International Journal of Innovative Research and Scientific Studies, 8(4) 2025, pages: 2304-2319

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

The impact of the digital economy on agricultural carbon emissions empirical evidence from China

Li Yang[1], Danai Tanamee[2*], Suppanunta Romprasert[3]

[1,2,3]*Faculty of Economics, Srinakharinwirot University, 114 Sukhumvit 23, Bangkok 10110, Thailand*.

Corresponding author: Danai Tanamee (*Email: danait@g.swu.ac.th*)

Abstract

The rapid development of the digital economy has increased attention to its impact on agricultural carbon emissions. Using panel data covering 30 Chinese provinces from 2012 to 2022, this study examines the relationship between the digital economy and agricultural carbon emissions, along with the underlying mechanisms. The results indicate that the digital economy significantly reduces overall agricultural carbon emissions, a finding that remains robust across various tests. Notably, the effect of the digital economy on the intensity of agricultural carbon emissions is heterogeneous, with more pronounced reductions observed in major grain-producing regions. Key intermediary mechanisms for this reduction include agricultural scale, the enhancement of digital financial services, and technological innovation. Based on these findings, we recommend focusing on strengthening digital infrastructure, enhancing the digitally inclusive financial system, promoting the development of digital agricultural talent, and exploring innovative models of digital agricultural development.

Keywords: Agricultural carbon emissions, Digital economy, Financial effect, Scale effect, Technological innovation effect.

DOI: 10.53894/ijirss.v8i4.8382
Funding: This study received no specific financial support.
History: Received: 23 May 2025 / **Revised:** 27 June 2025 / **Accepted:** 1 July 2025 / **Published:** 8 July 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Climate change poses one of the most critical challenges of our era, endangering global economic growth, ecosystem stability, and long-term societal advancement [1]. The urgent need to reduce carbon emissions and combat the escalating climate crisis has crystallized into a collective mission for the international community. The latest report from Song, et al. [2] warns that, without rigorous intervention, global greenhouse gas emissions could cause an increase in global temperatures exceeding 2°C by the end of the century, with catastrophic consequences for ecosystems and socioeconomic stability. Agriculture is a significant contributor to this crisis, accounting for approximately 23% of global annual greenhouse gas emissions [3]. This reality highlights the urgent need for emission mitigation strategies within this sector, which are essential to any comprehensive climate change response. As the largest developing nation, China's agricultural sector is pivotal to its economy, with agricultural carbon emissions representing nearly 15% of the nation's total emissions, making it a crucial source of greenhouse gases. In response to these substantial challenges, General Secretary Xi Jinping, during the 15th Conference of the Parties to the Convention on Biological Diversity (CBD) in 2021, announced the inclusion of "carbon peaking and carbon neutrality" within the framework of ecological civilization. He pledged to achieve peak carbon emissions by 2030 and carbon neutrality by 2060, thereby affirming China's resolute commitment to a sustainable, low-carbon future [2, 4, 5]. However, navigating a sustainable, low-carbon transition pathway for agriculture presents formidable challenges, particularly in reconciling the dual objectives of satisfying rising agricultural demand while fulfilling climate commitments.

In recent years, the digital economy has undergone robust and dynamic expansion. Between 2014 and 2023, China's digital industrialization value-added growth rate has consistently averaged approximately 15%. As reported in "China's [6]", the scale of the digital economy has increased significantly, now accounting for 41.5% of the national GDP. within the agricultural sector, digital penetration has reached 10.5%, indicating a substantial integration of digital technologies. this rapid growth of the digital economy offers new pathways for reducing carbon emissions in agriculture. the 2021 White Paper on Digital Carbon Neutrality underscores the critical role of digitalization as a key technological avenue for China in achieving carbon neutrality and contributing to global climate change mitigation efforts. furthermore, the "Plan for the Development of Digital Agriculture and Rural Areas (2019-2025)" highlights the necessity of strengthening foundational infrastructure for rural digital development, accelerating the implementation of big data analytics in agriculture, and fostering the advancement of smart agricultural practices. extant research demonstrates that the digital economy promotes green agriculture and enhances production efficiency by optimizing resource allocation [7]. Moreover, it catalyzes the digital transformation of agricultural modernization through the adoption of precision agriculture technologies [8] and innovative digital tools. These advancements enable agricultural producers to improve the management and control of production processes, leading to reductions in energy consumption, resource wastage, and ultimately, carbon emissions [9, 10]. Consequently, a thorough examination of the impact of the digital economy on agricultural carbon emissions is not only of significant practical importance but also carries substantial policy implications for the development of effective low-carbon agricultural strategies.

2. Literature Review

As a core component of modern technological advancement and industrial evolution, the digital economy plays a transformative role in reshaping agricultural production methods and strategic development. In light of the rapid evolution and widespread application of digital technologies, researchers have explored the implications, mechanisms, and developmental trajectories of the digital economy within the agricultural sector. For example, Yang, et al. [11] analyzed the carbon emissions reduction potential of the digital economy from the perspectives of digital industrialization and industrial digitization. Yang, et al. [12] provided a comprehensive examination of the mechanisms and pathways through which the digital economy transforms agricultural production modes, framed within a Marxist political economy context. A systematic review by Tang, et al. [13] further substantiated the claim that digital technology fundamentally alters traditional agricultural practices, emphasizing the transformative potential of smart agricultural big data. At the empirical level, Yi, et al. [14] and Guo, et al. [15] demonstrate that the digital economy significantly facilitates the upgrading of agricultural structures, technological innovation, and large-scale operations. This is consistent with the evolutionary pattern depicted in Wang, et al. [16] conceptual framework for a next-generation Agri-cultural Management Information System.

The digital economy is increasingly acknowledged as a critical enabler of productivity gains in agriculture, fundamentally transforming production paradigms and efficiency outcomes [17]. Research has demonstrated that the digital economy exerts a significant influence on agricultural productivity through technological innovation and the mobility of production factors [18]. It also facilitates the high-quality development of agriculture [19], particularly through the utilization of big data technologies, which reveal new opportunities and challenges in agricultural and environmental analysis [20]. Such advancements provide critical support for precision agriculture and enhance the efficiency of resource allocation [21], resulting in notable reductions in agricultural carbon emissions and effectively promoting a transition to greener production practices [22]. In contrast, enterprises or sectors characterized by outdated production practices and reduced efficiency face increasing difficulties in adapting to evolving production standards, leading to their gradual marginalization and potential extinction [23].

Additionally, Yue [24] examined the role of the digital economy in optimizing the spatial arrangement of the agricultural industry, thereby enhancing the synergistic development capacity of regional agriculture within the framework of industrial agglomeration. Elijah, et al. [22] assessed the implementation of Internet of Things (IoT) technology in contemporary agricultural production and its environmental benefits. Through a meta-analysis of 50 representative agricultural cases globally, this study elucidated the multifaceted mechanisms of IoT technology in resource optimization, precision agriculture, and carbon reduction. Weersink, et al. [25] systematically articulated the strategic objectives of digital agricultural transformation in mitigating climate change from the global perspective of the Food and Agriculture Organization of the United Nations (FAO). This analysis underscored the pivotal role of digital technology in reducing agricultural carbon emissions and enhancing climate resilience, while also proposing innovative strategies for developing countries to confront climate change challenges.

Although a substantial body of scholarship has investigated how the digital economy interfaces with agriculture, several gaps remain. First, existing studies largely focus on theoretical elaboration, lacking in-depth empirical validation and multi-dimensional mediation mechanism analysis. Second, the research perspective tends to be relatively narrow;

current research predominantly explores the digital economy's general influence on agriculture, with limited emphasis on its nuanced effects within rural contexts. Third, while heterogeneity analyses in existing literature predominantly emphasize geographical variation, comparatively few studies investigate disparities through the lens of agricultural production functional zones. Addressing this gap, the present study draws on panel data spanning 2012 to 2022 to systematically assess the digital economy's influence on agricultural carbon emissions, along with the mediating mechanisms at play, and the heterogeneous influences across grain-producing regions. By doing so, this research aims to provide quantitative evidence and theoretical insights to support the role of the digital economy in promoting low-carbon agricultural development.

3. Theoretical Basis and Research Hypotheses

3.1. Direct Effect

The digital economy exerts a direct influence on agricultural costs, resource utilization efficiency, supply chains, and environmental management, thereby impacting agricultural carbon emissions.

First, the digital economy reduces agricultural costs and facilitates the digitization of agricultural practices. By harnessing advanced information and communication technologies such as cloud computing and big data, traditional agricultural inputs are transformed into data-driven resources. For instance, the integration of digital technologies converts conventional machinery into intelligent systems, enhancing production efficiency while simultaneously reducing labor costs and energy consumption. Research demonstrates that a marginal 1% increase in digital economy development is statistically associated with a 0.595% reduction in agricultural carbon emissions [6].

Second, the digital economy significantly enhances resource utilization efficiency through precision agriculture technologies. The expansion of digital infrastructure promotes the comprehensive deployment of digital tools across networked, intelligent, and refined agricultural operations [22]. By utilizing smart machinery, sensors, drones, and data analytics, farmers can monitor crop growth and soil conditions in real time, allowing for precise fertilization and irrigation [26]. This targeted approach reduces fertilizer and water consumption, thereby decreasing agricultural carbon emissions and contributing to climate change mitigation [9].

Third, the digital agricultural supply chain facilitates the transformation of traditional agricultural practices toward intelligent, value-driven, and efficient development, ultimately improving the overall efficiency of sustainable agricultural production [6, 27]. Digital technologies enable producers to respond more effectively to market demand fluctuations, achieving a dynamic alignment between production and market needs. This adaptability allows for better management of energy consumption during agricultural production, resulting in reduced greenhouse gas emissions [28].

Finally, the role of the digital economy in environmental management is noteworthy [29]. Through digitalization, agricultural administrations can monitor and manage carbon emissions with greater precision, facilitating data-driven policy interventions. By fostering the digitalization and intelligent transformation of agricultural practices, the digital economy serves as a key driver in mitigating agricultural carbon emissions. Based on this theoretical foundation, the following hypothesis is proposed for empirical testing:

$H_{1:}$ The digital economy can directly and effectively reduce agricultural carbon emissions.

3.2. Indirect Effect

3.2.1. Scale Effects as a Transmission Mechanism in Digital Economy–Driven Carbon Reduction in Agriculture

Digital technology serves as a pivotal catalyst for contemporary agricultural reform, facilitating the reconfiguration of traditional small-scale business models. In an agroecological context dominated by smallholder operations, production is often constrained by high unit cultivation costs, low levels of mechanization, and inefficient management practices. The introduction of digital technology has enabled the integration of advanced agricultural machinery and digital management systems, gradually replacing conventional, fragmented, and decentralized production models with more standardized and scalable approaches.

This transformation not only enhances mechanization and digital management capabilities but also improves the flow of information. Digital technology promotes effective exchange of market and technical information among agricultural producers through information platforms, addressing issues of information asymmetry [30]. This enhanced information exchange increases resource allocation efficiency and facilitates the transition from traditional decentralized operations to moderate-scale farming. Furthermore, digital platforms reduce the financial costs associated with land transfers, enabling smoother and faster transactions [31]. As a result, it facilitates the efficient allocation of agricultural resources and promotes the scaling up of farm operations.

Research indicates that moderate-scale operations can enhance land use efficiency and reduce agricultural carbon emissions, thereby addressing concerns related to operational fragmentation and resource wastage. The integration of digital technology promotes the rational allocation of land resources, facilitating agricultural production through precise alignment of supply and demand. Expanding agrarian operations to a large scale has been shown to improve production efficiency, minimize resource waste, and mitigate pollution [29]. This shift not only lowers the costs associated with rural pollution management but also diminishes agricultural carbon emissions. Moreover, large-scale operations are often linked to higher levels of mechanization and automation, which can substantially decrease carbon emissions per unit of output. This transition directly reduces energy consumption and carbon emissions typically associated with small-scale farming. Based on this analysis, we propose the following hypothesis for the study:

$H_{2a:}$ The digital economy can effectively reduce agricultural carbon emissions through the scale effect of land use.

3.2.2. Financial Intermediation Effects of the Digital Economy on Agricultural Carbon Emissions

The rise of the digital economy has significantly broadened the scope of traditional finance, reducing service costs and enhancing the accessibility of inclusive financial solutions, thereby improving overall financial system efficiency. Historically, high costs have excluded many "long-tail groups" from financial services. However, the rapid development of digital finance has lowered these costs, facilitating access for underserved populations and yielding positive impacts on economic growth, income, consumption, innovation, and entrepreneurship [32].

The Guide to Digital Finance in Agriculture, published by the United States Agency for International Development [24] highlights that digital finance effectively expands access to the formal financial system by leveraging advances in digital and mobile infrastructure, along with the proliferation of branchless banking. This evolution has made financial services more accessible to rural households. In China, the limited reach of traditional financial institutions in rural areas often results in significant time and travel costs for farmers seeking financing, creating barriers to convenient access.

By employing internet technology and mobile payment systems, digital finance has dismantled the historically exclusive relationship between rural agriculture and financial capital. It provides services such as online agricultural loans and microcredit, effectively addressing the financing difficulties faced by farmers. This transformation enables agricultural producers to secure funding for sustainable agriculture development and encourages research institutions and enterprises to obtain financial support, thus fostering innovation in green agriculture technologies. This, in turn, enhances agricultural production efficiency and product quality. An empirical study by Sørensen, et al. [33] utilizing a series of exogenous events and the difference-in-differences methodology, it was confirmed that digital finance significantly contributes to carbon emission reductions. In light of this analysis, we propose the following hypothesis:

H_{2b}: The digital economy can effectively reduce agricultural carbon emissions through financial intermediation effects.

3.2.3. The Mediating Effect of Technological Innovation in the Relationship Between the Digital Economy and Agricultural Carbon Emissions

Technological innovation serves as a fundamental driver of economic progress, playing a pivotal role in enhancing environmental quality and fostering sustainable development. In the context of the digital economy, technological innovation strengthens interactions, collaboration, and knowledge exchange among key stakeholders, facilitating the pervasive adoption of digital technologies that significantly contribute to carbon emissions reduction [34].

By leveraging advanced digital tools, such as multidimensional sensors, enterprises can monitor production processes with precision, obtaining real-time data on various inputs and activities. This capability enables organizations to identify inefficiencies within their production systems and implement incremental improvements that enhance operational efficiency, thereby reducing carbon emissions [6].

Empirical evidence provided by Wang, et al. [35] utilizing an IPTA model that incorporates stochastic elements, underscores the critical influence of technological advancements on the mitigation of carbon emissions. Moreover, Yang, et al. [20] demonstrate that technological innovation exerts a positive influence on carbon reduction performance, contributing to decreased carbon dioxide emissions. Research conducted by Yang and Wang [32] among Japanese firms indicates that increased investment in research and development effectively catalyzes technological innovation and leads to substantial reductions in corporate carbon emissions. Supporting this, studies by Yu, et al. [8] and Li, et al. [10] affirm that technological innovation can significantly diminish carbon emissions over the long term.

The digital economy has facilitated the integration of technological innovation with agricultural production. By leveraging advanced technologies such as geographic information systems, remote sensing, and digital positioning, stakeholders can gain timely insights into crop growth, mitigate losses from natural disasters, and connect with experts to address challenges in cultivation. This enables the rational adjustment of agricultural inputs and fosters reductions in carbon emissions from agricultural practices.

Based on this analysis, we propose the following research hypothesis:

H_{2c}: The digital economy can effectively reduce agricultural carbon emissions through technological innovation.

4. Research Methodology

4.1. Variable Description

4.1.1. Explanatory Variable: Level of Digital Economy Development$(ADIG)$

The selection of these indicators is grounded in the 2021 China Statistical Classification of the Digital Economy and its Core Industries, alongside the research of Kamilaris, et al. [36] and other scholars. Nine indicators were chosen across three dimensions: rural digital infrastructure, rural industry digitization, and rural digital industrialization using the entropy method. This approach facilitates the assessment of the digital economy development level in China's provincial contexts. Detailed descriptions of these indicators are presented in Table 1.

Table 1.
Rural digital economy indicator system.

Primary Indicator	Secondary Indicator	Indicator Description
Rural Digital Foundation	Rural Internet Penetration Rate	Users of broadband internet in rural areas / rural population
	Computer Penetration Rate	Average number of computers owned per hundred households
	Communication Service Level	Population Served per Kilometer of Rural Delivery Route.
	Mobile Phone Penetration Rate	Number of mobile phone users per hundred individuals
Rural Industry Digitization	Rural Digital Transformation Model	Total Agricultural Machinery Power / Total Output Value of Agricultural, Forestry, Animal Husbandry, and Fishery Industries
	Digital Talent Investment	Number of personnel in information technology and software services (ten thousand)
Rural Digital Industry	Information Transmission Level	Number of Taobao Villages.
	E-commerce Sales Volume	Total e-commerce sales revenue
	Digital Finance Index	Index for digital financial services

4.1.2. Explained Variable: Total Agricultural Carbon Emissions(TAC)

Building upon the foundational studies of Yang and Wang [32] and Fabregas, et al. [37] additional scholars, the carbon emissions associated with six distinct carbon sources are quantified (Table 2, with their aggregate representing the total agricultural carbon emissions. The formula for estimating the total agricultural carbon emissions is as follows:

$$TAC = \sum TAC_i = \sum F_i \times \sum Y_i \quad (1)$$

TAC_i represents the carbon emissions from the i-th type of carbon source; F_i represents the absolute amount of the i-th type of carbon source; Y_i represents the carbon emission coefficient of the i-th type of carbon source.

Table 2.
Emission Factors of Agricultural Carbon Emission Sources.

Input Elements	Carbon Emission Coefficient	Data Selection	Reference Sources
Fertilizer	0.8956 kg C/kg	Application of Agricultural Fertilizer (Adjusted Amount)	Oak Ridge National Laboratory (ORNL)
Pesticide	4.9341 kg C/kg	Pesticide Application Quantity	Oak Ridge National Laboratory (ORNL)
Agricultural Film	5.18 kg C/kg	Usage of Agricultural Film	College of Resources and Environmental Sciences, Nanjing Agricultural University
Irrigation	20.476kg/hm²	Effective Irrigated Area	Dubey
Ploughing	3.126 kg /hm²	Total Area Under Crop Cultivation	Faculty of Biological Science and Technology, China Agricultural University

4.1.3. Mediating Variables

Agricultural Scale (ltr): The proxy variable for the scale effect used is the land transfer rate, defined as the ratio of transferred agricultural land area to the total contracted land area. This estimate is more appropriate for determining the actual scale of agricultural activities than previous proxies measuring total agricultural output or GDP. The transfer of land promotes more efficient, contiguous, and larger-scale operations, thereby improving the use of agricultural machinery and energy, which lowers carbon emissions per unit of output.

Agricultural Technology Adoption (ptech): We consider the impact of technological innovation on agriculture to be measured by patents for agricultural technology awarded relative to population levels. This measure is best suited as an agricultural-specific tech innovation rather than research spending or total patent numbers. The agricultural-specific patent enables approximately accurate measurement of innovation productivity, thus making per capita patents on agricultural technology a direct indicator of agricultural technological innovation in a region.

Agricultural Digital Financial Services (IDFB): We adopt the digital inclusion finance index for agriculture concerning rural regions as a proxy for financial impact. This indicator gauges more specifically the Agricultural Financial Services Features wrought through Digital Technologies, alternatively framed as the broader agricultural loan framework, more accurately. Agriculture-inclusive digital finance classifies agricultural cooperatives as financial institution clients, raising funds through loans and offering insurance, which aids them in obtaining green technology and equipment.

4.1.4. Control Variables

Drawing on existing literature, this study incorporates the following control variables: (1) urbanization rate (URB), measured as the ratio of urban to total population; (2) agricultural industrial structure (AIS), defined as the ratio of total agricultural output to the total output of farming, forestry, animal husbandry, and fisheries; (3) agricultural labor productivity (ALP), calculated as the total output of farming, forestry, animal husbandry, and fisheries per primary industry worker; (4) rural electricity consumption (ELEC), represented by agricultural electricity generation; and (5) agricultural disaster rate (ADR), measured as the ratio of affected farmland to total cultivated area. All variables are logarithmically transformed.

4.2. Data Sources

The selection of panel data for this study is constrained by data availability, focusing on 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2012 to 2022. Data were primarily sourced from the China Statistical Yearbook. Additionally, data were obtained from the China Agricultural Yearbook, China Rural Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and the China Rural E-Commerce Market Data Report, alongside other relevant statistical yearbooks, bulletins, and EPS databases from each province. The digital financial inclusion index was derived from the Digital Finance Research Center at Peking University. Missing data were addressed using linear interpolation and ARIMA regression techniques to ensure completeness and accuracy.

4.3. Model Construction

To investigate the impact of the digital economy on agricultural carbon emissions, we formulated the fixed effects model, drawing on the methodology established by Chen and Li [21]:

$$TAC = \partial_0 + \partial_1 \mathrm{ADIG}_{it} + \partial_2 \mathrm{X}_{it} + \delta_{it} + \tau_{\mathrm{it}} + \mu_{it} \qquad (1)$$

In Equation 1, TAC total agricultural carbon emissions; ADIG_{it} represents the level of digital economic development; X_{it} represents the relevant control variables; ∂_0 is a constant term; δ_{it} represents region effects, and τ_{it} represents time effects, and μ_{it} represents the random disturbance term.

To further explore the mediating mechanisms through which digital economy development influences agricultural carbon emissions, the following models are constructed based on the baseline regression framework, drawing on the research of Wen and Ye [6].

$$TAC = \gamma_0 + \gamma_1 \mathrm{ADIG}_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \delta_{it} + \tau_{it} + \mu_{it} \qquad (2)$$

$$M_{it} = \beta_0 + \beta_1 \mathrm{ADIG}_{it} + \beta_2 X_{it} + \delta_{it} + \tau_{it} + \mu_{it} \qquad (3)$$

In Equations 2 and 3 M_{it} denotes the mediating variables, which include the scale effect, financial effect, and technological innovation effect, represented by the land transfer rate, agricultural loans, and agricultural science and technology patents, respectively. β、 γ indicate the parameter estimates of the variables.

5. Results

5.1. Descriptive Statistics and Spatial-Temporal Characteristics

As detailed in Section 4, after collecting all the relevant data, we created a balanced panel dataset with 330 observations from 30 provinces, autonomous regions, and municipalities across mainland China from 2012 to 2022. Due to insufficient data, Tibet, Taiwan, Hong Kong, and Macao had to be excluded. Descriptive statistics for all the variables utilized in this study are provided in Table 3.

Table 3.
Variable Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
lntac	330	5.273	1.055	2.457	6.769
lnadig	330	0.120	0.083	0.028	0.539
lnurb	330	0.472	0.072	0.307	0.642
lnelec	330	4.917	1.27	1.495	7.606
lnais	330	0.422	0.055	0.31	0.542
lnalp	330	10.904	0.512	9.400	12.127
lnadr	330	0.119	0.089	0.004	0.528

As illustrated in Table 3, between 2012 and 2022, average agricultural carbon emissions stood at 5.273 (SD=1.055), with values ranging from 2.457 to 6.769, reflecting substantial regional variation likely driven by differences in economic development and technological adoption. The mean digital economy index was 0.12 (SD=0.083), spanning 0.028 to 0.539, indicating generally low levels of rural digitalization, yet with marked progress in select regions and significant potential for further expansion.

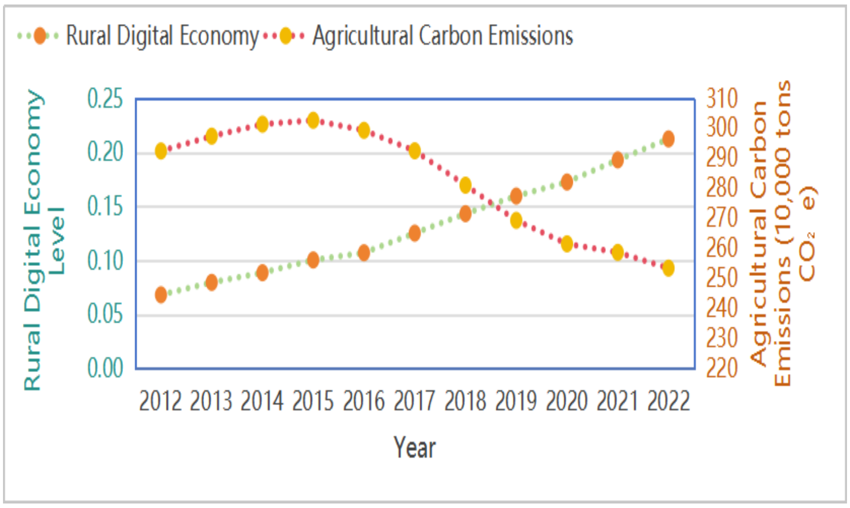

Figure 1.
Temporal Trends of Agricultural Carbon Emissions and Rural Digital Economy Level.

Figure 1 illustrates the temporal dynamics of rural digital economy development and agricultural carbon emissions in China from 2012 to 2022. Over this period, the level of rural digitalization exhibits a consistent upward trajectory, rising steadily from 0.06 to 0.22. In contrast, agricultural carbon emissions demonstrate a declining trend, decreasing from approximately 295 to 250 million tons of CO_2 equivalent. This inverse relationship suggests a potential negative correlation between digital economic advancement and agricultural emissions, highlighting the role of digitalization in promoting low-carbon agricultural transformation.

In order to analyze spatial patterns, we constructed a bar chart illustrating the provincial distribution of selected key variables for 2022. Figure 2 depicts the apportionment of the rural digital economy level, while Figure 3 depicts the spatial distribution of carbon emissions from agriculture. Figure 2 reveals substantial regional disparities. Eastern coastal provinces—most notably Zhejiang (0.715), Guangdong (0.658), and Jiangsu (0.418) exhibit the highest levels of rural digitalization, reflecting their advanced infrastructure and policy support. In contrast, western and northeastern provinces such as Yunnan (0.092), Xinjiang (0.099), and Heilongjiang (0.102) lag considerably behind. This spatial variation highlights the persistent digital divide and underscores the need for targeted interventions to promote equitable digital development in rural China.

Moreover, Figure 3 pronounced regional heterogeneity. Provinces such as Beijing, Qinghai, and Ningxia reported minimal emissions ($<50 \times 10^4$ tons CO_2e), reflecting limited agricultural activity or advanced decarbonization. In contrast, Henan (723.61), Shandong (591.28), and Xinjiang (439.73) recorded the highest emissions, underscoring their intensive agricultural output. Several provinces, including Jiangsu, Heilongjiang, and Guangdong, exhibited intermediate-to-high levels (150–450 $\times 10^4$ tons CO_2e), indicative of diverse production scales and technological capacities. These patterns highlight the need for regionally differentiated mitigation strategies tailored to local emission profiles.

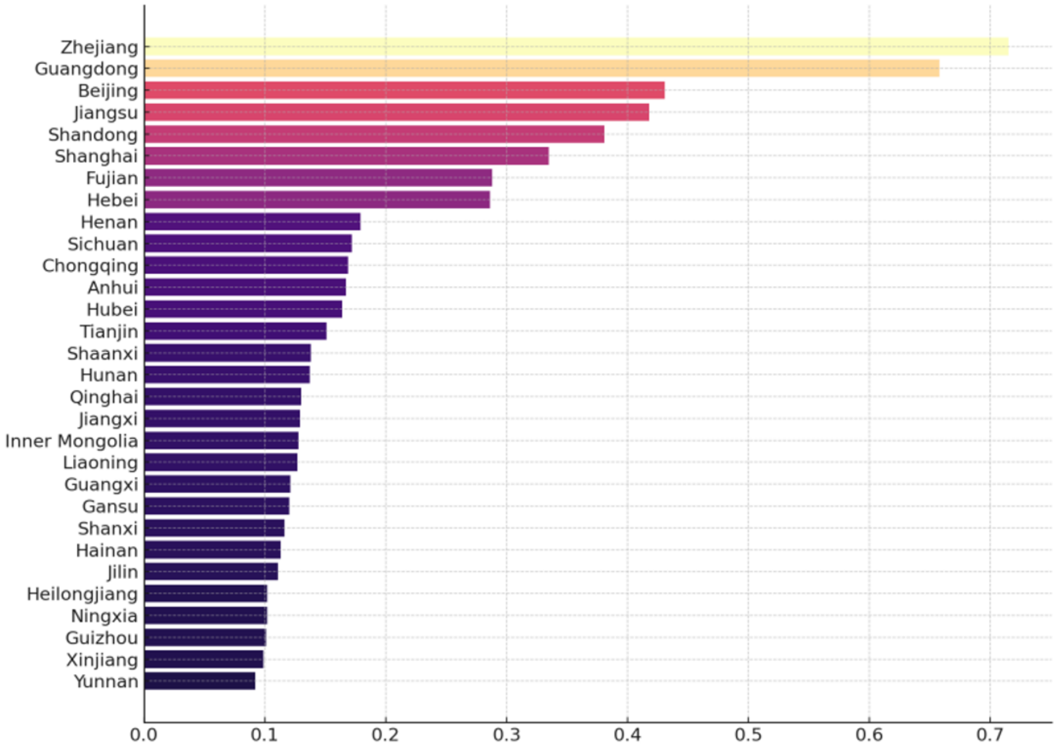

Figure 2.
Spatial Distribution of Agricultural Carbon Emissions (2022).

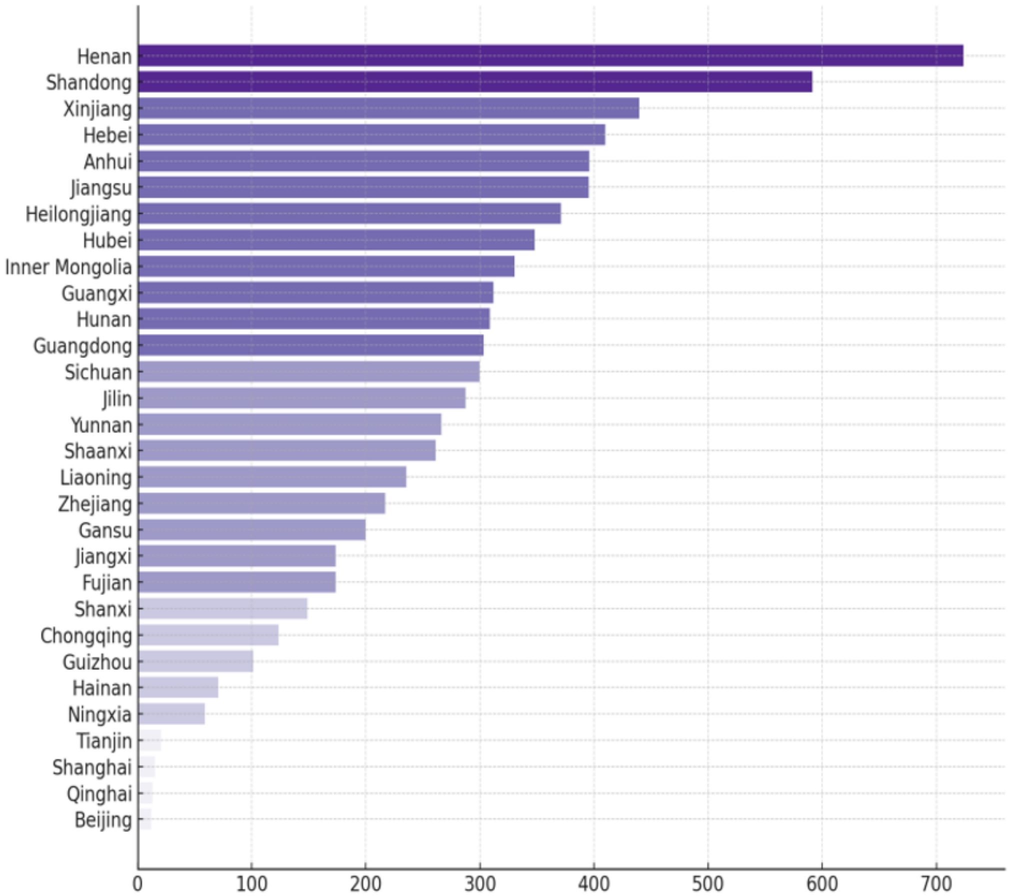

Figure 3.
Spatial Distribution of Agricultural Carbon Emissions (2022).

5.2. Analysis of the Benchmark Regression Results

Based on the model specification and the results of the Hausman test, the fixed-effects model is determined to be more appropriate. A stepwise regression approach is applied to the benchmark regression model, with the results detailed in Table 4. The estimation outcomes reveal that, regardless of the control variables included, the core explanatory variable the development level of the digital economy exhibits a significantly negative impact on agricultural carbon emissions, achieving significance at the 1% level. This finding underscores the substantial negative influence of the digital economy on agricultural carbon emissions, suggesting that the digital economy may facilitate significant reductions in total agricultural carbon emissions. Consequently, this outcome supports the initial hypothesis proposed in H1, which posits that the digital economy directly influences the reduction of agricultural carbon emissions.

Table 4:
Stepwise regression results on the impact of the digital economy on agricultural carbon emissions.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**lntac**	**lntac**	**lntac**	**lntac**	**lntac**	**lntac**
lnadig	-1.299***	-1.056***	-0.819***	-0.811***	-0.567***	-0.527***
	(0.105)	(0.132)	(0.137)	(0.137)	(0.137)	(0.137)
lnurb		-0.748***	-1.358***	-1.362***	0.975**	1.070**
		(0.252)	(0.275)	(0.275)	(0.479)	(0.478)
lnelec			0.062***	0.061***	0.057***	0.059***
			(0.013)	(0.013)	(0.012)	(0.012)
lnais				-0.328	-0.434	-0.443
				(0.382)	(0.362)	(0.360)
lnalp					-0.208***	-0.205***
					(0.036)	(0.036)
lnadr						0.166**
						(0.075)
Constant	5.430***	5.754***	5.710***	5.853***	7.047***	6.947***
	(0.0137)	(0.110)	(0.107)	(0.197)	(0.278)	(0.280)
N	330	330	330	330	330	330
R^2	0.338	0.357	0.403	0.405	0.466	0.475
Number of id	30	30	30	30	30	30

Note: *** p<0.01, ** p<0.05, * p<0.1.

Subsequent analyses of models (2) to (6), following the incremental inclusion of control variables, indicate that the negative impact of the digital economy's development level on agricultural carbon emissions remains statistically significant, albeit diminished, with the coefficient decreasing to -0.527 in model (6). This finding suggests that the carbon abatement effect attributed to the digital economy may be partially mediated by other variables. Notably, rural electricity consumption (lnelec) demonstrates a significant positive correlation across all models, with a regression coefficient of 0.975 in model (6). This implies that increased rural electricity consumption is associated with a substantial rise in agricultural carbon emissions. This observation highlights that while rural areas utilize clean energy sources to a degree, fossil fuel consumption still constitutes a major portion of their energy mix, serving as a critical driver of agricultural carbon emissions. Furthermore, the increase in electricity consumption may lead to energy inefficiencies, underscoring the necessity for improved resource utilization in the context of agricultural modernization and the urgent need to develop a sustainable rural green model.

The urbanization rate (lnurb) demonstrates a substantial negative correlation with agricultural carbon emissions, indicated by a coefficient of -1.070 in model (6) with a significance level of 5%. This finding suggests that the urbanization process promotes the optimal allocation of rural resources and effectively reduces the carbon emission intensity of the agricultural sector. This reduction is achieved through the transfer of rural labor and the optimization of the industrial structure. Furthermore, urbanization enhances low-carbon awareness and encourages green consumption behaviors among rural residents, indirectly contributing to carbon emissions reduction through changes in social behavior. The regression coefficient for agricultural labor productivity (lnalp) is -0.205 and is significant at the 1% level, highlighting the importance of increasing productivity in minimizing resource waste and high-pollution production activities, thereby leading to a marked decrease in agricultural carbon emission intensity. Notably, the regression coefficient for the agricultural disaster rate (lnadr) among the control variables is 0.166 and significant at the 10% level, indicating an upward trend in agricultural carbon emissions in affected areas. This increase may be attributed to heightened resource inputs, replanting of abandoned land, and intensified mechanized agricultural operations as part of the recovery process following natural disasters. To mitigate the adverse impact of natural disasters on agricultural carbon emissions, the government must allocate more resources toward climate risk management and disaster prevention. Additionally, promoting resilient green agricultural technologies is crucial for enhancing sustainability in the agricultural sector.

In summary, the stepwise regression analysis confirms the significant role of the rural digital economy in reducing agricultural carbon emissions, a finding that remains robust after accounting for control variables. This result provides a theoretical foundation for future investigations into the underlying mechanisms at play. Additionally, the substantial influence of control variables such as rural electricity consumption, urbanization rate, and agricultural labor productivity on agricultural carbon emissions highlights the necessity for a multifaceted strategy that integrates economic, energy, production technology, and environmental management considerations. This comprehensive approach requires the development of targeted policy recommendations tailored to specific pathways for action.

5.3. Robustness test

5.3.1. Replacement of Dependent Variable

In the benchmark regression, total agricultural carbon emissions serve as the dependent variable. To enhance the robustness of our findings, the model employs the log-transformed agricultural carbon emission intensity as an alternative dependent variable. The results are presented in Table 5 (Model 1). Even after this substitution, the digital economy continues to exert a significant negative effect on agricultural carbon emissions, thereby validating the conclusions of the benchmark regression.

5.3.2. Replacement of Explanatory Variable

To assess the level of digital economic development, we employ principal component analysis, as recommended by [19] and other scholars, to derive an index reflecting digital economy development across regions. The regression results using this approach are shown in Table 4(Model 2). Following the replacement of the core explanatory variable, the digital economy still demonstrates a significant negative impact on agricultural carbon emissions, further corroborating the benchmark regression results.

5.3.3. Exclude Municipalities Directly Under the Central Government

Recognizing the unique economic and administrative characteristics of the four municipalities (Beijing, Shanghai, Tianjin, and Chongqing), we exclude these municipalities to mitigate potential administrative biases in the benchmark regression outcomes. Informed by the findings of Zheng et al. [38], we rerun the regression after removing these municipalities from the sample. The results, presented in Table 5 (Model 3), are consistent with those of the benchmark regression, strengthening the study's overall conclusions.

Table 5.
Robustness test results.

	Replaced the Explained Variable	Replaced the Explanatory Variable	Excluding municipalities
	Model (1)	**Mode (2)**	**Model (3)**
Variables	**lnace**	**lntac**	**lntac**
lnadig	-0.294**	-0.030**	-0.297***
	(-2.365)	(-2.471)	(-3.160)
lnurb	-0.854	1.048**	-0.113
	(-1.633)	(2.158)	(-0.30)
lnelec	0.012	0.071***	0.026
	(0.963)	(5.961)	(1.570)
lnais	-3.698***	-0.542	-0.103
	(-9.532)	(-1.489)	(-0.350)
lnalp	-0.617***	-0.252***	-0.124***
	(-16.999)	(-7.316)	(-4.620)
lnadr	0.187**	0.230***	0.066
	(2.332)	(3.009)	(1.360)
_cons	13.582***	7.405***	6.881***
	(48.285)	(28.285)	(30.990)
N	330	330	286
R^2	0.898	0.460	0.995
F	433.452	41.669	

Note: *** p<0.01, ** p<0.05, * p<0.1

5.4. Endogeneity Test

To mitigate biases arising from endogeneity, we employ the instrumental variable method for testing. Specifically, we utilize the number of telephones per 10,000 people in 1984 as an instrumental variable for assessing the level of digital economic development. This choice is justified by the premise that the development of the rural digital economy is fundamentally linked to the proliferation of landline telephones. Consequently, the number of telephones per 10,000 people in 1984 across various provinces reflects the historical information technology endowments of these regions, which may facilitate the current expansion of internet access, thereby fulfilling the relevance condition for the instrumental variable. Conversely, the influence of the number of telephones per 10,000 people in 1984 on agricultural carbon emissions during the sample period is negligible, satisfying the exclusion condition for the instrumental variable. Given that our study employs balanced panel data with variations across provinces and time, using this historical invariant variable poses measurement challenges within fixed effects model estimation. To address this, we follow the methodology of Nunn and Qian [18] and introduce an interaction term between the number of national broadband internet users from the previous year (a time-varying variable) and the number of telephones per 10,000 people in 1984 as an instrumental variable for the level of digital economic development.

Table 6.
Endogeneity test results.

Variables	The first stage	The second stage
	lnadig	**lntac**
iv	0.000***	
	(6.020)	
lnadig		-4.117**
		(-2.370)
lnurb	0.096	-10.127***
	(1.230)	(-10.970)
lnelec	-0.026***	-0.628***
	(-9.550)	(14.030)
lnais	0.141**	1.040
	(-2.290)	(1.560)
lnalp	0.036***	0.776***
	(4.18)	(6.910)
lnadr	-0.017	1.285***
	(-0.430)	(3.080)
Constant	-0.420***	-1.593
	(-4.170)	(-1.250)
N	330	330
R2	0.842	0.996
Anderson canon. corr. LM statistic	33.33***	
Cragg-Donald Wald F statistic	36.29***	
Sargan statistic（P）		0.000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The results reveal that the Anderson-Cannon Correlation LM Statistic is 33.33, significant at the 1% level. Furthermore, the Cragg-Donald Wald F Statistic is 36.29, substantially exceeding the critical threshold of 10, indicating that the model passes both the identification and weak instrument tests. Additionally, the p-value for the Sargan statistic is 0.000, indicating that the model successfully passes the over-identification test and confirms the validity of the instrumental variables. Consequently, after addressing the model's endogeneity, the digital economy continues to demonstrate a significant capacity to reduce agricultural carbon emissions.

5.5. Heterogeneity Analysis

5.5.1. Regional Heterogeneity Analysis

China’s extensive territory exhibits considerable heterogeneity in both natural geographical environments and economic development levels among regions. This structural variation inherently results in distinct regional characteristics concerning the effects of the digital economy on agricultural carbon emissions. Accordingly, the study segments China into three major geographical and economic regions: Eastern, Central, and Western, following the regional framework defined by the National Bureau of Statistics of China. This categorization aims to investigate the differentiated mechanisms by which the digital economy influences agricultural carbon emissions across these diverse regions.

Table 7.
Heterogeneity analysis results (1).

VARIABLES	East	Central	West
	lntac	**lntac**	**lntac**
lnadig	-0.264***	-1.193**	-1.227**
	(-2.670)	(-2.430)	(-2.090)
lnurb	5.168***	0.067	2.006**
	(5.080)	(0.170)	(2.080)
lnelec	0.038***	-0.000	0.054
	(3.710)	(-0.010)	(1.270)
lnais	0.845	-0.018	-0.186
	(1.470)	(-0.050)	(-0.390)
lnalp	-0.053	-0.092**	-0.216***
	(-0.790)	(-2.490)	(-3.200)
lnadr	0.074	-0.080	0.105
	(0.850)	(-1.230)	(1.070)
Constant	2.458***	6.938***	6.521***
	(3.090)	(21.730)	(15.130)
N	132	88	121
R^2	0.997	0.994	0.995

Note: *** p<0.01, ** p<0.05, * p<0.1

The heterogeneity analysis results presented in Table 7 reveal substantial regional disparities in the impact of the digital economy on agricultural carbon emissions across the Eastern, Central, and Western regions of China. In the Eastern region, the coefficient for digital economic development is -0.264, indicating a significant negative correlation; however, the magnitude of this effect is relatively modest. This limited impact may be attributed to the advanced stage of agricultural modernization in this region, which has resulted in a stable production structure. As a consequence, the reduction of agricultural inputs faces significant short-term challenges, which attenuate the effectiveness of the digital economy in driving carbon reduction. Conversely, the Central region exhibits a coefficient of -1.193 for digital economic development, signifying a strong negative correlation. In this context, the digital economy promotes more efficient resource allocation and drives innovation in production techniques throughout agricultural transformation, thereby contributing to significant carbon emission reductions. In the Western region, the coefficient is even more pronounced at -1.227, underscoring the digital economy's considerable influence on agricultural carbon reduction. This heightened effect can be attributed to the region's ongoing agricultural transformation, where deep integration of digital technologies not only alters traditional farming practices but also promotes the emergence of new industries, enhancing off-farm employment opportunities for farmers and mitigating their reliance on chemical inputs.

In summary, the influence of the digital economy on agricultural carbon emissions demonstrates significant heterogeneity across regions, particularly marked in the Central and Western areas, where its effects are notably stronger.

5.5.2. Distinction of Major Grain Production Areas

Agricultural carbon emissions are significantly influenced by the functional zones of grain production, which exhibit notable variations in aspects such as cropping systems, production practices, and pesticide application. These differences directly affect both the scale and trajectory of agricultural carbon emissions. To examine the heterogeneous effects of the digital economy on agricultural carbon emissions, this study classifies the 30 provinces into two subgroups: major grain production areas and non-major grain production areas, based on their designated roles in grain production. Specifically, the major grain production areas include the provinces of Anhui, Hunan, Hubei, Henan, Heilongjiang, Hebei, Jiangxi, Jiangsu, Jilin, Liaoning, Inner Mongolia, Sichuan, and Shandong, totaling 13 provinces. The remaining provinces are categorized as non-major grain production areas. By analyzing and comparing the heterogeneous characteristics of these regions, we aim to comprehensively assess the differentiated mechanisms through which digital economic development impacts agricultural carbon emissions.

Table 8.
Heterogeneity analysis results (2).

	Major grain areas	Non-major grain areas
VARIABLES	**lntac**	**lntac**
lnadig	-0.681***	-0.371
	(-3.860)	(-1.500)
lnurb	-0.470	2.595***
	(-1.210)	(3.070)
lnelec	0.085***	0.051***
	(3.950)	(2.820)
lnais	0.213	-0.653
	(0.610)	(-1.160)
lnalp	-0.101***	-0.300***
	(-3.280)	(-4.490)
lnadr	-0.071	0.326***
	(-1.210)	(2.990)
Constant	6.835***	6.877***
	(21.370)	(14.460)
N	132	198
R^2	0.986	0.992

Note: *** p<0.01, ** p<0.05, * p<0.1

The findings demonstrate a statistically significant inverse relationship between digital economic development and agricultural carbon emissions in major grain production areas at the 1% level, suggesting that digital economy growth effectively mitigates emissions and supports environmental sustainability. In contrast, in non-grain production areas, while a negative relationship persists, it lacks statistical significance. This is likely due to the limited scale of agricultural production, lower digitalization levels, and traditional industry structures, which impede the effective integration of digital technologies and constrain their potential to reduce agricultural carbon emissions.

5.6. Analysis of Intermediation Effects

The digital economy influences agricultural carbon emissions through three primary channels: scale effects, financial effects, and technological innovation. An empirical analysis, summarized in Table 9, reveals that all three effects are statistically significant, highlighting their mediating roles in the relationship between the digital economy and agricultural carbon emissions.

Table 9.
Results of the Mediation Effect Regression Analysis.

	Benchmark model	**Scale Effects**		**Financial Effects**		**Technological Innovation Effects**	
	Lntac (1)	**Ltr (2)**	**lntac (3)**	**Lnflb (4)**	**Lntac (5)**	**Ptech (6)**	**lntac (7)**
lnadig	-0.527***	58.355***	-0.356**	3.053***	-0.372**	1.344***	-0.427***
	(-3.853)	(6.771)	(-2.460)	(6.971)	(-2.549)	(3.471)	(-3.121)
M			-0.003***		-0.051***		-0.075***
			(-3.212)		(-2.819)		(-3.709)
lnurb	1.070**	179.304***	1.596***	3.522**	1.249***	5.169***	1.457***
	(2.241)	(5.965)	(3.205)	(2.306)	(2.623)	(3.828)	(3.042)
lnelec	0.059***	-1.418*	0.055***	0.042	0.061***	-0.012	0.058***
	(4.843)	(-1.842)	(4.548)	(1.079)	(5.067)	(-0.340)	(4.872)
lnais	-0.443	-25.213	-0.516	1.233	-0.380	-1.432	-0.550
	(-1.229)	(-1.112)	(-1.453)	(1.071)	(-1.065)	(-1.407)	(-1.554)
lnalp	-0.205***	-7.524***	-0.227***	0.504***	-0.180***	0.127	-0.196***
	(-5.792)	(-3.371)	(-6.392)	(4.447)	(-4.965)	(1.266)	(-5.627)
lnadr	0.166**	1.092	0.169**	-0.396	0.146*	-0.658***	0.117
	(2.206)	(0.230)	(2.283)	(-1.644)	(1.952)	(-3.092)	(1.559)
_cons	6.947***	41.712**	7.069***	-0.860	6.903***	-2.544***	6.756***
	(24.827)	(2.368)	(25.420)	(-0.961)	(24.922)	(-3.216)	(24.242)
N	330	330	330	330	330	330	330
R^2	0.475	0.437	0.493	0.708	0.489	0.543	0.498
F	44.308	38.104	40.656	119.076	40.012	58.128	41.590

Note: ***p<0.01, **p<0.05, *p<0.10.

Models (2) and (3) indicate that the digital economy exerts a negative effect of –0.356 on carbon emissions, which is statistically significant at the 5% level. This suggests that the digital economy reduces agricultural emissions through the scale effect, partially mediated by improved information networks and trading platforms. These platforms lower search and coordination costs, enabling small-scale farmers to integrate resources and align production factors more efficiently. Additionally, digital technologies support large-scale operations, such as precision farming and supply chain collaboration, overcoming the geographical and scale limitations of traditional agriculture.

Further analysis (4) and (5) reveals an impact coefficient of -0.372, which is also significant at the 5% level, indicating that digital finance reduces carbon emissions through its financial effect. Digital finance, with its inclusive nature, broadens financial access in rural areas. Tools like mobile banking and WeChat Pay enhance financial services for farmers, increasing convenience and access.

Finally, analyses (6) and (7) find a coefficient of -0.427, significant at the 1% level, underscoring the role of technological innovation in reducing carbon emissions. Digital technology accelerates innovation, improves information transmission, and facilitates the adoption of new agricultural practices. It also enhances the efficiency of key agricultural inputs, such as seeds, pesticides, fertilizers, and irrigation technologies, fostering both productivity and sustainability.

6. Conclusions

Against the strategic backdrop of China's "dual carbon" goals and the accelerating integration of the digital and real economies, promoting the development of the digital economy has emerged as a key pathway for addressing the longstanding tension between agricultural development and ecological environmental protection. This chapter serves as the final synthesis of the study, systematically reviewing the research undertaken in previous sections, summarizing the core conclusions, and proposing corresponding policy recommendations and future research directions. This study aims to generate policy-relevant insights into how the digital economy can be harnessed to promote carbon mitigation in the agricultural sector.

This research clarifies the relationship between digital economic progress and agricultural carbon emissions. From the perspectives of scale effects, financial effects, and technological innovation effects, it reveals the underlying mechanisms of interaction between the two. Finally, building on this theoretical foundation, the study employs a fixed-effects model to empirically test the influence of digital economy development on agricultural carbon emissions. The key conclusions derived from the analysis are as follows:

1. The development of the digital economy has a statistically significant suppressive effect on agricultural carbon emission intensity. This conclusion remains robust even after addressing potential endogeneity through the introduction of instrumental variables, incorporating additional control variables, excluding municipalities, and conducting a series of robustness checks.
2. The carbon reduction effect of the digital economy exhibits clear regional heterogeneity: it exerts a significant mitigating effect on emission intensity in economically underdeveloped and moderately developed regions, as well as in major grain-producing areas. In contrast, this effect is not significant in economically advanced regions or non-grain-producing areas.
3. From the perspective of transmission mechanisms, the digital economy mitigates agricultural carbon intensity through multiple channels. These include leveraging scale effects to facilitate farmland transfer, harnessing technological effects to enhance agricultural production services, and utilizing financial effects to improve access to inclusive finance. Additionally, the demonstration role of new agricultural business entities plays a key part in guiding smallholder farmers toward green production practices, thereby contributing to a reduction in regional agricultural carbon emission intensity.

6.1. Policy Recommendations

The rise of the digital economy presents novel opportunities for advancing green and low-carbon transitions in agriculture. Drawing on empirical evidence concerning its current state, underlying mechanisms, and regional disparities, this study offers policy recommendations across four key dimensions: infrastructure enhancement, technological innovation, regional integration, and institutional strengthening.

6.1.1. Strengthen Digital Infrastructure in Rural Areas

With the rapid expansion of the digital economy, its emissions-reducing effects in agriculture have become increasingly prominent. However, the underdevelopment of digital infrastructure in rural areas remains a major bottleneck. It is therefore imperative to accelerate investment in digital infrastructure, particularly in remote regions. First, financial channels for rural infrastructure projects should be expanded to address challenges such as outdated hardware, funding shortages, and weak management. Second, continuous efforts are needed to enhance the coverage, speed, and stability of 5G, IoT, and gigabit broadband networks in rural areas, thereby enabling the integration of digital technologies into traditional agricultural practices and facilitating the flow and allocation of new production factors between urban and rural regions. Lastly, the digital and intelligent transformation of agricultural infrastructure should be promoted, including the development of smart irrigation systems, intelligent power grids, satellite remote sensing, Beidou navigation, and intelligent agricultural machinery, thus creating favorable digital conditions for green agricultural development.

6.1.2. Implement Region-Specific Digital Economy Development Strategies

Heterogeneity analysis suggests that the digital economy's impact on agricultural carbon emissions is more pronounced in moderately and underdeveloped regions, as well as in major grain-producing areas. Given the diversity of agricultural contexts across regions, differentiated strategies are essential. First, targeted awareness campaigns in less developed regions can deepen farmers' understanding of digital technologies, promoting their application in scaled agricultural operations and supporting the transition toward low-carbon agriculture. Second, non-major grain-producing areas should capitalize on their unique resource advantages to develop and disseminate innovative, low-carbon agricultural technologies. By doing so, the technological spillover effect of the digital economy can be harnessed to further reduce emissions. Finally, mechanisms for attracting and retaining agricultural digital talent in underdeveloped areas should be strengthened, with appropriate incentives and career pathways, thereby ensuring sustained human capital support for digital-driven green transformation.

6.1.3. Promote Innovation and Application of Digital Technologies in Agricultural Production

Enhancing the application of digital technologies is critical for achieving carbon reduction in agriculture. At the pre-production stage, advanced technologies such as IoT, AI, and blockchain can support the establishment of robust monitoring systems to collect, transmit, and apply data, thereby reducing risk and uncertainty while improving efficiency and quality. During the production phase, digital upgrades of agricultural machinery and equipment, such as precision farming, drone-based pesticide spraying, and intelligent fertilization, can significantly enhance production accuracy and sustainability while reducing labor intensity. Post-production, robust traceability systems should be developed to ensure transparency in food sourcing, strengthening consumer trust. Additionally, building smart logistics networks can reduce post-harvest loss and waste, thereby enabling the digitization and greening of agricultural product distribution.

6.1.4. Enhance Institutional Support for Digital Inclusive Finance in Green Agriculture

Establishing a well-functioning, digitally inclusive finance system is crucial for lowering the financial threshold for agricultural digitization. On one hand, financial institutions such as commercial banks and rural credit cooperatives should be encouraged to develop tailored digital lending products that offer targeted financial support. On the other hand, a comprehensive digital agricultural credit evaluation framework and diversified credit guarantee mechanisms should be established to ease access to finance. Concurrently, regulatory frameworks for digital finance must be reinforced to mitigate potential risks. By constructing a multilayered, integrated network of financial services, access to financial resources for agricultural producers can be substantially improved.

6.1.5. Establish a Coordinated Governance Framework Integrating Digital and Carbon Reduction Policies

At the national level, top-level design is needed to align green agricultural development with digital economy strategies and overcome fragmented policy implementation. It is recommended that responsibilities across agriculture, environment, industry, and finance departments be integrated to jointly promote the issuance of an "Agricultural Digital Carbon Reduction Action Plan." Such a plan should include systematic policy guidance, standard-setting, and performance evaluation. In parallel, a governance framework should be developed encompassing carbon labeling for agricultural products, a comprehensive carbon footprint database, and standardized carbon accounting methods, laying the institutional foundation for achieving dual carbon goals in agriculture.

References

[1] R. Chen, Y. He, S. Zhu, and J. Xu, "Duality of agricultural carbon emissions and coordination with economic development in China," *Soft Science,* vol. 34, no. 1, pp. 132-138, 2020.

[2] J. Song, R. Peng, L. Qian, F. Yan, I. Ozturk, and S. Fahad, "Households production factor mismatches and relative poverty nexus: A novel approach," *Polish Journal of Environmental Studies,* vol. 31, no. 4, pp. 3797–3807, 2022. https://doi.org/10.15244/pjoes/146987

[3] C. Işık, E. Aydın, T. Dogru, A. Rehman, E. Sirakaya-Turk, and D. Karagöz, "Innovation research in tourism and hospitality field: A bibliometric and visualization analysis," *Sustainability,* vol. 14, no. 13, p. 7889, 2022. https://doi.org/10.3390/su14137889

[4] T. Searchinger et al, "Agriculture and climate change," " *Nature Climate Change,* vol. 9, no. 7, pp. 574-581, 2019.

[5] S. Fahad, D. Bai, L. Liu, and V. Dagar, "Comprehending the environmental regulation, biased policies and OFDI reverse technology spillover effects: A contingent and dynamic perspective," *Environmental Science and Pollution Research,* vol. 29, pp. 1-13, 2022. https://doi.org/10.1007/s11356-021-17450-1

[6] Z. Wen and B. Ye, "Analyses of mediating effects: the development of methods and models," *Advances in psychological Science,* vol. 22, no. 5, pp. 731-745, 2014.

[7] H. Liu, "Driving agricultural modernization with precision agriculture to accelerate the digital transformation of modern agriculture," *China Agricultural Resources and Zoning,* vol. 4, no. 1, pp. 1-6, 2019.

[8] B. Yu, G. Zhao, R. An, J. Chen, J. Tan, and X. Li, "Research on China's CO 2 emission pathway under carbon neutral target," *Journal of Beijing Institute of Technology Social Sciences Edition,* vol. 23, no. 2, pp. 17-24, 2021. https://doi.org/10.15918/j.jbitss1009-3370.2021.7380

[9] China Academy of Information and Communications Technology, "China academy of information and communications technology," Digital Carbon Neutrality White Paper, 2021. http://www.caict.ac.cn/kxyj/qwfb/bps/202112/t20211220_394303.htm

[10] Y. Li, T. Zhao, and T. Shu et al, "The impact of digital economic development level on agricultural production efficiency under carbon emission constraints," *Journal of China Ecological Agriculture (Chinese and English),* vol. 32, no. 11, pp. 1829-1842, 2024.

[11] C. Yang, Y. Tian, and X. Xu, "The path of price and tax mechanism to achieve carbon peak and carbon neutrality," *Price: Theory & Practice,* vol. 1, pp. 20-26, 2021. https://doi.org/10.19851/j.cnki.cn11-1010/f.2021.01.22

[12] G. Yang, H. Wang, H. Fan, and Z. Yue, "Carbon reduction effect of digital economy: Theoretical analysis and empirical

evidence," *China Industrial Economics,* vol. 5, pp. 80-98, 2023.
[13] J. Tang, J. Gong, and Q. Song, "Digital inclusive finance and agricultural total factor productivity-a perspective based on factor mobility and technology diffusion," *China Rural Economy,* vol. 7, pp. 81-102, 2022.
[14] E. Yi, J. Wang, and J. Zhu, "Digital economy, resource allocation efficiency and high-quality development of agriculture," *Modern Finance and Economics-Journal of Tianjin University of Finance and Economics,* vol. 43, no. 12, pp. 20-37, 2023.
[15] B. Guo, D. Zhang, Z. Yu, Y. Liang, Z. Wang, and X. Zhou, "From the internet of things to embedded intelligence," *World Wide Web,* vol. 16, pp. 399-420, 2013.
[16] F. Wang, H. Wang, and F. Kong, "The improvement effect of rural digital development on agricultural total factor carbon productivity," *China Population, Resources and Environment,* vol. 3, pp. 79-90, 2024. https://doi.org/10.12062/cpre.20230707
[17] H. Kaila and F. Tarp, "Can the internet improve agricultural production? Evidence from Viet Nam," *Agricultural Economics,* vol. 50, no. 6, pp. 675-691, 2019.
[18] N. Nunn and N. Qian, "US food aid and civil conflict," *American Economic Review,* vol. 104, no. 6, pp. 1630-1666, 2014. https://doi.org/10.1257/aer.104.6.1630
[19] L. Nie, X. Bao, S. Song, and Z. Wu, "The impact of the digital economy on total-factor carbon emission efficiency in the yellow river basin from the perspectives of mediating and moderating roles," *Systems,* vol. 12, no. 3, p. 99, 2024.
[20] X. Yang, Y. Wang, and J. Wang, "The impact effects and mechanism of digital rural development on agricultural carbon emission intensity: An empirical examination," *Statistical Observation,* vol. 11, p. 11, 2023. https://doi.org/10.13546/j.cnki.tjyjc.2023.11.011
[21] Y. Chen and M. Li, "How does the digital transformation of agriculture affect carbon emissions? Evidence from China's provincial panel data," *Humanities and Social Sciences Communications,* vol. 11, no. 1, pp. 1-17, 2024.
[22] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, "An overview of internet of things (IoT) and data analytics in agriculture: Benefits and challenges," *IEEE Internet of Things Journal,* vol. 5, no. 5, pp. 3758-3773, 2018.
[23] C. Dai, "Empowering high-quality agricultural development through platform economy: A theoretical analysis framework," *East China Economic Management,* vol. 5, p. 59, 2024.
[24] X. Yue, "The configuration path of digital transformation driving high-quality agricultural development," *Journal of Harbin Institute of Technology Social Sciences Edition,* vol. 26, no. 3, p. 153, 2024.
[25] A. Weersink, E. Fraser, D. Pannell, E. Duncan, and S. Rotz, "Opportunities and challenges for big data in agricultural and environmental analysis," *Annual Review of Resource Economics,* vol. 10, no. 1, pp. 19-37, 2018.
[26] B. Kelly, D. Papanikolaou, A. Seru, and M. Taddy, "Measuring technological innovation over the long run," *American Economic Review: Insights,* vol. 3, no. 3, pp. 303-320, 2021.
[27] G. Sylvester, "E-agriculture and digital agricultural transformation," Food and Agriculture Organization of the United Nations, 2019.
[28] V. Kupriyanovsky, S. Sinyagov, D. Namiot, N. Utkin, D. Nikolaev, and A. Dobrynin, "Industries transformation in the digital economy–the design and production," *International Journal of Open Information Technologies,* vol. 5, no. 1, pp. 50-70, 2017.
[29] H. Tian and H. Guan, "The impact of the digital economy on carbon emissions in grain production: Empirical evidence from 108 prefecture-level cities in the yangtze economic belt," *China Agricultural Resources and Zoning,* p. 145, 2023.
[30] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming–a review," *Agricultural Systems,* vol. 153, pp. 69-80, 2017.
[31] Y. Liu and S. Xu, "Research on the impact of digital economic development on agricultural carbon emissions in China," *China Agricultural Resources and Zoning,* pp. 1-11, 2024.
[32] J. Yang and Q. Wang, "Digital technology and high-quality agricultural development: A perspective based on digital productivity," *Journal of Shanxi University of Finance and Economics,* vol. 4, p. 47, 2023. https://doi.org/10.13781/j.cnki.1007-9556.2023.04.004
[33] C. G. Sørensen *et al.*, "Conceptual model of a future farm management information system," *Computers and Electronics in Agriculture,* vol. 72, no. 1, pp. 37-47, 2010.
[34] S. Zhou and F. Wang, "The impact of the digital economy on agricultural development," *China Rural Economy,* vol. 7, pp. 4-20, 2022.
[35] D. Wang, C. Chen, N. Zhu, and X. Xu, "Impact of agricultural digitalization on carbon emission intensity of planting industry: Evidence from China," *Heliyon,* vol. 10, no. 10, p. e31215, 2024.
[36] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, "A review on the practice of big data analysis in agriculture," *Computers and Electronics in Agriculture,* vol. 143, pp. 23-37, 2017.
[37] R. Fabregas, M. Kremer, and F. Schilbach, "Realizing the potential of digital development: The case of agricultural advice," *Science,* vol. 366, no. 6471, p. eaay3038, 2019.