threshold. All provincial samples are divided into a high agricultural carbon emissions group (above the median) and a low agricultural carbon emissions group (below the median), and a grouped heterogeneity regression test is conducted. The results of the group-specific regression analysis show that the digital economy has a significant mitigating effect on agricultural carbon emissions in both groups of regions, but the magnitude of emission reductions varies markedly across regions. Specifically, the regression coefficient for the digital economy in regions with low agricultural carbon emissions is -0.467, while in regions with high agricultural carbon emissions it is -0.614; both coefficients are statistically significant at the 1% level. A comparison of the absolute values of the coefficients reveals that the digital economy exerts a stronger mitigating effect on carbon emissions in regions with high agricultural carbon emissions.

This difference may stem from the fact that regions with high agricultural carbon emissions rely more heavily on traditional, extensive farming and livestock production models, where issues such as redundant inputs of production factors—including chemical fertilizers and fuel for agricultural machinery—are particularly pronounced, leaving ample room for reducing carbon emissions in agricultural production. With the implementation of digital tools such as digital agricultural monitoring, precision fertilization, and smart agricultural machinery management, agricultural input structures can be directly optimized and inefficient energy consumption reduced, allowing the emission reduction benefits of digital technology to be fully realized. In contrast, in regions with low agricultural carbon emissions, local agricultural production models have already shifted toward intensive, low-carbon practices. The marginal potential for further carbon reduction through digital transformation continues to narrow, and the emission reduction achieved by a given level of digital economic development is relatively limited.

Table 9. Results of the Heteroscedasticity Test

Variables	(1) Southeast	(2) Northwest	(3) Low carbon emissions	(4) High carbon emissions
x	-0.533***	-0.780***	-0.467***	-0.614***
	(-4.032)	(-3.124)	(-2.619)	(-4.037)
_cons	1.069	16.344***	-0.195	-5.123**
	(0.502)	(3.674)	(-0.069)	(-2.395)
Controlvariables	Yes	Yes	Yes	Yes
Province and year are fixed	Yes	Yes	Yes	Yes
Adj-R^2	0.998	0.997	0.994	0.960
Observed value	294	126	210	210

6. Conclusions and Suggestions

Based on provincial-level panel data from China for 2011–2024, this paper measures agricultural carbon emissions and develops a comprehensive multi-indicator evaluation system to assess the development level of the digital economy. It then constructs a two-way fixed-effects model to systematically examine the impact, mechanisms, and boundary conditions of the digital economy on agricultural carbon emissions. The study's conclusions are

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as follows: First, the digital economy has a significant mitigating effect on agricultural carbon emissions, revealing that advancing the development and application of the digital economy can effectively reduce agricultural carbon emission intensity. This conclusion remains statistically significant after a series of robustness tests, including replacing the explanatory variable, excluding municipalities directly under the central government, and applying data truncation. Second, the digital economy improves energy input efficiency and reduces energy intensity, while simultaneously reshaping agricultural machinery allocation patterns and lowering the per capita stock of heavy agricultural machinery. These two mediating pathways collectively contribute to agricultural carbon emission reductions. Third, the impact of the digital economy on agricultural carbon emissions exhibits significant regional heterogeneity, with a more pronounced mitigating effect observed in the Northwest region and in areas with high carbon emissions.

Based on the above conclusions, this paper proposes the following policy recommendations:

(1) Leverage the practical value of digital technologies in driving agricultural carbon reduction and efficiency gains, and coordinate macro-level planning with grassroots implementation to establish a comprehensive and precise system for digital carbon reduction in agriculture. Building on the achievements of the nationwide integrated computing power deployment, coordinate the allocation of computing resources across regions to promote the establishment of specialized computing clusters tailored to agricultural production and carbon emissions monitoring at the grassroots level. This will effectively reduce the computing costs for agricultural entities adopting digital carbon reduction technologies, remove barriers to the widespread and inclusive application of computing power in rural agricultural sectors, and ensure that low-cost, high-quality computing resources support low-carbon agricultural production in all regions. In light of the practical challenges of agricultural carbon reduction and the overall goals of low-carbon development, it is recommended to improve the pilot and fault-tolerance mechanisms for the application of digital agricultural technologies and to relax restrictions on innovation in the digital low-carbon transformation of grassroots agricultural operators and agribusinesses.

(2) Focus on the core pathways through which the digital economy empowers low-carbon agricultural development. Strengthen the dual support of a digital agricultural machinery sharing system and digital energy-saving upgrades to eliminate the two key bottlenecks in agricultural carbon reduction: factor misallocation and high-carbon energy consumption.

To optimize agricultural machinery allocation, we will establish a special fund to support digital agricultural machinery. Agricultural operators and research institutions will be guided to build innovative collaborative platforms for agricultural machinery sharing, tackle key technologies such as online machinery dispatch and lightweight smart agricultural machinery, simplify the subsidy process for smart agricultural machinery services, and improve the county-level socialized trading system for agricultural machinery. By leveraging digital platforms to break down information barriers between supply and demand, we will promote shared leasing models that separate ownership from usage rights, thereby reducing farmers' duplicate purchases of heavy agricultural machinery, lowering regional machinery surpluses, and cutting fuel-related carbon emissions caused by excessive machinery inventories.

To upgrade the agricultural energy structure, we will coordinate and improve digital infrastructure such as the rural Internet of Things and smart energy monitoring systems, prioritize resource allocation to remote agricultural areas, and narrow regional disparities in digital facilities.

(3) Implement differentiated emission reduction policies with targeted, category-specific measures to fully unleash the potential of the digital economy in enabling agricultural carbon reduction and to narrow regional disparities in low-carbon agricultural development.

ISSN: 2710-0170

For the southeastern region, which has a solid low-carbon agricultural foundation and relatively low total agricultural carbon emissions, we will leverage the well-developed supporting system for digital agriculture to prioritize the establishment of smart agriculture innovation demonstration bases. We will focus on cutting-edge applications such as precision crop farming and livestock breeding, digital monitoring of agricultural carbon sinks, and the recycling of agricultural inputs. By capitalizing on the region's strengths in the digital industry, we will create model projects for low-carbon digital agriculture and develop standardized, replicable digital carbon reduction models to be rolled out nationwide.

For the northwestern region, where extensive agricultural production is more prevalent and the carbon emission baseline is higher, we must move away from the extensive model of simply replicating the eastern region's digitalization path. Instead, we should leverage local agricultural and livestock resources to promote the deep integration of digital technologies with specialty crop cultivation and large-scale livestock farming. A collaborative platform for agricultural digitization between the eastern and western regions should be established to introduce mature low-carbon digital agricultural technologies and specialized digital talent from the southeast to the northwest, thereby fully tapping into the region's marginal emission reduction potential in digital agriculture. Through two-way coordination, the regional digital agriculture development gap can be bridged, the carbon reduction benefits of the digital economy in agriculture can be fully realized across regions, and a coordinated agricultural development framework featuring east-west linkages and complementary low-carbon advantages can be established.

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