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Research Article

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Posted Date: October 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11198818/v1>

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Additional Declarations: No competing interests reported.

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Abstract: Amid global climate change and resource constraints, reducing agricultural carbon emissions is critical for sustainability. Digital technologies offer a pathway for agriculture's green transformation. Using panel data from 31 Chinese provinces (2010 – 2023), this study employs IPCC and entropy methods to measure emissions and digital technology, examining the relationship via two-way fixed effects and structural equation models. Results show that: (1) digital technology directly reduces emissions through precision management and resource optimization; (2) it exerts a significant negative indirect effect by improving the financing environment and stimulating green innovation; (3) a nonlinear “U-shaped” relationship exists, with a turning point at 0.540, where higher labor productivity delays this turning point, extending the emissions-reduction period; and (4) effects vary across regions, farm sizes, and emission sources. This study elucidates the direct, indirect, and nonlinear mechanisms of digital technology in agricultural carbon reduction, providing empirical evidence and policy insights for China's green agricultural development.

JEL classifications: *Q16; Q56; O33*

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Emissions? Evidence from China

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Introduction

Against the backdrop of intensifying global climate change and tightening resource and environmental constraints, the green and low-carbon transformation of economies and societies has become an international consensus (Thamo et al., 2017). Agriculture, a foundational sector of the national economy, is indispensable to global food security, rural livelihoods and inclusive development. However, its long-standing reliance on carbon-intensive chemical inputs has made it a significant source of greenhouse gas emissions (Aragón et al., 2021). Green and low-carbon agricultural development is therefore crucial not only for addressing climate change but also for easing resource and environmental pressures and promoting agricultural sustainability (Lawrence et al., 2025). As a major agricultural country, China has maintained total grain output above 1.3 trillion jin for nine consecutive years, reaching 1,390.82 billion jin in 2023 and thereby safeguarding national food security (Yang et al., 2024). Nevertheless, the structural limitations of traditional yield-oriented approaches have become increasingly evident: excessive reliance on fertilizers and pesticides has resulted in low water-use efficiency, depleted soil organic matter and intensified non-point source pollution (Peng & Wang, 2024; Wang & Qiu, 2024). These challenges are especially relevant for developing economies that must raise agricultural productivity while controlling emissions. Emerging technologies, including digital and biotechnologies, are therefore needed to optimize input allocation, restructure production systems and guide farmers toward low-carbon practices

In this context, digital technology is emerging as a disruptive force that offers new possibilities for addressing agriculture's systemic dependence on high-carbon inputs (Zhou & Wang, 2022). Underpinned by modern information technologies such as the Internet of Things, big data, artificial intelligence and blockchain, agricultural digital technology is becoming deeply integrated into every link of the agricultural value chain. It facilitates the efficient flow and value creation of data, ultimately driving the systemic transformation of agricultural production toward digitalization and

intelligent operation (Hidalgo et al., 2023; Mushi et al., 2025). For agricultural economics, the central question is not only whether digital tools are technically feasible, but whether they improve resource allocation, financing access, technology adoption and production efficiency under environmental constraints (Guo et al., 2024; Mushi et al., 2025). Scientifically identifying and evaluating the net effect of agricultural digital technology on agricultural carbon emissions is therefore important for China's "dual carbon" goals and for countries seeking policy lessons from China's agricultural and rural development experience (Lin & Ma, 2022).

Current academic debate on the relationship between digital technology and carbon emissions has yet to reach a consensus on the direction of the effect, and empirical evidence remains limited. Some studies emphasize the technological benefits of digital technology, arguing that precision fertilization, smart irrigation, and intelligent pest monitoring can optimize agricultural resource allocation and reduce the intensity of chemical inputs such as fertilizers and pesticides, thereby suppressing agricultural carbon emissions (Chen & Li, 2024). Other scholars, however, note that the application of digital technology in agriculture may entail substantial energy and environmental costs. In particular, the construction and operation of smart agricultural infrastructure consume considerable energy, while a rebound effect arising from widespread technology adoption may instead increase the agricultural system's overall carbon emissions (Abdullahi et al., 2025; Li et al., 2024). These opposing effects generate substantial cross-country differences in both the strategic pathways adopted to promote agricultural transformation through digital technology and the resulting emission-reduction outcomes (Huisings et al., 2015).

Meanwhile, existing research provides an insufficient account of the internal mechanisms through which digital technology affects agricultural carbon emissions. Most studies focus on correlations between technology and outcomes without systematically examining the complex transmission processes underlying these effects. Theoretically, the effect of digital technology on agricultural carbon emissions is not necessarily direct but may be transmitted systematically through multiple indirect pathways. This study examines two such pathways: improvements in the financing environment and green technological innovation. Their selection is grounded not merely in functional descriptions but in well-established economic theory. First, information asymmetry theory and financial development theory suggest that an improved corporate financing environment is primarily reflected in a substantial increase in the stock of listed agricultural enterprises. By reducing information asymmetry, digital technology improves the information environment of capital markets, enabling more agricultural enterprises to cross financing thresholds and enter the capital market. Growth in the stock of enterprises indicates a substantive improvement in the regional financing environment and the agglomeration of capital, providing the financial support needed for enterprises to meet ESG governance requirements and invest in long-term green assets, thereby alleviating the funding bottleneck constraining the green transformation of agriculture (Jin et al., 2024). Second, endogenous growth theory identifies green technological innovation as a core driver of overcoming resource and environmental constraints and achieving endogenous growth. Agricultural digital technology directly stimulates the research, development, and iteration of green technologies by accelerating knowledge spillovers and factor reorganization. Green technological innovation has dual externalities and can provide full-chain technical solutions for reducing agricultural carbon emissions, from clean energy substitution at the source and precise input control during production to waste resource utilization at the end of the process (Bao et al., 2024). However, this logic remains largely theoretical and lacks empirical testing using large-sample, long-term data.

In particular, the failure to incorporate multiple pathways into a unified analytical framework constrains a deeper understanding of how digital technology affects agricultural carbon emissions and limits the precise design and effective implementation of relevant policies.

To address these research gaps, this paper uses Chinese provincial panel data to investigate the impact of agricultural digital technology on agricultural carbon emissions through a multilayered empirical analysis. The paper contributes to the literature in three ways. First, it provides province-level evidence on the net carbon effect of agricultural digital technology, thereby clarifying whether digital transformation reduces or increases emissions in a large developing agricultural economy. Second, it incorporates the financing environment and green technological innovation into a unified mechanism framework, showing how digital technology can influence low-carbon agriculture through capital allocation and innovation incentives rather than only through production-side efficiency. Third, it identifies nonlinear and heterogeneous effects across labor productivity, farm scale, region and emission source, offering targeted evidence for agricultural and rural policy design. These contributions connect empirical identification with actionable implications for China and other developing economies.

1 Literature Review

Existing research on agricultural digital technology and agricultural carbon emissions can be grouped into three main areas:

(1) Research on agricultural carbon emissions. First, regarding emission sources and composition, scholars broadly agree that agricultural carbon emissions arise mainly from material waste, the consumption of production inputs, and crop burning (Mwalupaso et al., 2019). Using methods such as life-cycle analysis, researchers have further identified the dynamic evolution of emission structures. For example, a long-term study of China found that, between 1978 and 2008, indirect carbon emissions from energy-intensive products such as fertilizers and pesticides increased by nearly 4 times, significantly faster than direct emissions from energy consumption, which increased by nearly 3 times. This finding highlights the urgency of controlling indirect emissions, particularly by optimizing the input structure (Yun & Jun-Biao, 2013). The development of rural renewable energy and changes in land-use patterns have also been identified as important boundaries affecting agricultural carbon emissions, substantially broadening the scope of research in this field (Cicea et al., 2014; Fargione et al., 2008). Second, after identifying emission sources, scholars have extensively examined the drivers and mechanisms of agricultural carbon emissions. For example, investment in agricultural technology and improvements in the quality of farmers inhibit carbon emissions, whereas agricultural economic growth is generally accompanied by increased emissions, reflecting the tension between development and environmental protection (Lu et al., 2025). However, such macro-level conclusions cannot fully reveal the underlying structure of the problem, necessitating more refined measurement methods to identify specific key factors. Field experiments in Canada, for instance, confirmed that the consumption of fertilizers, pesticides, and diesel for agricultural machinery is a leading direct contributor to carbon emission growth (Pelletier et al., 2010). Using index decomposition analysis, Thibert and Badami (2011) further showed that input efficiency, industrial structure, and operational scale are structural drivers with greater explanatory power than production consumption alone (Thibert & Badami, 2011). The multiple linear regression model developed by Jin et al. (2024) further demonstrated significant correlations between carbon emission efficiency and macro-level variables such as industrial structure, arable

land area, and natural disasters (Jin et al., 2024). In summary, agricultural carbon emissions are not determined by a single factor but result from the combined effects of direct consumption and indirect structural factors. Rather than merely listing factors identified at different levels and through different methods, future research should develop a multilevel analytical framework that reveals their internal connections and hierarchical relationships.

(2) Research on agricultural digital technology. Compared with research on agricultural carbon emissions, studies of agricultural digital technology focus more on conceptual definitions and technical applications. Its connotation has evolved from basic definitions to increasingly diverse application scenarios and from individual technical elements to system integration (Lawrence et al., 2025). Early studies focused on defining core technologies such as artificial intelligence, big data, and blockchain (Le et al., 2021; Yang et al., 2023). Subsequent research emphasized their integrated value within the agricultural economic system, regarding agricultural digital technology as a “disruptive force” driving high-quality agricultural development or as the “integrated application” of new-generation information technology to improve agricultural production efficiency (Chen & Li, 2024; Li et al., 2025). Alongside this conceptual evolution, methods for measuring agricultural digital technology have also developed and can be grouped into three categories: word-frequency methods based on textual analysis (Forman & van Zeebroeck, 2019; Kajikawa et al., 2010), factor-input-based measurement methods (Lotriet, 2024), and comprehensive evaluation methods based on multidimensional indicators (Li et al., 2024). However, existing measurement methods have clear limitations. First, they generally operate at a single level, with most indicators focusing on the macro-level agricultural industry and thus failing to capture the depth of adoption and application effects among micro-level actors such as farmers and enterprises. Second, they cover limited dimensions because textual analysis and factor-input methods reflect only specific aspects of technological application and cannot capture its comprehensive effects. Third, they exhibit conceptual mismatches, as indicators such as patent data primarily reflect the level of technological research and development rather than actual socioeconomic effects. Consequently, existing research cannot accurately assess the true development level of agricultural digital technology, obscuring its actual influence on outcomes such as agricultural carbon emissions. Addressing this limitation requires a more comprehensive and rigorous measurement system. Drawing on China’s policy practices and industry needs, this study constructs a comprehensive evaluation system encompassing the digital technology foundation layer and the digital technology application layer and applies the entropy-weight method to more accurately capture the actual level and structural characteristics of agricultural digital technology use.

(3) Research on agricultural digital technology and agricultural carbon emissions. Building on these two strands of literature, the relationship between agricultural digital technology and agricultural carbon emissions has emerged as a frontier research topic. At the macro level, studies generally agree that agricultural digital technology is a key driver of the green transformation of agriculture and can significantly improve green development efficiency (Zhao et al., 2025). Existing research explains this macro-level phenomenon primarily from two perspectives: specific technological forms and internal mechanisms. Regarding technological forms, digital e-commerce encourages farmers to adopt environmentally friendly production practices through market incentives (Sánchez-Torres, 2019; Xie et al., 2021), while precision agriculture technologies, including the Internet of Things and big data, enable precise control of inputs such as fertilizers and pesticides through real-time monitoring and intelligent diagnosis, thereby reducing carbon

emissions at the source (Zamnuri et al., 2024). Regarding internal mechanisms, agricultural digital technology operates mainly through two pathways. The first is the optimization of factor allocation, whereby data-driven processes improve the utilization efficiency of land, labor, and capital and reduce the carbon footprint per unit of output (Abdulai et al., 2023; Deichmann et al., 2016). The second is the restructuring of production and operational systems, whereby digital platforms integrate industrial chains and facilitate the transition of agriculture toward precision-based, intensive, and low-carbon models (Akinwale et al., 2023; Kamilaris et al., 2017; Wang et al., 2024).

Although the existing literature provides a foundation for understanding the relationship between agricultural digital technology and agricultural carbon emissions, important research gaps remain. First, the measurement of agricultural carbon emissions and agricultural digital technology development remains fragmented, limiting comparability across regions and studies. Second, many studies emphasize direct correlations but pay insufficient attention to economic mechanisms, particularly the roles of financing conditions and green technological innovation. Third, nonlinear effects and contextual heterogeneity remain underexplored, even though agricultural digitalization may produce different outcomes depending on farm scale, regional development stage and production links.

This study therefore constructs a systematic analytical framework following the sequence of “overall effect-mechanism testing-context dependence”. It incorporates the financing environment and green technological innovation into the empirical model, examines the U-shaped relationship between digital technology and carbon emissions, and tests heterogeneity across farm scale, region and emission source. By doing so, the study provides evidence for agricultural policy-making, digital rural development and the design of low-carbon agricultural transition strategies.

2 Theoretical Analysis and Research Hypotheses

The impact of agricultural digital technology on agricultural carbon emissions is complex and multidimensional. Its mechanisms extend beyond direct changes in production processes to the broader restructuring of the agricultural industrial ecosystem and often become nonlinear as development advances. This section develops a theoretical framework and proposes research hypotheses along four dimensions: direct effects, two indirect pathways, and nonlinear effects.

2.1 Direct Effects of Agricultural Digital Technology on Carbon Emissions

Agricultural carbon reduction fundamentally requires the systematic substitution of low-carbon alternatives for high-carbon inputs while maintaining output levels. Endogenous growth theory regards technological progress as an intrinsic driver of this structural transformation, while digital factor empowerment theory further emphasizes that data, as a new factor of production, improves the efficiency of traditional inputs (Bailey et al., 2019; Matsuyama, 1991). Accordingly, the development of agricultural digital technology directly reshapes the agricultural production function and reduces carbon emissions through three parallel pathways. First, the source reduction pathway uses sensors, drones, and other devices to allocate water, fertilizers, and pesticides according to demand, directly reducing embodied carbon inputs and suppressing soil nitrous oxide emissions. Second, the process optimization pathway uses smart irrigation and autonomous agricultural machinery to shift energy consumption from extensive to precision use, thereby reducing dependence on fossil fuels. Third, the decision optimization pathway employs big data-driven decision-support systems to simulate the carbon footprints of different production modes, guiding farmers to avoid high-carbon practices at the decision-making stage (Abbasi et al., 2022).

By facilitating information flows, agricultural digital technology thus fundamentally transforms the production logic of traditional high-carbon agriculture and enables effective carbon control at the source.

Hypothesis 1: The development of agricultural digital technology has a significant direct inhibitory effect on agricultural carbon emissions.

2.2 Indirect Effects of Agricultural Digital Technology on Carbon Emissions

2.2.1 Improving the Financing Environment

The contribution of agricultural digital technology to carbon emission reduction stems not only from direct technological empowerment on the production side but also from structural optimization on the financial supply side. Information asymmetry theory identifies information barriers as a primary cause of imbalanced credit allocation and inefficient capital allocation. Agricultural digital technology quantifies information on agricultural operations to generate credible “digital reputation” signals, thereby alleviating information asymmetry between capital suppliers and demanders and correcting information biases in capital markets (Farquharson et al., 2013). This lowers the institutional barriers that agricultural enterprises face in accessing capital markets and ultimately promotes the continued growth of the stock of listed agricultural enterprises (Welch & Graham, 2000). From the perspective of financial development theory, this growth not only demonstrates how digital technology empowers capital markets but also reflects a structural shift in the regional financing environment from tight to accommodative and in capital availability from scarce to abundant.

How does an improved financing environment translate into a driving force for emission reduction? Based on information asymmetry theory and financial development theory, this effect primarily arises from the synergy between capital supply and market supervision. On the one hand, financial development theory emphasizes that an efficient financial system can reduce financing costs. A favorable financing environment lowers enterprises’ capital barriers and provides the low-cost funding required to purchase expensive low-carbon equipment and undertake green technological transformation, thereby easing the financial constraints on the agricultural green transition (Gabrisch, 2015). On the other hand, reduced information asymmetry enhances the effectiveness of external governance. Improvements in the financing environment are accompanied by greater capital market maturity, with ESG investment principles and stringent information disclosure systems imposing binding external constraints on enterprises (Abbas & Najam, 2025). Agricultural enterprises operating in this environment must proactively comply with green governance standards and adopt low-carbon production practices to preserve their capital market reputation and refinancing eligibility. This capital-screening mechanism, driven by improvements in the financing environment, accelerates the concentration of capital in low-carbon sectors and forces outdated high-carbon production capacity to exit the market, thereby reducing the overall carbon emission intensity of the agricultural sector (Johnson & Mitchell-McCallister, 2025). Accordingly, this paper proposes Hypothesis 2: The development of agricultural digital technology has a significant inhibitory effect on agricultural carbon emissions by improving the financing environment.

2.2.2 Promoting Green Technological Innovation

Agricultural digital technology also indirectly promotes carbon reduction by transforming the green innovation paradigm and creating a data-driven innovation ecosystem. Technological innovation theory regards innovation as a core driver of solutions to environmental problems.

Digital technology is not only a form of technological innovation in itself but also transforms the traditionally linear and slow “lab-to-field” process into an open, data-driven innovation ecosystem (Etzkowitz & Leydesdorff, 2000; La Rocca et al., 2024). Within this ecosystem, digital tools, such as AI-assisted breeding simulations, shorten R&D cycles, while online platforms and remote diagnostics accelerate technology diffusion and lower barriers to adoption. More importantly, integrated solutions combining meteorological, soil, and market data enable systemic green innovations, including circular agriculture models. These innovations ultimately reduce agricultural carbon emissions (Storm et al., 2024).

Hypothesis 3: Agricultural digital technology reduces agricultural carbon emissions by promoting green technological innovation.

2.3 Nonlinear Effects of Agricultural Digital Technology on Carbon Emissions

The relationship between agricultural digital technology and agricultural carbon emissions is not simply linear and negative. Rather, it reflects the combined effects of the “technological dividend” and the “rebound effect,” together with changes in factor structure, resulting in complex nonlinear characteristics (Stern, 2004). During the early stage of technology diffusion, known as the technological dividend stage, digital technology primarily generates an “optimization effect” by rapidly correcting resource misallocation through precision management. At this stage, the marginal emission-reduction benefit of technological progress is substantial, and carbon emissions decline (Shin et al., 2023). However, once technological development crosses a critical threshold, structural factors, alongside the conventional scale rebound effect, begin to dominate the nonlinear dynamics (Rypdal et al., 2007). As digital technology becomes deeply embedded, agricultural production factors undergo profound restructuring. In traditional agricultural production, land and labor are the main carbon sources, whereas at advanced stages of digitalization, digital infrastructure, such as data centers and intelligent equipment, becomes the new primary source of carbon emissions (La Rocca et al., 2024). This “shift in the carbon-source structure” implies that agricultural emission reduction increasingly depends on a cleaner energy structure. If the supply of clean energy lags behind the growth in energy consumption by digital facilities, or if the increase in emissions caused by production expansion exceeds the emission-reduction dividend from improved technological efficiency, total agricultural carbon emissions will shift from declining to rising, producing a U-shaped relationship (Baylis et al., 2019). Agricultural labor productivity also plays a key moderating role in this nonlinear relationship. According to capital deepening theory, improvements in agricultural labor productivity are generally accompanied by the substitution of capital for labor. Higher labor productivity indicates that agricultural production has a strong material and technological foundation and has achieved a certain scale, thereby providing favorable factor-matching conditions for the intensive application of digital technology (Li et al., 2022; Melo & Foster, 2021). On the one hand, when labor productivity is high, the application of digital technology is more likely to emphasize “qualitative improvement” than inefficient “quantitative expansion,” effectively delaying the onset of diminishing returns to scale. On the other hand, high labor productivity is often associated with more advanced management practices and greater capacity to use clean energy, which can partially offset the additional energy consumption generated by digital infrastructure. Therefore, improvements in agricultural labor productivity can mitigate the pressure of carbon emission rebound and shift the turning point of the U-shaped curve to the right, meaning that the rebound in carbon emissions occurs only at a higher level of digital technology development (Baylis et al., 2019; Gao et al., 2025). Accordingly, this paper proposes Hypothesis 4: The

development of agricultural digital technology has a U-shaped nonlinear relationship with agricultural carbon emissions, and improvements in agricultural labor productivity delay the turning point of this U-shaped relationship. The framework of this paper is presented in Figure 1.

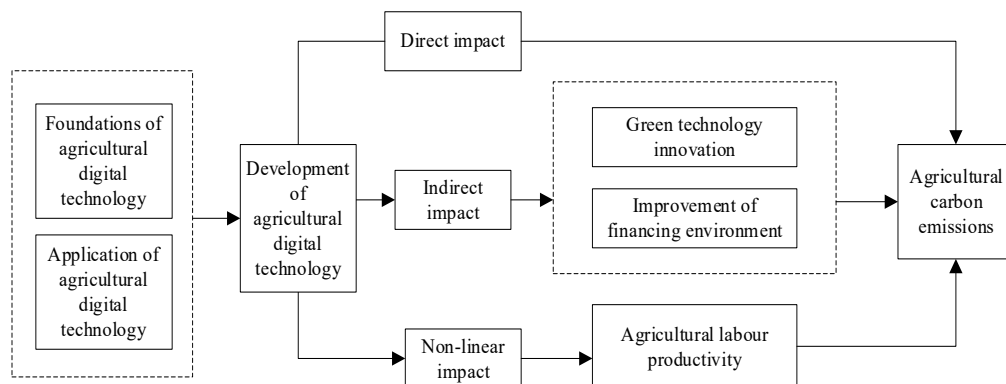


Figure 1. Research Framework

3 Research Design

3.1 Data Description

This study uses provincial panel data spanning 2010 to 2023. The main data sources are as follows: the China Statistical Yearbook provides macroeconomic and social development data; the China Ali Research Institute platform provides data on "Taobao Villages"; the China Research Data Service Platform (CNRDS) provides data on green technological innovation; and Zhejiang University's Carter-Enterprise Research Agricultural Database (CCAD) provides data on the level of agricultural financial services, the scale of listed agricultural enterprises, the number of organic food certifications, and the number of green agricultural utility model patent applications. To ensure data quality, the few missing values were imputed using interpolation or analogous observations. This process yielded a balanced panel dataset covering 31 provinces over 14 years.

3.2 Variable Definitions

(1) Dependent variable: To ensure scientific rigor and comparability, agricultural carbon emissions are calculated using the methodology recommended by the Intergovernmental Panel on Climate Change (IPCC), following an established approach (Li et al., 2024). The measurement system covers the main carbon sources in agricultural production across three categories: input-related emissions from fertilizers, pesticides, and plastic films; energy-related emissions from diesel use, tillage, and electricity consumption for irrigation; and livestock-related emissions from enteric fermentation and manure management in pig, cattle, and sheep farming. The calculation formula is as follows:

$$CO_2 = \sum K E_K \times EF_K \quad (1)$$

In this formula, CO_2 denotes total agricultural carbon emissions, E_k represents the activity data for carbon emission source k (such as fertilizer application, diesel consumption, and tilled area), and EF_k denotes the emission factor for each carbon emission source. The specific emission factors are presented in Table 1.

Table 1. Agricultural Carbon Emission Sources, Coefficients, and Data Sources

Emission source	Activity indicator	Emission factor	Unit	Reference source
Chemical fertilizer	Chemical fertilizer use	0.8956	kg/kg	Oak Ridge National Laboratory (ORNL)
Pesticide	Pesticide consumption	4.9341	kg / kg	Oak Ridge National Laboratory (ORNL)
Agricultural plastic film	Agricultural plastic film use	5.1800	kg / kg	Nanjing Agricultural University Institute of Agricultural Resources and Ecological Environment
Agricultural diesel	Consumption of agricultural diesel oil	0.5927	kg / kg	IPCC United Nations Intergovernmental Panel of Experts on Climate Change
Crop sown area	Total sown area of crops	3.1260	kg/ha	College of Biology and Technology, China Agricultural University
Irrigated area	Effective irrigated area	25.0000	kg/ha	Agricultural College of Nanjing Agricultural University
Pigs	Year-end pig inventory	34.091	kg/head/year	IPCC United Nations Intergovernmental Panel of Experts on Climate Change
Cattle	Year-end cattle inventory	415.910	kg/head/year	IPCC United Nations Intergovernmental Panel of Experts on Climate Change
Sheep	Year-end sheep inventory	35.182	kg/head/year	IPCC United Nations Intergovernmental Panel of Experts on Climate Change

(2) Core explanatory variable: The development of agricultural digital technology is a dynamic process that extends from the installation of hardware facilities to the deep penetration of digital technologies, making it difficult for any single indicator to capture comprehensively. Accordingly, this study uses the entropy method to construct a comprehensive index comprising two dimensions. First, digital technology infrastructure measures the physical capacity and accessibility of digital technology in rural areas and constitutes the material foundation for the digital transformation of agriculture. According to information infrastructure theory, network coverage and equipment adoption are essential for bridging the urban–rural digital divide and enabling information exchange (Li et al., 2026). Drawing on Lawrence et al. (2025), this study selects three indicators: the number of rural broadband access subscribers, the number of mobile phones owned per 100 rural households, and the length of rural delivery routes. The number of rural broadband access subscribers reflects the extent of internet coverage in rural areas, while the number of mobile phones owned per 100 rural households measures farmers' access to the terminal devices required to connect to digital networks. The length of rural delivery routes captures the completeness of the logistics infrastructure that supports the distribution of agricultural products to external markets and the delivery of industrial products to rural areas. Together, these indicators constitute the “hard foundation” through which digital technology empowers agriculture. Second, digital technology application measures the actual penetration and integration of digital technology across agricultural production, operations, and management. According to technology diffusion theory, technology application is the final stage through which technological value is realized. Drawing on Zhang et al. (2025), this study selects five indicators: the development scale of digital enterprises, the number of Taobao

Villages, the number of rural financial institution outlets, the number of operating agricultural meteorological observation stations, and the number of granted digital patents. The development scale of digital enterprises and the number of granted digital patents directly reflect R&D investment and the depth of digital technology integration within agricultural business entities. The number of Taobao Villages measures the agglomeration of rural e-commerce and the level of operational digitalization. The number of operating agricultural meteorological observation stations reflects the intelligent monitoring capacity of digital technology in agricultural production. The number of rural financial institution outlets reflects the breadth of coverage of digital inclusive financial services. Together, these indicators capture the practical effectiveness of the transformation of digital technology from a “tool” into a “factor.” The specific measurement steps are as follows:

① Data standardization: Because the indicators differ in units, magnitudes, and positive or negative orientation, the raw data must first be standardized. Assuming m evaluation subjects (e.g., different regions) and n evaluation indicators (e.g., internet penetration and the stock of agriculture-related digital enterprises), the raw data matrix is denoted by $X = (X_{ij})_{m \times n}$, where x_{ij} represents the value of the j th indicator for the i th evaluation subject.

For positive indicators:

$$X'_{ij} = \frac{X_{ij} - \min X_j}{\max X_j - \min X_j} \quad (2)$$

For negative indicators:

$$X'_{ij} = \frac{\max X_j - X_{ij}}{\max X_j - \min X_j} \quad (3)$$

② Calculate the weight of the j th indicator value in the i th year:

$$Y_{ij} = X'_{ij} \sum_{i=1}^m X'_{ij} \quad (4)$$

③ Calculate the information entropy of each indicator:

$$e_j = -k \sum_{i=1}^m (Y_{ij} \times \ln Y_{ij}) \quad (5)$$

Let $k = \frac{1}{\ln m}$; then $0 \leq e_j \leq 1$, and when $Y_{ij} = 0$, set $Y_{ij} \times \ln Y_{ij} = 0$;

④ Calculate the information entropy redundancy:

$$d_j = 1 - e_j \quad (6)$$

⑤ Determine the indicator weights:

$$w_j = \frac{d_j}{\sum_{j=1}^n d_j} \quad (7)$$

⑥ The agricultural digital technology index used in this study differs from general digital economy indicators. It focuses on digital infrastructure and application scenarios directly related to agricultural production, rural circulation, agricultural information services and rural financial access. This design enables the index to capture the agricultural relevance of digital technology rather than the broader development level of the digital economy:

$$S_i = \sum_{j=1}^n w_j X'_{ij} \quad (8)$$

where X'_{ij} and X_{ij} denote the standardized and original values, respectively, of the j th indicator for the i th evaluation subject; $\max X_j$ and $\min X_j$ denote the maximum and minimum values, respectively, of the j th indicator across all evaluation subjects. $\sum_{j=1}^n X'_{ij}$ represents the sum of the standardized values for all evaluation subjects under the j th indicator. The entropy value e_j reflects the information redundancy of the j th indicator: a higher entropy value indicates that the indicator provides less information and should therefore receive a lower weight; conversely, a lower entropy value indicates that the indicator provides more information and should receive a higher weight.

The coefficient of variation d_j indicates the degree of variation in the j th indicator. A larger d_j value signifies that the indicator plays a greater role in the evaluation. m denotes the number of evaluation years, and n denotes the number of indicators. The weight W_i reflects the relative importance of the j th indicator in the comprehensive evaluation. The sum of all indicator weights equals 1, as denoted by $\sum_{j=1}^n w_j = 1$. S_i represents the comprehensive agricultural digital technology index for the i th evaluation subject. This index captures the overall level of agricultural digital technology development across regions at both the foundational and application levels. A higher index value indicates a more advanced level of agricultural digital technology development in the region. Details of the measurement and data sources for the agricultural digital technology development index are presented in Table 2.

Table 2. Indicators and Data Sources for Agricultural Digital Technology Development

Primary dimension	Secondary dimension	Tertiary indicator	Measurement indicator
Digital technology infrastructure	Network coverage	Internet penetration	Rural broadband subscribers (10,000 households)
	Digital access	Mobile phone coverage	Mobile phones per 100 rural households (units)
	E-commerce foundation	Coverage of postal services	Length of rural delivery routes (km)
Digital technology application	Digitalization of management	Development of agriculture-related digital enterprises	Number of agriculture-related digital enterprises
		E-commerce activity of agricultural products	Number of Taobao Villages (units)
	Digitalization of production	Agricultural financial service level	Number of rural financial institution outlets
		Digitalization of agrometeorological monitoring	Number of operational agrometeorological stations

Primary dimension	Secondary dimension	Tertiary indicator	Measurement indicator
		Digital transformation of agriculture-related enterprises	Digital patents granted to agriculture-related enterprises (units)

(3) Indirect Mechanism Variables

To examine the transmission pathways through which agricultural digital technology development affects agricultural carbon emissions, this study uses two mechanism variables. The first is the financing environment. By reducing information barriers, digital technology eases financing constraints and improves the regional allocation of capital, thereby alleviating the funding bottleneck in agriculture's green transformation. Following prior research (Davydenko et al., 2021), the financing environment is measured as the logarithm of the total number of listed agricultural enterprises in each province. As a direct outcome of capital market access, the stock of listed agricultural enterprises provides an observable indicator of improvements in the regional financing environment and captures both the concentration of financial resources and the availability of financing. The second variable is green technological innovation. According to endogenous growth theory, digital technology stimulates green innovation by lowering R&D thresholds and accelerating information flows, thereby facilitating emissions reduction throughout the production chain. Following prior research (Zhou & Wang, 2022), green technological innovation is measured by the number of green patents granted in each province and transformed as $\ln(\text{variable} + 1)$ to capture green R&D activity and the capacity to supply low-carbon technologies. Agricultural labor productivity is also introduced as a moderator of the nonlinear effect, following prior research (Melo & Foster, 2021), to assess how factor-allocation efficiency shapes the emissions-reduction threshold. It is calculated by dividing provincial agricultural GDP by the number of agricultural employees.

(4) Control Variables

Based on a review of the existing literature, this paper classifies the factors affecting agricultural carbon emissions into several categories, including the regional economy, government support, household consumption, and climate variables. To account for these factors, the model incorporates economic indicators, including the level of agricultural economic development, the intensity of fiscal support for agriculture, and the consumption level of rural residents, as well as indicators of natural conditions, including agricultural water resources, climatic conditions, and forest area. To mitigate heteroscedasticity, all control variables are logarithmically transformed. The descriptive statistics for each variable are presented in Table 3.

Table 3. Descriptive Statistics

Variable	Measurement	Mean	Standard deviation	Minimum	Maximum
Agricultural carbon emissions	Agricultural carbon emissions (ten thousand tons)	489.420	304.696	16.398	1475.331
Development of agricultural digital technology	Agricultural digital technology development index	0.134	0.112	0.026	0.790
Agricultural	Gross output value of primary	3637.232	2677.463	100.770	12531.900

Variable	Measurement	Mean	Standard deviation	Minimum	Maximum
economic development	industry (100 million yuan)				
Financial support for agriculture	Expenditure of local finance on agriculture, forestry and water affairs (100 million yuan)	557.163	297.199	67.140	1455.200
Consumption level of rural residents	Consumption level of rural residents (yuan)	13360.270	7822.770	2567.000	46531.000
Agricultural water resources	Total agricultural water consumption (100 million cubic meters)	121.140	105.458	2.500	563.600
Agroclimatic conditions	Affected area of crops (1000 hectares)	717.538	752.548	0.400	4223.700
Forest area	Forest area (10,000 hectares)	767.212	640.642	6.810	2614.850
Improvement of financing environment	Number of agricultural listed enterprises in provinces (units)	10780.470	14230.170	57.000	115262.000
Green technology innovation	Number of green patents granted by province (units)	32.055	47.008	0.000	276.000
Agricultural labor productivity	Provincial agricultural GDP divided by agricultural labor force (%)	4.972	2.525	0.841	17.408

4 Model Specification and Empirical Analysis

4.1 Baseline Model

To test the direct effect of agricultural digital technology development on agricultural carbon emissions, the baseline model is specified as follows:

$$CO_{2it} = \alpha + \beta \cdot Digital_{it} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (9)$$

where CO_{2it} denotes agricultural carbon emissions per unit in province i at time t (the dependent variable); $Digital_{it}$ denotes the level of agricultural digital technology development (the core explanatory variable); X_{it} is a vector of control variables; μ_i and λ_t are province and time fixed effects, respectively; and ϵ_{it} is the random error term.

4.2 Direct Effects of Agricultural Digital Technology on Carbon Emissions

To examine the direct effect, we employ a two-way fixed-effects model with stepwise regression; the results are reported in Table 4. The baseline regressions consistently show that agricultural digital technology development significantly reduces agricultural carbon emissions. Across all specifications, the coefficient on the core explanatory variable is negative and significant at the 10% level, confirming a robust negative relationship between agricultural digital technology development and agricultural carbon emissions and thus supporting Hypothesis 1. The underlying mechanism is that digital technologies, such as the Internet of Things (IoT) and intelligent irrigation, optimize input management, reduce resource waste and avoidable carbon emissions, and promote the transition toward more resource-efficient and environmentally friendly agricultural practices (DeLay et al., 2021).

A comparison of Models (1)–(3) further confirms the robustness of the model specification and the main conclusion. In Model (1), which includes neither fixed effects nor control variables, the

coefficient on agricultural digital technology development is -0.703 and is significant at the 1% level. After time and province fixed effects are included, Model (2) yields a coefficient of -0.508, significant at the 5% level. Finally, after all relevant variables are controlled for, the coefficient in Model (3) is -0.324 and remains significant at the 10% level. These stepwise regressions demonstrate that the carbon-reducing effect of agricultural digital technology remains robust after accounting for potentially confounding economic, climatic, and other factors.

The baseline results provide strong empirical evidence that agricultural digital technology development is a key driver of reductions in agricultural carbon emissions, thereby supporting China's dual carbon goals. These findings are consistent with the existing literature. For example, Northrup et al. (2021) argue that emerging agricultural digital technologies are essential for reducing carbon emissions from agriculture, while Li and Gao (2024) find that the expansion of China's digital economy reduces the carbon intensity of agricultural energy use, further corroborating the emission-reducing effect of digital technology (Li & Gao, 2024; Northrup et al., 2021).

Table 4. Benchmark Regression Results

Variable	Agricultural carbon emissions		
	Model (1)	Model (2)	Model (3)
Development of agricultural digital technology	-0.703*** (0.153)	-0.508** (0.197)	-0.324* (0.180)
Control variables	No	No	Yes
Time fixed effects	No	Yes	Yes
Province fixed effects	No	Yes	Yes
Constant	5.984*** (0.153)	5.961*** (0.021)	4.378 (2.627)
R ²	0.0572	0.0199	0.0074
Sample size	434	434	434

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses. The same convention applies below.

4.3 Indirect Effects of Agricultural Digital Technology on Agricultural Carbon Emissions

To investigate the internal transmission pathways through which agricultural digital technology development affects agricultural carbon emissions, this study employs structural equation modeling (SEM). SEM offers important advantages over traditional stepwise regression and bootstrap methods. When analyzing multiple mediation effects, traditional methods often underestimate standard errors or overlook interactions among variables, whereas SEM incorporates the financing environment and green technological innovation into a unified analytical framework and simultaneously estimates multiple path coefficients within a single model (Barrett, 2007; Dong et al., 2024). This approach reduces parameter-estimation bias and enables an overall assessment of the consistency between the theoretical model and the observed data using model-fit indices. Because the core explanatory variable, agricultural digital technology development, is a multidimensional construct encompassing network coverage, equipment adoption, and application depth, it cannot be accurately measured using a single indicator. This study therefore treats it as a latent variable and constructs a corresponding measurement model. Specifically, agricultural digital

technology development is specified as the latent variable, while the observed indicators of the previously described “digital technology foundation” and “digital technology application” dimensions serve as its manifest variables; their measurement relationships are established through confirmatory factor analysis. Meanwhile, the financing environment, green technological innovation, and agricultural carbon emissions are included as observed variables. The model is specified as follows: the measurement model defines the relationships between the latent variable and its observed indicators, thereby reflecting the extent to which the multidimensional indicators explain the level of agricultural digital technology; the structural model estimates both the direct effect of the latent variable on the outcome variable and its indirect effects through the mediating variables. The model-fit indices are CFI = 0.995 (>0.95), TLI = 0.944 (>0.9), and SRMR = 0.005 (<0.08). All indices meet the recommended criteria, indicating a good model fit and supporting the model’s suitability for evaluating the pathways through which agricultural digital technology development affects agricultural carbon emissions. The results are reported in Table 5.

(1) Analysis of the Indirect Mechanism through Improvements in the Enterprise Financing Environment

The development of agricultural digital technology indirectly affects agricultural carbon emissions by optimizing capital allocation and governance in the agricultural industry. The path analysis shows that the standardized path coefficient of agricultural digital technology development on the financing scale of enterprises is 0.098, significant at the 1% level. This result indicates that agricultural digital technology, including agricultural IoT applications and big data analytics platforms, broadens the information channels available to listed agricultural enterprises and enhances the information transparency and creditworthiness of agricultural business entities, thereby easing financing constraints and significantly improving the financing environment for agricultural enterprises. As an observable indicator of the financing environment, the stock of listed agricultural enterprises reflects expansion in enterprise scale and, more directly, the regional agglomeration of financial resources and a more accommodating financing environment. More importantly, improvements in the enterprise financing environment significantly inhibit agricultural carbon emissions, with a standardized path coefficient of -0.398, significant at the 1% level. This effect arises because an improved financing environment provides enterprises with the financial resources needed to allocate green assets, respond to external oversight and ESG requirements, and make long-term investments in low-carbon technologies, thereby overcoming the funding bottleneck in agriculture’s green transformation. The view that the agglomeration of capital factors drives industrial transformation is also supported by studies showing that digital inclusive finance improves factor allocation among agricultural enterprises and promotes their development by alleviating financing constraints (Abbas & Najam, 2025).

Therefore, agricultural digital technology generates a significant indirect effect through the pathway “agricultural digital technology development → improvement of the enterprise financing environment → reduction of agricultural carbon emissions.” Overall, agricultural digital technology does not operate directly on the production side; instead, it harnesses the capital market to promote green and low-carbon development throughout the agricultural sector by optimizing the financing ecosystem and strengthening enterprises’ capital capacity. This finding is highly consistent with the conclusions of Yang et al. (2024), thereby supporting Hypothesis 2.

(2) Indirect Mechanism through Green Technological Innovation

Agricultural digital technology also indirectly reduces agricultural carbon emissions by

promoting green technological innovation. The standardized path coefficient from agricultural digital technology development to green technological innovation is 0.124, significant at the 1% level, indicating that digital technologies provide essential data, intelligent tools, and innovation platforms for advances such as biological breeding and circular agriculture. Furthermore, green technological innovation directly reduces agricultural carbon emissions, with a standardized path coefficient of -0.146, significant at the 1% level. This result indicates that adopting green technologies, such as low-carbon cultivation and resource recycling, optimizes input use and improves energy efficiency, making such technologies a core means of mitigating carbon emissions in agriculture (Zhao et al., 2025). Thus, the pathway “agricultural digital technology development → promotion of green technological innovation → reduction of agricultural carbon emissions” generates a significant indirect effect. Consistent with prior evidence (Luo et al., 2023), this finding confirms that green technological innovation is a key indirect channel and supports Hypothesis 3.

Table 5. Indirect Effects via Green Technological Innovation and the Financing Environment

Explanatory variable	Direction	Outcome variable	Standardized coefficient (1)	OIM standard error (2)	p-value (3)
Development of agricultural digital technology	→	Green technology innovation	0.124	0.041	0.002
Development of agricultural digital technology	→	Financing environment	0.098	0.028	0.000
Green technology innovation	→	Agricultural carbon emissions	-0.146	0.024	0.000
Financing environment	→	Agricultural carbon emissions	-0.398	0.035	0.000

Note: Control variables are included at each step of the regression analysis.

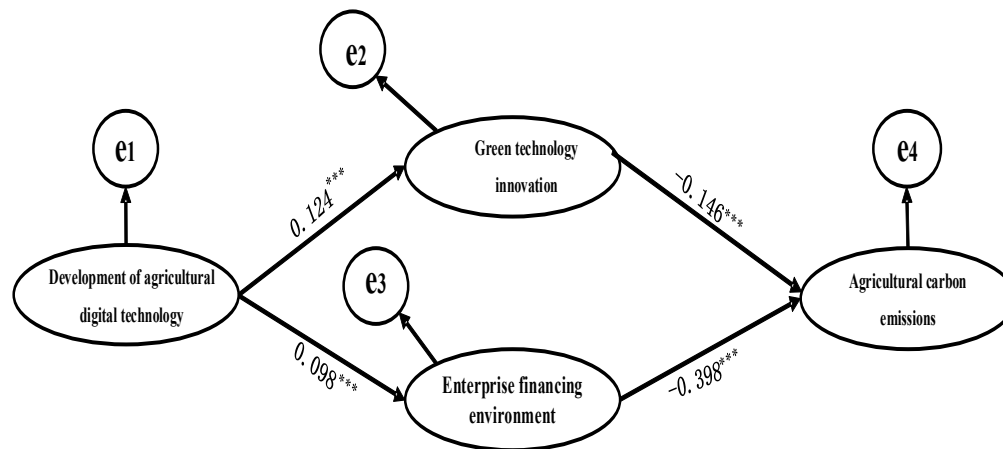


Figure 2. Indirect Effects of Agricultural Digital Technology on Agricultural Carbon Emissions

4.4 Nonlinear Effects of Agricultural Digital Technology on Carbon Emissions

This study further investigates the potential nonlinear relationship between agricultural digital technology development and agricultural carbon emissions. Following the baseline regression specification, the model includes a quadratic term for agricultural digital technology development. The results in Table 6 show that the linear term is significantly negative at the 5% level ($\beta = -1.544$, $p < 0.05$), whereas the quadratic term is significantly positive at the 5% level ($\beta = 1.430$, $p < 0.05$). These results confirm a U-shaped relationship: agricultural carbon emissions initially decline as agricultural digital technology develops but eventually increase, supporting the first part of Hypothesis 4. This finding is consistent with evidence that the digital economy has a U-shaped effect on carbon-emission intensity, with initial reductions followed by potential rebound effects (Wang et al., 2024). Related evidence shows that early-stage adoption of agricultural digital technology reduces emissions through precision management, whereas excessive deployment raises energy consumption and creates new emissions pressures (Zhang et al., 2025), consistent with the observed pattern of an initial decline followed by an increase.

To further examine the dynamics of this nonlinear relationship, the turning point of the U-shaped curve is calculated. In the baseline model (Column 2), the turning point is 0.540. After agricultural labor productivity is introduced as a moderating variable (Column 3), the turning point shifts rightward to 0.547, indicating that a one-unit increase in labor productivity delays the turning point by approximately 1.3%. This result implies that higher agricultural labor productivity prolongs the net carbon-reduction effect of agricultural digital technology by mitigating rebound effects arising from efficiency-driven production expansion (Chen & Li, 2024). For provinces in the top 30% of the labor-productivity distribution, the time required to reach the turning point increases by approximately 1.8 years, creating a valuable window for policy and technological adjustments supporting regional green transformation. Overall, these results confirm not only the nonlinear effect of agricultural digital technology on agricultural carbon emissions but also its dynamic adjustment according to labor productivity. Policies promoting digital transformation should therefore also enhance labor productivity to fully realize the emission-reduction potential of agricultural digital technology.

Table 6. Nonlinear Effects of Agricultural Digital Technology on Agricultural Carbon Emissions

Variable	Agricultural carbon emissions	Agricultural carbon emissions
Development of agricultural digital technology	-1.544** (0.649)	-1.581** (0.660)
Squared term of agricultural digital technology development	1.430** (0.642)	1.445** (0.647)
Agricultural labor productivity		0.010 (0.011)
Control variables	Yes	Yes
Time fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Constant	4.557* (2.417)	4.256* (2.507)
R ²	0.0682	0.0187
Sample size	434	434

4.5 Heterogeneity Analysis

To identify the boundary conditions governing the effect of agricultural digital technology on agricultural carbon emissions, this study examines heterogeneity across farm size, geographic region, and carbon emission sources (Table 7).

(1) Farm Size Heterogeneity

To examine the role of farm scale, the sample was divided into high- and low-scale groups based on the median crop-sown area. As shown in Table 7, the carbon-reduction effect of agricultural digital technology is clearly scale-dependent. In regions with larger farming operations, the coefficient of agricultural digital technology development is significantly negative at the 5% level (-0.741), indicating a substantial reduction in agricultural carbon emissions. By contrast, in regions with smaller farming operations, the coefficient is insignificant and close to zero (-0.175), indicating a negligible observable emission-reduction effect. This finding confirms the presence of economies of scale in the adoption of agricultural digital technology. Large-scale agricultural operators, such as major farms and cooperatives, have both the capacity and willingness to undertake substantial digital investments and are better positioned to realize the scale benefits of technological applications, thereby reducing costs and emissions through precision management. Smallholders, however, face fragmented landholdings, limited capital, and weak technology-adoption capacity, making it difficult to bear the upfront costs of deploying sensors and integrating data platforms and thus hindering the implementation of agricultural digital technology (Li et al., 2025). This scale dependence implies that digital agriculture generates stronger low-carbon effects where land, machinery and service systems allow fixed digital costs to be spread over larger production units. In smallholder-dominated areas, cooperatives, agricultural service organizations and platform-based shared services may be needed to reduce adoption costs.

(2) Geographic Heterogeneity

The regression results in Table 7 show that the carbon-reduction effect of agricultural digital technology varies significantly across regions. Among the regressions for eastern, central, and western China, only the central region has a significantly negative coefficient at the 5% level (-1.879), indicating a clear carbon-reduction effect. In the eastern region, the coefficient is positive and significant at the 10% level (0.241), suggesting that agricultural digital technology may have produced a net increase in emissions. In the western region, the coefficient is negative but insignificant, implying that the potential for emission reduction has not yet been fully realized. These findings indicate that the carbon-reduction benefits of agricultural digital technology are unevenly distributed and are most pronounced in the central region. One possible explanation is that the central region, a major grain-producing area in China, is undergoing a critical transition from traditional to modern agriculture, during which the adoption of agricultural digital technology can effectively alleviate productivity bottlenecks and unlock substantial emission-reduction potential. By contrast, the eastern region already has relatively advanced agricultural modernization and digitalization, resulting in diminishing marginal emission-reduction effects; its high equipment density and energy consumption may even generate rebound emissions. In the western region, complex terrain and inadequate infrastructure hinder the diffusion and implementation of agricultural digital technology, limiting its emission-reduction potential. These results are consistent with Jin et al. (2024), who emphasize that the environmental effects of digital technologies depend strongly on regional development stages, resource endowments, and institutional contexts (Jin et al.,

2024). The stronger effect in central China may reflect its role as a major grain-producing region, where digital tools have greater marginal value in improving input allocation and process management. The weaker effect in western China suggests that infrastructure constraints and fragmented production conditions may limit the carbon-reduction potential of digital technology.

(3) Carbon Emission Source Heterogeneity

This study further decomposes agricultural carbon emissions into input-related emissions (fertilizers and pesticides) and process-related emissions (tillage and irrigation) to examine the distinct pathways through which agricultural digital technology affects emissions. Table 7 shows that agricultural digital technology development significantly reduces process-related emissions (-0.286, significant at the 1% level) but has almost no effect on input-related emissions (0.003, not significant). This result indicates that agricultural digital technology has a more direct and pronounced emission-reduction effect through the optimization of agricultural production processes. For example, smart irrigation systems can precisely regulate water use, thereby directly reducing irrigation-related energy consumption. By contrast, the negligible effect on input-related emissions may reflect practical constraints, including farmers' agronomic knowledge and data accuracy, that prevent precision fertilization and pesticide reduction from fully translating into lower emissions. This finding is consistent with Deichmann et al. (2016), who argue that although digital fertilization systems can theoretically reduce nitrogen fertilizer use, their effectiveness is constrained by farmers' risk aversion and climate uncertainty. The result indicates that digital tools are currently more effective in managing process-related emissions than input-related emissions. Reductions in fertilizer and pesticide emissions may require complementary agronomic knowledge, extension services and risk-management tools for farmers.

Table 7. Heterogeneity Analysis

	Small planting scale	Large planting scale	Eastern region	Central region	Western region	production n goods carbon dioxide emission	mode of production carbon dioxide emission
Developm ent of agricultura l digital technolog y	-0.175 (0.199)	-0.741** (0.311)	0.241* (0.113)	-1.879** (0.722)	-3.663 (1.008)	0.003 (0.112)	-0.286*** (0.088)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.309 (2.933)	7.769*** (1.691)	8.236** (2.966)	2.390 (3.644)	-2.030 (4.048)	7.044*** (2.527)	3.726** (1.608)
R ²	0.0498	0.0271	0.4460	0.0637	0.4846	0.0031	0.0347
Sample size	217	217	154	112	168	434	434

4.6 Robustness Checks

To assess the reliability of the baseline regression results, robustness tests were conducted using alternative core variables, sample adjustments, lagged effects, and endogeneity mitigation.

The results are reported in Table 8.

(1) Alternative Core Variables and Sample Adjustments

First, to assess sensitivity to the measurement of the core explanatory variable, the agricultural digital technology development index was recalculated using principal component analysis, and the model was re-estimated. As shown in Column (1) of Table 8, the coefficient remains significantly negative at the 5% level (-0.094), confirming that the emission-reduction effect of agricultural digital technology is robust to alternative measurement methods. Second, to exclude the influence of regions with special administrative status, the four municipalities of Beijing, Tianjin, Chongqing, and Shanghai were removed from the sample. As shown in Column (2), the coefficient remains significantly negative at the 1% level (-0.530) and increases in absolute magnitude, indicating that the baseline result is not driven by these municipalities and that the emission-reduction effect is stronger in other provinces.

(2) Lagged Effects

Given the potential lagged effects of agricultural digital technology on agricultural production and carbon emissions, both the core and control variables were lagged by one period. As shown in Column (3), the lagged coefficient remains significantly negative at the 10% level (-0.371), suggesting that the emission-reduction effect of agricultural digital technology persists into the following year and confirming its role as a long-term driver of carbon mitigation.

(3) Endogeneity Mitigation

To mitigate potential endogeneity arising from omitted variables and reverse causality, this study follows Li et al. (2022) in constructing a “corrected comprehensive shift-share instrumental variable.” The instrumental variable comprises two components: a “share” component and a “shift” component. The “share” component uses the historical (initial-period) stock of infrastructure related to agricultural digital technology in each province as weights. These weights capture historical endowments and underlying regional differences in the development of the agricultural digital economy, which are typically shaped by early policy orientations or geographical resources and are relatively stable. The “shift” component uses the national growth rate of agricultural digital technology development, excluding the focal province, as an external shock. This indicator captures the overall national trend in technological progress and fluctuations in market demand, making it exogenous to any individual province. By interacting each province’s historical share with the national growth rate, the instrumental variable simulates the province-specific level of technological development driven exogenously by the overall national trend.

The exogeneity of the instrumental variable rests on two considerations. First, the historically accumulated stock of digital infrastructure is often shaped by early policy pilots or geographical conditions and is not directly related to current agricultural carbon emissions, thereby satisfying the exclusion restriction. Second, the national-level growth rate of agricultural digital technology is independent of agricultural production behavior in any individual province and affects agricultural carbon emissions only indirectly by increasing the local level of agricultural digital technology development. This approach effectively mitigates interference from reverse causality and omitted variables (Yang et al., 2024). Although the Bartik instrument helps mitigate endogeneity, its validity depends on the exclusion restriction; therefore, the instrumental-variable results should be interpreted as supportive evidence rather than as a complete solution to all identification concerns.

The first-stage regression results in Column (4) of Table 8 show that the coefficient on the Bartik instrumental variable is significantly positive at the 1% level (1.365). Moreover, the Cragg–

Donald Wald F statistic is 1426.708, far exceeding the critical value of 16.38 at the 10% significance level. This finding indicates that weak instruments are not a concern and that the constructed instrumental variable is valid and strongly correlated with the endogenous explanatory variable. The second-stage regression results in Column (5) further show that, after accounting for endogeneity bias, the coefficient on the development of agricultural digital technology remains significantly negative at the 1% level (-0.178). This result provides strong evidence that the negative relationship between the development of agricultural digital technology and agricultural carbon emissions reflects a causal effect rather than a spurious correlation. The development of agricultural digital technology can therefore effectively reduce agricultural carbon emissions, providing an important and reliable pathway for emissions reduction.

Table 8. Robustness Tests

	replace Explanatory variable	adjust Sample range	consider hysteretic nature	figure technology	agriculture carbon dioxide emission
	(1)	(2)	(3)	(4)	(5)
Development of agricultural digital technology	-0.094** (0.039)	-0.530*** (0.160)			-0.178*** (0.059)
Agricultural digital technology development, lagged one period			-0.371* (0.207)		
<i>Bartik</i>				1.365*** (0.114)	
Control variables	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	4.228 (2.527)	2.645 (3.111)	4.883* (2.483)	—	—
R ²	0.0150	0.3348	0.0475	—	—
Sample size	434	341	403	378	378

5 Conclusions and Policy Implications

(1) The development of agricultural digital technology has a significant direct inhibitory effect on agricultural carbon emissions. The benchmark regression confirms a robust negative relationship between the two. The mechanism analysis identifies two pathways underlying this effect. First, by improving the financing environment, agricultural digital technology harnesses the agglomeration of capital factors and the external governance benefits arising from the accumulation of listed agricultural enterprises, thereby providing financial support for the green transformation of agriculture. Second, by stimulating green technological innovation, it provides a core driving force for emissions reduction.

(2) The impact of agricultural digital technology on agricultural carbon emissions exhibits a U-shaped nonlinear relationship. Below the inflection point (0.540), agricultural digital technology has a significant emissions-reduction effect. Beyond the inflection point, its net effect shifts toward increasing emissions because of the rebound effect and the energy consumption of infrastructure. Improving agricultural labor productivity can effectively delay the inflection point and extend the period of emissions-reduction benefits.

(3) The effect of agricultural digital technology on reducing agricultural carbon emissions exhibits significant heterogeneity. Regionally, this effect is more pronounced in areas with larger

planting scales and in central China. In terms of pathways, emissions reductions are achieved primarily by optimizing production processes such as tillage and irrigation, whereas the effects on reducing inputs such as chemical fertilizers and pesticides are not yet significant.

Based on the findings of this study, the following policy recommendations are proposed to fully harness the role of agricultural digital technology in reducing carbon emissions:

(1) Strengthen the enabling role of agricultural digital technology to facilitate the dual drivers of capital agglomeration and technological innovation. An agricultural credit information platform should be established using digital technology, alongside a program to cultivate listed agricultural enterprises, thereby leveraging the expansion of the capital market to direct social capital toward low-carbon sectors. Meanwhile, a dedicated guidance fund for green technological innovation should be established to stimulate corporate R&D, maximizing the emissions-reduction potential of agricultural digital technology through synergies between its direct effects and indirect pathways.

(2) Implement a coordinated strategy of “efficiency improvement and green infrastructure.” Given the U-shaped impact of agricultural digital technology on carbon emissions, the policy focus should shift from technology diffusion to improving the efficiency of factor allocation. Digital skills training can delay the carbon-emissions inflection point and extend the period of emissions-reduction benefits. Meanwhile, dual controls on total energy consumption and energy intensity should be imposed on new agricultural digital infrastructure to prevent an energy-consumption rebound caused by infrastructure expansion.

(3) Promote an adoption model characterized by “regional differentiation and targeted interventions across production links.” Digital agriculture pilot zones should be established first in the major grain-producing areas of central China, using economies of scale to amplify the emissions-reduction effect. Policy support should also extend to the management of inputs such as chemical fertilizers and pesticides. Dedicated subsidies for “input reduction and efficiency enhancement” and a negative-list system should be established to compel the deep integration of digital technology and agronomy, thereby achieving substantial emissions reductions throughout the entire production chain.

6 Limitations and Future Research Directions

Despite advances in theoretical analysis and empirical testing, this study has several limitations related to data availability, methodological constraints, and the current model specifications, which also suggest directions for future research.

(1) Data limitations. The precision of the core variable measurements could be further improved. Although the agricultural digital technology development index constructed in this study encompasses multiple dimensions, county-level data are occasionally missing because of limited public data availability, potentially preventing the index from fully capturing the depth of technology adoption and application at the micro level. Future research could conduct large-scale surveys of farmers or enterprises to collect primary data on adoption frequency, usage intensity, and investment returns, thereby developing more accurate micro-level indicators and enabling more refined validation of the current findings.

(2) Causal identification. Endogeneity could be addressed more comprehensively. Although this study employs a Bartik instrumental variable to mitigate bias arising from omitted variables and reverse causality and obtains robust results, the validity of this approach depends on specific assumptions. Moreover, the selection of pilot regions for national digital agriculture policies may

not be entirely random, potentially introducing selection bias. Future studies could employ quasi-natural experimental methods, such as propensity score matching combined with difference-in-differences (PSM-DID), to isolate the net policy effect more precisely and provide stronger causal evidence of the emission-reduction effects of agricultural digital technology.

(3) Dynamic effects. The current model primarily examines the static or short-term effects of agricultural digital technology on agricultural carbon emissions, whereas changes in agricultural production practices and the environmental impacts of digital technologies unfold through long-term, dynamic processes. The current specification does not fully capture the long-term effects of technological iteration, learning curves, or policy adjustments. Future research could employ dynamic panel models (e.g., system GMM) or distributed lag models to examine the lagged, persistent, and long-term evolution of emission-reduction effects, thereby informing forward-looking strategic planning.

Funding

This study was supported by the National Natural Science Foundation of China (grant no. 72503235), the Humanities and Social Sciences Youth Foundation of the Ministry of Education (grant no. 24YJC790047), and the Fundamental Research Funds for the Central Universities (grant no. 2025SK12).

Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Supporting Information

Supporting information is available in the online version of this article.

CRedit Authorship Contribution Statement

Conceptualization, Tianzhi Gao; methodology, Hui Feng; investigation, Zeyu Sun; writing—original draft preparation, Tianzhi Gao; writing—review and editing, Hui Feng and Fei Yuan.

Acknowledgments

We thank Professor Lu Qian and his team for their methodological guidance. We also acknowledge the support of the National Natural Science Foundation of China and the Humanities and Social Sciences Fund of the Ministry of Education.

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