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Empowering agricultural ecological quality development through the digital economy with evidence from net carbon efficiency

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The drive of the rural digital economy in agricultural development and the enhancement of agricultural net carbon efficiency are integral to ensuring the quality development of agricultural ecology. To better understand the impact of the digital economy on agricultural ecological quality, this paper utilizes panel data from 30 provinces (municipalities, autonomous regions) in China from 2013 to 2020 and employs the instrumental variable method to analyze the impact of digital economy development on agricultural net carbon efficiency. The results reveal that the advancement of the rural digital economy significantly enhances the net carbon efficiency of agriculture, and this finding remains robust even after substituting explanatory variables and excluding samples from direct-administered municipalities. Heterogeneity analysis indicates that the aforementioned impact is more pronounced in major grain-producing areas, regions with high agricultural industrial concentration, and areas with low government intervention. Further analysis reveals that the rural digital economy can enhance agricultural net carbon efficiency through two primary mechanisms: improving human capital and promoting technological progress. The conclusions of this study have significant implications for improving the level of rural digital economy development and optimizing agricultural net carbon efficiency.

Keywords Rural digital economy, Agricultural ecological quality, Agricultural net carbon efficiency, Human capital, Agricultural technological innovation

In recent years, with the development of Chinese agriculture, the carbon emission brought by agricultural production has also grown. "2023 China Agriculture and Rural Low-carbon Development Report" shows that China's total carbon emissions from agricultural production in 2014 reached 828 million tons of CO_2 equivalent, accounting for 6.7% of the country's total emissions. However, when the scope is expanded to include the entire agri-food system, agriculture-related greenhouse gas emissions account for more than 30% of global emissions, indicating that agriculture has become the main source of carbon dioxide emissions. On September 22, 2020, during the 75th session of the United Nations General Assembly, President Xi Jinping delivered a keynote speech announcing China's commitment to peaking carbon emissions before 2030 and achieving carbon neutrality by 2060. Effectively reducing agricultural carbon emissions has become a critical pathway to advancing the "dual carbon" goals. And Azam (2017) conducted an early study revealing that agricultural economic growth and carbon emissions are interrelated in some EU countries[1]. As a new driver of economic growth, the digital economy should also play an active role in the pursuit of carbon peaking and carbon neutrality. Studies have shown that the digital economy has a strong carbon reduction ability in industry[2], manufacturing[3], transportation[4], logistics[5] and other fields. Will the digital economy also bring new momentum to the increase of net carbon efficiency in agriculture? What is the mechanism of action?

Previous literature has explored the relationship between the development of the digital economy and the net carbon efficiency of agriculture, but no uniform conclusion has been reached. On the one hand, some scholars believe that the digital economy, as a key driver of social development, can effectively reduce the carbon emission intensity of agricultural production[6].Jin et al. further highlight from a spatial perspective that the development of the rural digital economy can significantly reduce agricultural carbon emissions. However, due to diminishing marginal returns and technological iteration, its impact exhibits a threshold effect[7]. Zhang et

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al.[8]found that a digital economy can promote the improvement of agricultural green total factor productivity by improving agricultural technological innovation. On the other hand, when the level of a digital economy is low, the effect of rural digital economy development on agricultural carbon emission reduction is not obvious, but the construction of digital infrastructure will generate energy consumption such as electricity[9], thus increasing agricultural carbon emissions and inhibiting the improvement of agricultural net carbon efficiency. This paper believes that the energy consumption and carbon emissions generated by digital applications are affected by the continuous upgrading of rural energy consumption structure and the gradual improvement of the modern energy system, and are not the key to rural energy conservation and emission reduction control. The development of a digital economy will play a more significant role in promoting agricultural carbon emission reduction, thus improving the quality of agricultural ecology.

The development of the rural digital economy is widely acknowledged as a critical driver for enhancing agricultural productivity and stimulating economic growth. However, existing studies predominantly explore the impact of the digital economy on agricultural productivity and rural economic development, often overlooking its effects on agricultural ecological quality. This research addresses this gap by introducing the concept of agricultural ecological quality and utilizing agricultural net carbon efficiency as a proxy variable for empirical analysis, thereby broadening the scope of existing literature. Our findings not only confirm that the rural digital economy significantly enhances agricultural net carbon efficiency but also elucidate the dual impact mechanisms of human capital and technological innovation. This dual mechanism analysis provides a deeper insight into how the digital economy improves agricultural ecology. Furthermore, the study investigates the heterogeneous impacts across major grain-producing areas, agricultural industrial concentration zones, and regions with varying degrees of government intervention. Compared to previous research, this paper offers a more comprehensive and detailed perspective, presenting an integrated research framework that combines digital economy development with sustainable agricultural practices. This framework provides valuable practical guidance for policymakers in formulating and implementing strategies to promote sustainable agriculture through digital economic advancements.

Research hypothesis

Mechanism of rural digital economy impacting agricultural net carbon efficiency

Based on externality theory, public goods possess significant positive externalities[10]. Distinguished from traditional agricultural economies, the digital economy, due to its high coverage and high penetration, possesses significant external economies. Because the digital economy inherently has green economic attributes, it transforms traditional production factors in agriculture into digital productivity[11]. The resulting inclusive effect can enhance agricultural net carbon efficiency.

Specifically, the development of internet infrastructure and meteorological observation networks serves as a fundamental prerequisite for the growth of the rural digital economy. Well-established digital infrastructure helps mitigate geographical constraints[12], facilitates information sharing in rural areas, and enables farmers to access real-time market and weather information via the internet. This reduces uncertainties in agricultural production and enhances the efficient allocation of resources. Additionally, the advancement of rural logistics infrastructure minimizes losses during the transportation of agricultural inputs, improves the overall utilization efficiency of agricultural production factors, and promotes resource intensification, thereby enhancing agricultural net carbon efficiency.

Moreover, the digital economy plays a crucial role in reducing agricultural carbon emissions. Increased investment in agricultural information technology and the inflow of IT professionals have significantly accelerated the development of precision agriculture. Technologies such as smart irrigation and variable-rate fertilization help reduce the excessive use of fertilizers and pesticides, ultimately lowering carbon emissions in agricultural production.

Furthermore, the digital economy also strengthens agriculture's carbon absorption capacity. The widespread adoption of digital technologies promotes the development of low-carbon agriculture, while the expansion of green farming practices, such as organic and eco-friendly cultivation models, further enhances the sector's ability to sequester carbon.

Finally, digital technology penetration effectively mitigates technical adoption barriers for farmers while cultivating ecological awareness through cognitive interventions and enhanced social interactions. This dual mechanism not only enhances agricultural production engagement but also addresses participation gaps in environmental governance. These multi-tiered mechanisms collectively enable digital technologies to enhance agricultural sustainability through dual pathways: Instrumental rationality manifests through improved carbon efficiency metrics, while value rationality facilitates paradigm shifts in agricultural ecosystem operations. This synergy between technological applications and value reconstruction ultimately elevates agricultural net carbon efficiency through three interconnected dimensions: technological empowerment, behavioral modification, and institutional innovation. Based on this, this paper proposes Hypothesis 1:

H_1 The inclusive effect of the rural digital economy will have a positive impact on agricultural net carbon efficiency.

The previous discussion established that, at a theoretical level, the development of the rural digital economy can enhance agricultural net carbon efficiency. However, during the nascent stage of digital economic development, three critical constraints exist: (1) According to the Statistical Report on China's Internet Development, the internet penetration rate in rural China was only 33.1% in 2016, rising to 67.4% by 2020. The fragmentation of digital infrastructure and the limited adoption of digital technologies prevented the formation of network synergy effects, making data-driven decision-making ineffective for farmers in the initial stages. (2) The application of digital technology remained confined to basic functions such as information transmission, without direct integration into agricultural production. (3) The high cost of digital equipment hindered widespread adoption, meaning that the potential for carbon reduction remained constrained by low farmer adoption rates and high factor-matching costs. These factors limited the positive impact of the digital economy on agricultural net carbon efficiency in the early stages. However, once digital economic development surpasses a critical threshold—characterized by improved digital infrastructure, higher adoption rates, and deeper technological integration—these constraints are overcome. At this stage, the inherent economies of scale and technological complementarities of the digital economy will drive systemic transformations in the agricultural ecosystem, significantly enhancing agricultural net carbon efficiency.

Consequently, this paper postulate Hypothesis 2:

H_2 The relationship between rural digital economy development and agricultural net carbon efficiency exhibits a nonlinear threshold effect— insignificant at lower levels of digital economic development but significant at higher levels.

Mechanisms of intermediary effects

Based on modern economic growth theory, labor quality, and agricultural technology levels are important factors influencing agricultural production efficiency, which in turn is highly related to agricultural net carbon efficiency[13]. Specifically, the higher the level of human capital among farmers and the better the agricultural technology, the higher the agricultural ecological efficiency and the stronger the agricultural net carbon efficiency. The digital economy facilitates the effective and reasonable allocation of agricultural production factors. On one hand, it expands farmers' access to information and channels, thereby enhancing their human capital levels[14]. On the other hand, the introduction of digital technologies to rural areas brings technological advancements, significantly improving the level of agricultural production technology. These two effects continuously enhance agricultural net carbon efficiency. Therefore, this paper posits that the rural digital economy can influence agricultural net carbon efficiency by affecting agricultural human capital levels and technological progress.

Mechanism for enhancing human capital

Farmers' human capital endowment refers to the knowledge, skills, and abilities that farmers possess in the process of making a living, serving as the premise and foundational conditions for agricultural production. Numerous empirical studies in China indicate that, on one hand, the development of the rural digital economy promotes the flow of high-quality educational resources to rural areas. This enables farmers to acquire knowledge and skills not only through conventional educational channels but also through new methods such as digital platforms, thereby improving their human capital levels and effectively narrowing the digital access gap between urban and rural areas[15]. The improvement in human capital significantly influences the research, development, use, and dissemination of new technologies, reducing agricultural carbon emissions and thereby enhancing agricultural net carbon efficiency. On the other hand, digital network platforms disseminate agricultural production knowledge related to the ecological environment and green production more conveniently. They also promote and popularize low-carbon agricultural production techniques to agricultural laborers through online video platforms, helping farmers gradually transition from a "knowledge effect" to a "learning effect," and shaping farmers' values towards low-carbon production. According to the theory of planned behavior, farmers' green production cognition can be translated into behavior[16], effectively reducing agricultural carbon emissions and non-point source pollution, thus increasing agricultural carbon sequestration and comprehensively promoting the enhancement of agricultural net carbon efficiency. Based on this, this paper proposes Hypothesis 3:

H_3 The rural digital economy can enhance agricultural net carbon efficiency by improving human capital.

Mechanism for technological innovation

The level of agricultural technology refers to the degree of advancement of the techniques and equipment used in agricultural production, and it is crucial for agricultural productivity. The development of the digital economy fosters technological innovation by facilitating the free and efficient flow of innovative elements and reducing the coordination and integration costs of technological innovations. Additionally, the construction of digital infrastructure can drive reforms in the management systems of village collectives and regional governments, creating a more inclusive and free rural innovation environment that supports the collaborative development of agricultural technological innovation[17]. Endogenous economic growth theory emphasizes that technological innovation is the intrinsic driver of economic growth[18], and it is also the internal driving force for green agricultural production. Relevant research indicates that the impact of agricultural technological advancement on agricultural net carbon efficiency unfolds through the following three aspects:

Firstly, Expected Agricultural Output: Technological innovation can enhance the marginal output of input factors, thereby improving the efficiency of the green agricultural economy and increasing agricultural carbon absorption. From the perspective of non-expected agricultural output, technological innovation can drive the transformation of traditional agriculture to modernization, accelerate the use of clean energy, and promote the cyclical utilization of production factor resources, thereby reducing agricultural carbon emissions[19].

Secondly, Improvement of Agricultural Production Factors: Agricultural technological innovation can strengthen agricultural net carbon efficiency by improving production factors. Pesticides, fertilizers, and other agricultural inputs are major sources of agricultural carbon emissions. Technological innovation can create new types of green labor production materials, reducing the use of pesticides and fertilizers, and consequently lowering agricultural carbon emission levels.

Thirdly, Spillover and Radiative Effects of Technology and Talent: Agricultural technological innovation can enhance agricultural net carbon efficiency through the continuous and radiative spillover of technology and talent. On one hand, technological progress can promote the clustering of agricultural industries, forming agricultural economies of scale[20], thus improving regional agricultural net carbon efficiency. On the other hand, agricultural technological innovation encourages the cross-regional flow of high-tech talent, leading to the "spillover of knowledge," which facilitates the diffusion of resources and experiences from high-net carbon efficiency regions to lower- efficiency regions, promoting overall regional development[21].

Based on this, this paper proposes Hypothesis 4:

H_4 The rural digital economy can enhance agricultural net carbon efficiency by promoting agricultural technological innovation.

Based on the above research hypotheses, the study maps the theoretical framework as shown in Fig. 1.

Research design

Model setup

To test the aforementioned research hypotheses, this paper constructs a fixed effects model (1) to examine the direct impact of rural digital economy development on agricultural net carbon efficiency:

$$NCE_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_i Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

Building upon the theoretical propositions, this paper hypothesize a nonlinear relationship between rural digital economy development and agricultural net carbon efficiency. Following Hansen's (1999) panel threshold regression methodology[22], we specify the threshold effect model as follows:

$$NCE_{it} = \alpha_0 + \alpha_1 DIG_{it} \cdot I(DIG_{it} \leqslant \gamma) + \alpha_2 DIG_{it} \cdot I(DIG_{it} > \gamma) + \alpha_i Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

To examine the intrinsic impact mechanism of rural digital economy development on agricultural net carbon efficiency, the previous section elaborated on the theoretical framework of the effects of human capital and technological progress on agricultural net carbon efficiency. Drawing on the research by Jiang Ting[23]. , this paper verifies the impact of rural digital economy development on agricultural human capital and technological progress by setting up models (2) and (3) as follows:

$$EDU_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_i Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

$$agRD_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_i Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

In the above models, *i* and *t* represent province and year, respectively. *NCE* denotes agricultural net carbon efficiency, *EDU* represents the level of agricultural human capital, *agRD* indicates the level of agricultural technological innovation, *DIG* signifies the level of the rural digital economy, *Control* denotes control variables,

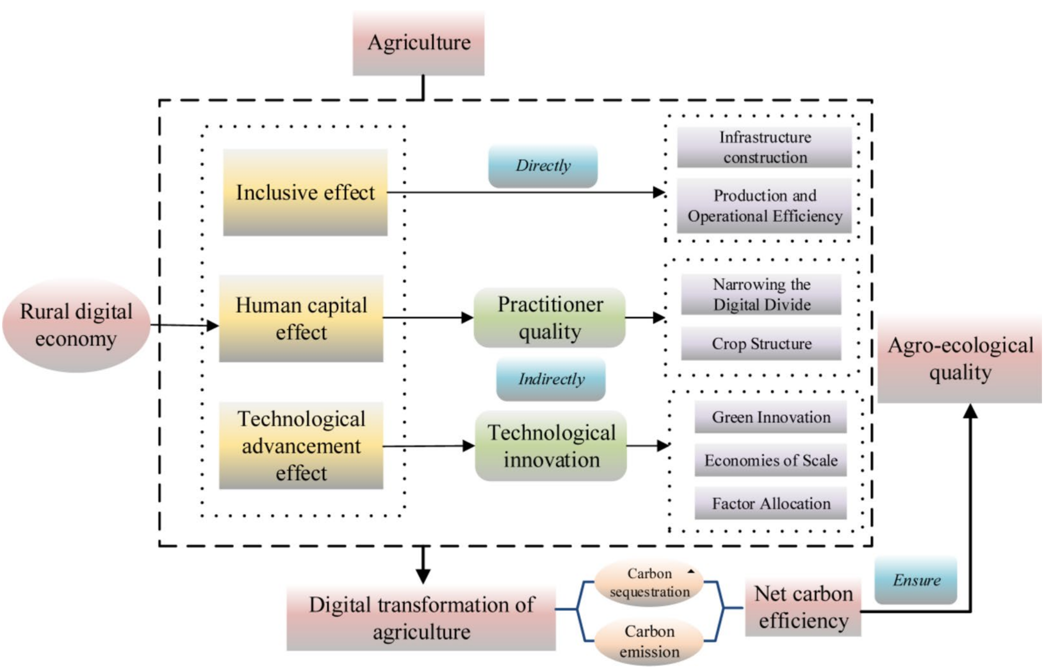

Fig. 1. The theoretical framework of digital economy empowering agricultural ecological quality.

α represents the parameters to be estimated in the model, μ_i denotes individual fixed effects, δ_i represents time fixed effects, and ε_{it} represents the random error term. I(•) is the indicator function. γ indicates the corresponding threshold value. This paper employs heteroskedasticity-robust standard errors.

It is important to note that the rural digital economy variable of interest in this paper may be endogenous. During the process of agricultural modernization, the improvement in net carbon efficiency may also promote the development of the rural digital economy. To address this potential endogeneity issue, this paper introduces an instrumental variable for re-estimation of the baseline regression. After repeated testing, the number of post offices per million people in 1984 is selected as the instrumental variable, mainly for the following reasons: First, relevance. The proliferation of telephones and the internet forms the foundation of digital economy development. Before the advent of telephone and internet development, information transmission and communication were primarily carried out through post office networks. Additionally, post office networks were the early sites for the installation of fixed telephone lines, and access to internet cables is closely related to telephone lines. Therefore, the number of post offices and the development of the digital economy are correlated. Second, exclusivity. The number of post offices in 1984 has a negligible impact on the current development of agricultural net carbon efficiency, thus satisfying the exclusivity condition. However, the number of post offices per million people in 1984 is cross-sectional data and cannot be regressed with the panel data of the sample period using a fixed effects model. To resolve this issue, and drawing on the research of Huang Qunhui et al.[24], this paper constructs an interaction term between the number of post offices per million people in 1984 and the number of internet broadband access users in each year of the sample period as the instrumental variable.

Variable selection

Explained variable: agricultural net carbon efficiency

Considering the dual effects of carbon emissions and carbon absorption in agriculture, this study uses agricultural net carbon efficiencyNCE to measure the development of agricultural ecological quality, focusing on the narrower scope of agriculture—namely, the planting industry. To emphasize the net carbon efficiency of the planting industry, this paper improves upon previous research by using the ratio of net carbon sinks to carbon emissions to measure agricultural net carbon efficiency. The constructed formula is as follows:

$$NCE = \frac{(S - E)}{E} \tag{5}$$

In the formula, *NCE* represents agricultural net carbon efficiency, *S* is the amount of carbon absorption in agriculture, and *E* is the amount of carbon emissions in agriculture.

This study measures agricultural carbon emissions by primarily considering three sources: agricultural land cultivation, agricultural input, and methane emissions from rice paddies, with agricultural land cultivation and agricultural input combined into one category for calculation. Due to the difficulty in obtaining data related to crop straw management, this study excludes straw return and straw burning to ensure scientific rigor. The constructed carbon emissions calculation formula is as follows:

$$E = E_1 + E_2 \tag{6}$$

$$E_1 = \sum E_{1k} = \sum A_k f_k \tag{7}$$

$$E_2 = \sum E_{2i} = \sum B_i m_i \times a \tag{8}$$

In the formula, E represents the total carbon emissions from the planting industry; E_1 represents the carbon emissions from agricultural land cultivation and agricultural input; E_2 represents the carbon emissions from methane emissions in rice paddies; E_{1k} represents the carbon emissions generated by a specific type of carbon source; A_k represents the total amount of a specific type of carbon source; f_k represents the carbon emission coefficient for a specific type of carbon source; and k represents the type of carbon source. This study draws on the research of Wu Guoyong et al.[25]to select crop planting areas, agricultural irrigation areas, fertilizers, pesticides, agricultural film, and diesel as the primary sources for calculating carbon emissions from the planting industry. The specific carbon emission coefficients and carbon sources are shown in Table 1. E_{2i} represents the carbon emissions from rice paddies in province i; B_i represents the planting area of rice paddies in province i; m_i

Carbon Source	Unit	Coefficient
Crop sowing area	kg/km^2	312.6
Agricultural irrigation area	kg/hm^2	19.8575
Fertilizer	kg/kg	0.8956
Pesticide	kg/kg	4.9341
Agricultural film	kg/kg	5.18
Diesel fuel	kg/kg	0.5927

Table 1. Carbon emission sources and carbon emission coefficients in crop cultivation.

Crop type	S	h	r%	Crop type	S	h	r%
Rice	0.414	0.45	12	Cotton	0.450	0.10	8
Wheat	0.485	0.40	12	Sugarcane	0.450	0.50	50
Corn	0.471	0.40	13	Sugar beet	0.407	0.70	75
Potato	0.423	0.70	70	Vegetables	0.450	0.60	90
Bean	0.450	0.34	13	Fruits	0.450	0.70	90
Peanut	0.450	0.43	10	Tobacco	0.450	0.55	85
Rapeseed	0.450	0.25	10	Other Crops	0.450	0.40	12

Table 2. Carbon absorption rates, economic coefficients, and moisture content of major crops in agriculture.

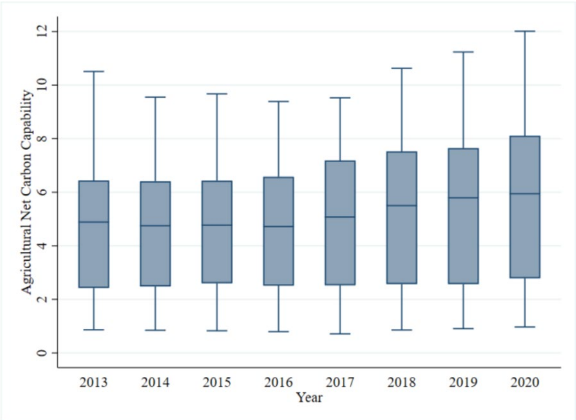

Fig. 2. Box plot of agricultural net carbon efficiency.

represents the methane emission factor for rice paddies in province *i*, based on the research of Tas Thamo et al.[26], with given factor coefficients. *a* represents the global warming potential coefficient for methane, which is 6.82.

The total amount of organic carbon absorbed by crops during their growth and development processes, which constitutes agricultural carbon sequestration, is calculated using the following carbon absorption measurement formula:

$$S = \sum_{i=1}^{m} S_i = \sum_{i=1}^{m} s_i \frac{Q_i}{h_i}(1 - r_i) \tag{9}$$

In the formula, *S* represents the total amount of carbon absorbed by crops in the agricultural system. S_i is the carbon absorption amount of a specific type of crop. s_i is the carbon absorption rate of a specific type of crop, Q_i is the economic yield of a specific type of crop, h_i is the economic coefficient of a specific type of crop, and, r_i is the moisture content of a specific type of crop, Q_i/h_i represents the biological yield of the crop, and *m* is the number of crop types. The specific agricultural crops studied include food crops, economic crops, and vegetable crops, mainly including Food crops: rice, wheat, corn, potatoes, and beans; Oil crops: peanuts, rapeseed; Fiber crops: cotton; Sugar crops: sugarcane, sugar beet; Economic crops: tobacco, fruits, vegetables, and other crops. Coefficient values for various crops are shown in Table 2.

As can be seen from Fig. 2, the box plot for agricultural net carbon efficiency shows a fluctuating upward trend during the study period, which may be due to the limitations of agricultural transformation and upgrading, resulting in relatively slow development. The variations in the box plot indicate significant differences in data among provinces, demonstrating inconsistent levels of agricultural development across provinces. This trend may be attributed to the constraints on agricultural transformation and upgrading, resulting in relatively slow development. Additionally, significant variations in data across provinces indicate disparities in agricultural development levels, which have been confirmed in previous studies[27].

Figure 3illustrates the spatiotemporal evolution characteristics of agricultural net carbon efficiency, from 2013 to 2020 and also shows varying levels of change among provinces. Provinces such as Gansu, Sichuan, and Guizhou rose from a medium-low level to a medium level. Previous studies indicate that these regions are water-scarce areas in the western part of the country[28]. Their improvement in agricultural net carbon efficiency may be due to increased focus on water resource management and ecological protection in recent years, enhancing agricultural production efficiency. Meanwhile, Hebei, Henan, and Shandong provinces advanced from a medium level to a medium-high level. As major agricultural provinces, this progression might be attributed to a recent emphasis on agricultural technological innovation and the promotion of agricultural techniques, which have simultaneously reduced carbon emissions and increased carbon absorption, placing them in a leading

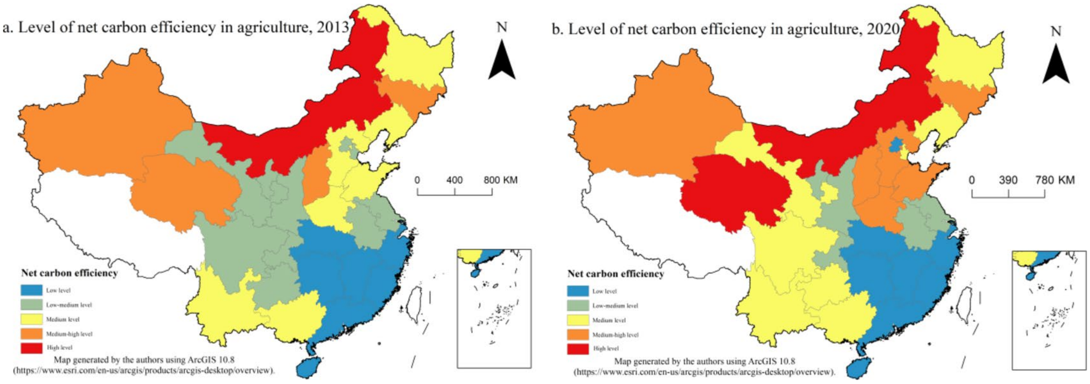

Fig. 3. Spatiotemporal evolution map of agricultural net carbon efficiency. Map generated by the authors using ArcGIS 10.8 (https://www.esri.com/en-us/arcgis/products/arcgis-desktop/overview).

Target Layer	System Layer	Index layer	Index Explanation
Rural Digital Economy	Innovation	E-commerce Development Level	Number of Taobao Villages(+)
		Rural Innovation and Entrepreneurship Level	Number of Rural Innovation and Entrepreneurship Parks(+)
		Level of Information Technology Investment	Fixed Asset Investment in the Information Technology Service Industry(+)
		IT Professionals	IT Workforce(+)
	Infrastructure	Rural Logistics Infrastructure Development	Rural Delivery Route Density(+)
		Rural Postal Accessibility	Number of Administrative Villages with Postal Service(+)
		Agricultural Meteorological Infrastructure Development	Number of Agricultural Meteorological Observation Stations(+)
	Digital popularization	Rural Mobile Phone Penetration	Average Number of Mobile Phones per Hundred Households in Rural Residences(+)
		Rural Internet Penetration	Number of Rural Broadband Access Households(+)
		Rural Internet Penetration	Average Number of Computers per Hundred Households in Rural Residences(+)
	Digital application	Digital Trading of Agricultural Products	Online Retail Sales of Agricultural Products(+)
		Rural Postal Delivery Level	Average Weekly Postal Delivery Frequency in Rural Areas(+)
		Rural Internet Culture Development	Average Weekly Postal Delivery Frequency in Rural Areas(+)
		Rural Information Technology Application	Average Population Served by Rural Postal Service Points(+)
		Digital Service Consumption by Farmers	Expenditure on Transportation and Communication by Farmers(+)
		Service Consumption Level of Farmers	Engel Coefficient of Rural Residents(-)

Table 3. Evaluation index system for the rural digital economy.

position. Conversely, Beijing's net carbon efficiency decreased from a medium-low level to a low level. Both its agricultural carbon emissions and carbon absorption are extremely low, likely because the economic focus is not on agriculture. Consequently, insufficient exploration of agricultural technology has resulted in weaker agricultural net carbon efficiency.

Explanatory variable: rural digital economy

The level of rural digital economy development (*DIG*) is the core explanatory variable in this paper. Following the principles of data availability, scientific validity, comprehensiveness, and effectiveness in selecting measurement indicators, an evaluation index system for the rural digital economy is constructed from the dimensions of innovation development, infrastructure, digital penetration, and digital application. The specific components are shown in Table 3.

Drawing on previous research, the entropy method is employed to measure the level of the rural digital economy.

Box plots are used to analyze the temporal characteristics of rural digital economy levels (Fig. 4). From the figure, it is evident that from 2013 to 2020, the level of China's rural digital economy has shown a continuous upward trend, with the range of fluctuations also expanding each year. The presence of outlier points indicates significant differences in the development of the agricultural digital economy among provinces, suggesting that the digital economy, as a new economic form, has developed rapidly in recent years. However, due to disparities in macroeconomic conditions, educational resources, human capital, and foundational infrastructure, the rural digital economy exhibits uneven regional development[29].

Figure 5displays the temporal and spatial evolution of China's rural digital economy development level. To provide a clearer depiction of the results, the study divides the timeframe of rural digital economy development

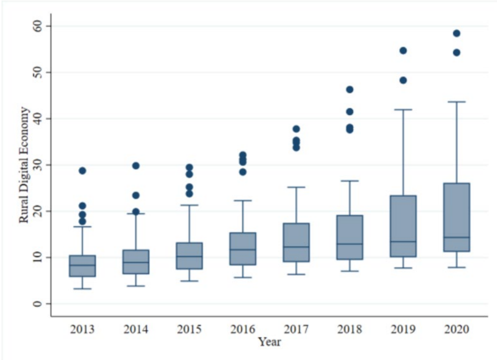

Fig. 4. Box plot of the rural digital economy.

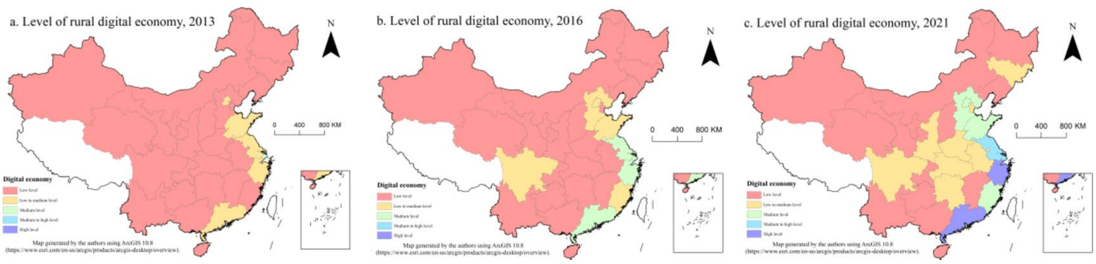

Fig. 5. Spatiotemporal evolution map of the rural digital economy. Map generated by the authors using ArcGIS 10.8 (https://www.esri.com/en-us/arcgis/products/arcgis-desktop/overview).

levels into three specific years: 2013, 2016, and 2020, instead of just using the endpoints of 2013 and 2020. The figure reveals that in recent years, the rural digital economy development level in most provinces has been continuously rising. This trend is driven by market demand in the broader context of national economic development, with strong support from government policies and infrastructure projects. However, there are notable differences in the growth trends of the rural digital economy across regions. In 2013, the level of the rural digital economy across China tended to be uniform, but by 2020, the eastern coastal regions had gradually risen to medium-high and high levels, while the central and western regions remained at low to medium-low levels. This disparity is likely due to differences in technological innovation capabilities and application degrees. The development of the digital economy is closely related to economic foundations, and the eastern coastal regions possess favorable conditions in terms of geographical location, resource advantages, technological innovation, market demand, and policy support[30].

Mediating variables
The first mediating variable selected in this paper is agricultural human capital (*EDU*). The level of agricultural human capital is measured by the average years of education of rural residents. The formula for the average years of education of rural residents is as follows:

Average years of education of rural residents =(Number of rural residents with no education×0 + Number of preschoolers×3 + Number of primary school graduates×6 + Number of middle school graduates×9 + Number of high school graduates×12 + Number of residents with college education or above×12)/ Total rural population.

The second mediating variable in this study is the level of agricultural technological innovation, measured by the investment in agricultural research and innovation. Currently, the available statistical data only includes research and innovation investment for the entire industry, and specific data for agricultural research and innovation investment is not available. In this study, the formula for measuring agricultural research and innovation investment is established as follows:

$$agRD_{it} = E_{it} \times RD_{it} \tag{10}$$

$$E_{it} = 0.5 \times \frac{agR_t}{R_t} + 0.5 \times \frac{agGDP_{it}}{GDP_{it}} \tag{11}$$

In the formula, $agRD_{it}$ represents the agricultural research and innovation investment of the province i in the year t, RD_{it} represents the research and innovation investment of the province i in the year t, agR_t represents the national agricultural research expenditure data, R_t represents the national research expenditure data, $agGDP_{it}$ represents the total agricultural output value of province i in the year t, and GDP_{it} represents the total output value of province i in the year t.

Control variables
To minimize the endogeneity problem caused by omitted variables, this paper adds control variables at the regional and agricultural levels, drawing on the studies of F Wang, Fengting[31], Wang, Haoran, et al.[32].

The regional-level control variables include Economic development level (*pgdp*), measured by the per capita GDP of each province; Urbanization level (*urb*), measured by the ratio of urban population to total population in each province; Urban-rural income gap (*gap*), measured by the ratio of disposable income between urban and rural residents.

The agricultural-level control variables include Rural fixed asset investment (*inves*); Expenditure on agriculture, forestry, and water affairs (*aff*); Agricultural disaster area (*dis*); Agricultural industrial structure (*str*), represented by the ratio of the value of forestry, animal husbandry, and fishery to the total output value of agriculture, forestry, animal husbandry, and fishery.

Data sources

Due to the more comprehensive availability of data related to rural digital economy metrics starting from 2013, this study selects the period from 2013 to 2020 as the sample interval. The primary data used in this study are derived from various sources, including the annual editions of the "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Population and Employment Statistical Yearbook," the "National Greenhouse Gas Emission Inventory," and data from the National Bureau of Statistics, the Ministry of Commerce, and relevant research reports. Some data are also sourced from the websites of provincial and municipal statistical bureaus. The Rural Digital Inclusive Finance Development Index is obtained from the Peking University Digital Inclusive Finance Index Research Report[33].

Given data availability, the study focuses on 30 provinces (municipalities and autonomous regions) in mainland China, excluding Tibet, Hong Kong, Macau, and Taiwan. To eliminate the effects of different measurement units among various indicators, the logarithms of some indicators are taken. Descriptive statistics of the indicators are presented in Table 4.

Results

Benchmark regression results

This section presents the regression results based on the benchmark model (1), as shown in Table 5. Column (1) is the fixed effects model with the core explanatory variables included. Column (2) includes the core explanatory variables and some control variables. Column (3) includes the core explanatory variables and all control variables. Column (4) considers the potential endogeneity by introducing instrumental variables for estimation.

Comparing the regression results reveals that as control variables are gradually included, the regression coefficients for the rural digital economy are consistently positive and pass the significance tests at the 1% and 5% levels. This indicates that the development of the rural digital economy significantly enhances the net carbon efficiency of agriculture, thereby validating hypothesis H_1.

This study addresses the issue of endogeneity caused by omitted variables by incorporating control variables and employing a two-way fixed effects model for empirical regression. This approach aims to mitigate endogeneity arising from time-invariant and unobservable factors. However, the model may still be subject to endogeneity due to potential bidirectional causality. To address this, the study adopts the instrumental variable (IV) method to re-estimate the baseline regression. The number of post offices per million people in 1984 is selected as the instrumental variable, based on the following considerations: (1) Relevance: The penetration of telecommunication and internet services serves as the foundation of digital economy development. Before the widespread adoption of telephones and the internet, information exchange and communication primarily relied on postal networks. Moreover, post office locations were among the early sites for the deployment of fixed telephone lines, and internet infrastructure is closely linked to telephone networks. Therefore, the number of post

Variable	Observed value	Mean value	Standard deviation	Minimum	Maximum
NCE	240	5.975	2.758	1.710	13.01
DIG	240	14.699	9.975	3.239	58.444
lnEDU	240	2.057	0.078	1.771	2.282
lnagRD	240	2.459	1.072	−0.874	4.263
lninves	240	5.396	1.128	1.194	6.874
lnaff	240	6.268	0.537	4.812	7.199
lndis	240	5.954	1.541	0.693	8.349
str	240	9.524	5.111	0.3	25.1
gap	240	2.573	0.384	1.845	3.803
urb	240	0.603	0.116	0.379	0.896
lnpgdp	240	10.913	0.143	10.053	12.013
lncseq	240	7.413	1.265	3.755	9.057
lnDuf	240	5.537	4.228	4.771	6.068
lntool	240	12.274	1.698	7.584	14.915

Table 4. Variables and descriptive statistics.

	OLS			2SLS
	(1)	(2)	(3)	(4)
DIG	3.403*** (4.34)	1.557** (2.11)	1.810** (2.37)	2.819** (2.24)
lninves		−0.800*** (−4.20)	−0.766*** (−3.92)	−0.746*** (−3.76)
urb		5.783*** (4.62)	5.290*** (3.92)	5.232*** (3.92)
gap		−0.686* (−1.94)	−0.524 (−1.57)	−0.523 (−1.61)
lnpgdp		−1.735*** (−4.04)	−1.145** (−2.01)	−1.267** (−2.24)
lndis			−0.001 (−0.04)	0.000 (0.01)
lnaff			−0.028 (−0.11)	−0.051 (−0.19)
str			0.646 (1.52)	0.704* (1.66)
Constant	5.474*** (47.30)	33.787*** (6.48)	25.350*** (3.44)	
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	240	240	240	240
Adjusted R^2	0.962	0.976	0.976	
Estimated F-value				58.56

Table 5. Baseline regression results. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses, as in the following tables.

Variable	Number of thresholds	F value	*P* value	10% threshold	5% threshold	1% threshold	Number of BS
DIG	Single-threshold	18.04	0.0550	15.7239	19.0101	28.0528	300
	Double-threshold	6.76	0.5050	13.8328	17.8936	22.8302	300

Table 6. Threshold effect tests.

offices is strongly correlated with the development of the digital economy. (2) Exclusivity: The number of post offices in 1984 has a negligible direct impact on the current development of agricultural net carbon efficiency, thereby satisfying the exclusivity condition. However, since the number of post offices per million people in 1984 is cross-sectional data, it cannot be directly regressed alongside the panel data of the sample period using the fixed effects model. To address this issue, following the previous research[34], this study constructs an interaction term between the number of post offices per million people in 1984 and the number of broadband internet subscribers in each sample year as the instrumental variable.

In Column (4), a two-stage estimation was conducted. In the first stage of the instrumental variable estimation, the F-value was 58.56, indicating no weak instrument variable problem. Therefore, using the interaction term between the number of post offices per million people in 1984 and the number of internet broadband access users in each sample year as an instrumental variable is appropriate. In the estimation of Column (4), the estimated coefficient of the digital economy is significant at the 5% level, indicating that the digital economy has a significant positive impact on agricultural ecological quality. Although the OLS regression results may lead to biased estimates of the rural digital economy, the extent of bias is not substantial. Therefore, in subsequent regressions, this study will use OLS for regression analysis.

Analysis of threshold effects

Following the testing approach of the threshold effect model, it is necessary to first determine the existence of a threshold effect and the number of threshold values before applying the model. The test results are presented in Table 6.

As shown in Table 6, when utilizing the level of rural digital economy development as the threshold variable, the single-threshold test passes the 10% significance level, with a p-value of 0.0550, while the double-threshold test fails to pass the significance test. The estimated single-threshold value for rural digital economy development is 0.1436.

Table 7 reveals the nonlinear relationship between rural digital economy development and agricultural net carbon efficiency. When the rural digital economy level is below the threshold value of 0.1436, its development does not contribute to the improvement of agricultural net carbon efficiency. However, when the rural digital economy exceeds this threshold, the estimated coefficient is 1.556, indicating that rural digital economy

Variable	Agricultural net carbon efficiency	
	Coefficient	t-value
Index(DIG ≤ 0.1436)	−1.132	−0.94
Index(DIG > 0.1436)	1.556**	2.05
Control	YES	YES
Constant	11.818**	2.49
N	240	240
R^2	0.398	0.398

Table 7. Coefficient regression results of the threshold model.

	(1) Agricultural carbon sequestration	(2) Digital Inclusive Finance Index	(3) Excluding municipalities	(4) Winsorize	(5) Change Cluster
DIG	0.165* (1.81)		1.236* (1.81)	2.907*** (2.67)	1.810** (2.37)
lnDuf		0.488*** (3.07)			
Control	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Constant	11.947*** (11.63)	24.372*** (3.37)	23.815*** (3.10)	27.983*** (3.86)	25.350*** (3.44)
N	240	240	208	240	240
Adjusted R^2	0.997	0.977	0.981	0.979	0.976

Table 8. Robustness test results.

development significantly enhances agricultural net carbon efficiency. This confirms the existence of a threshold effect in the impact of rural digital economy development on agricultural net carbon efficiency, supporting a nonlinear relationship between the two. Thus, Research Hypothesis H_2 is validated. Specifically, in the early stages of digital economy development, weak infrastructure and the presence of "sunk cost" effects hinder its impact on agricultural net carbon efficiency. Additionally, the limited scale of pilot projects for agricultural digital technologies, such as the Internet of Things (IoT), prevents the formation of economies of scale, making it difficult for the digital economy to significantly enhance agricultural net carbon efficiency. However, once digital economy development surpasses the threshold value, institutional frameworks—such as data-sharing mechanisms and standardized digital agriculture practices—gradually improve. The integrated application of digital technologies fosters a "synergistic multiplication" effect, wherein the digital economy and agricultural net carbon efficiency mutually reinforce and amplify each other.

Robustness checks

Changing the dependent variable

This paper comprehensively examines the dual effects of agricultural carbon emissions and carbon absorption. Given the carbon sink characteristics of agriculture, agricultural carbon absorption indicators are used to approximate the net carbon efficiency of agriculture. The results are shown in Column (1) of Table 8. The regression coefficient for the rural digital economy is 0.165, maintaining the same sign as the benchmark regression and passing the 10% significance level test, confirming the robustness of the benchmark regression results.

Changing the core explanatory variable

Previous studies often include digital inclusive finance to measure the development level of the digital economy[35]. From a financial perspective, the development of digital inclusive finance can represent the development of the digital economy to some extent. Therefore, this paper replaces the original core explanatory variable with the digital inclusive finance index for regression, as shown in Column (2) of Table 8. The results indicate that even after changing the core explanatory variable, the regression results remain significantly valid, confirming the robustness of the benchmark regression results.

Excluding directly governed municipalities

Considering the differences in agricultural subsidies and other policy preferences as well as development speeds between directly governed municipalities and other provinces (autonomous regions), these municipalities are excluded. The regression results after exclusion are shown in Column (3) of Table 8. The regression results for the core explanatory variable still align with the sign direction in the benchmark regression and pass the 10% significance test, confirming the robustness of the benchmark regression results.

Winsorization
To avoid the influence of extreme values in certain years or individual samples on the regression results, this paper performs a 2.5% bilateral winsorization on the dependent variable and core explanatory variable before re-running the regression. The results are shown in Column (4) of Table 8. The regression coefficient for the rural digital economy is 2.907, passing the 1% significance level test, confirming the robustness of the benchmark regression results.

Replacing robust standard error tests
Although heteroskedasticity-robust standard errors can mitigate potential heteroskedasticity issues in the model, clustered robust standard errors provide more reliable statistical inference when the data exhibit a clustered structure. To ensure the robustness of the empirical results, this study further employs clustered robust standard errors to re-examine the baseline regression results. Specifically, the standard errors are clustered at the “province-year” level. As shown in column (5) of Table 8, the regression coefficient is 1.810 and remains significant at the 5% level, indicating that the research conclusions are robust.

Heterogeneity analysis
Given the significant economic development disparities across different regions in China, along with varying levels of digital economy development, infrastructure, and industrial structure, this paper analyzes the heterogeneous effects of the digital economy on agricultural net carbon efficiency from the following perspectives:

Firstly, agricultural production functional zones The 30 provinces are divided into 13 major grain-producing areas and 17 non-grain-producing areas based on differences in agricultural production functions. Major grain-producing areas have natural conditions suitable for grain crop cultivation, yielding high grain output that not only ensures self-sufficiency but also supplies surplus grain. In contrast, non-grain-producing areas have lower agricultural planting levels and a gap between grain production and demand. The impact of the digital economy on agricultural net carbon efficiency, which is based on agricultural planting, may vary across different agricultural production functional zones.

Secondly, agricultural industry clustering Based on the location quotient indicator, the 30 provinces are divided into high and low agricultural industry clustering areas. Agricultural industry clustering is highly correlated with regional agricultural production efficiency and resource allocation efficiency, which in turn are linked to agricultural carbon efficiency[36]. Therefore, the impact of the digital economy on agricultural net carbon efficiency may differ across regions with varying degrees of agricultural industry clustering.

Thirdly, government intervention levels The sample is divided into regions with high and low government intervention levels based on the ratio of general government budget expenditure to GDP. The degree of government intervention also represents the level of marketization in the region. The level of marketization significantly affects the development of the digital economy and high-quality agricultural development[37]. Thus, the impact of the digital economy on agricultural net carbon efficiency varies with the degree of government intervention.

Based on models (1) and (2) in Table 9, it is evident that the digital economy has a significant positive impact on the net carbon efficiency of agriculture in major grain-producing areas at the 1% significance level, whereas non-grain-producing areas did not pass the significance test.

From models (3) and (4) in Table 9, it can be seen that the digital economy significantly promotes the net carbon efficiency of agriculture in regions with high agricultural industry concentration at the 1% significance level, while it has no significant effect in regions with low agricultural industry concentration.

	(1) major grain-producing	**(2) non-grain-producing**	**(3) High industry clustering**	**(4) low industry clustering**	**(5) high government intervention**	**(6) low government intervention**
DIG	5.808*** (2.69)	0.739 (1.08)	11.073*** (5.20)	0.992 (1.21)	7.808 (0.93)	1.669** (2.47)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	31.989*** (3.70)	15.142 (1.33)	17.662** (2.16)	35.539** (2.14)	16.358 (1.47)	32.404*** (4.74)
N	104	136	152	88	120	120
Adjusted R^2	0.987	0.972	0.978	0.984	0.960	0.989

Table 9. Heterogeneity test results.

	(1) EDU	(2) AgRD
DIG	0.571** (2.12)	0.599*** (4.05)
Control	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Constant	0.522 (1.07)	−10.022*** (−5.41)
N	240	240
Adjusted R^2	0.924	0.990

Table 10. Mediation effect test results.

According to models (5) and (6) in Table 9, the digital economy has a significant positive effect on the net carbon efficiency of agriculture in areas with low government intervention, whereas there is no significant impact in areas with high government intervention.

Mechanism analysis

The previous discussion has confirmed the significant positive impact of rural digital economy development on agricultural net carbon efficiency. But through which pathways is this impact achieved? To verify the underlying mechanisms, this paper introduces mediating variables and conducts further analysis based on models (2) and (3) mentioned earlier. The results are presented in Table 10.

As shown in Column (1) of Table 10, rural digital economy development significantly improves the level of human capital. Combining the results from Jiang Ting et al. (2022) on mediation models with the theoretical analysis discussed earlier, it can be reasonably inferred that the rural digital economy can enhance agricultural net carbon efficiency through the human capital effect, thus validating Hypothesis H_3.

As shown in Column (2) of Table 10, rural digital economy development significantly enhances the level of agricultural technological innovation. This suggests that the rural digital economy can enhance agricultural net carbon efficiency through the effect of technological innovation, thereby validating Hypothesis H_4.

Discussion

Previous studies have predominantly measured agricultural ecological quality from the perspectives of agricultural production inputs and outputs, with agricultural ecological efficiency being a common measure. For example, Wu Guoyong et al.[38]incorporated agricultural non-point source pollution into their assessment. However, these studies tend to focus on carbon emissions and often overlook agricultural carbon absorption. As agriculture is a dual system that involves both carbon absorption and carbon emissions, its net carbon efficiency is crucial. This study proposes that measuring agricultural net carbon efficiency provides a more reasonable assessment of agricultural ecological quality by considering both the environmental costs and ecological benefits of agricultural production. In measuring the rural digital economy, this study takes into account various indicators and synthesizes the methods frequently used by current scholars. For instance, some scholars measure the rural digital economy based on internet penetration, general equipment, digital penetration, digital integration, and investment levels[39]. However, these selected indicators are relatively singular and fail to comprehensively measure the digital economy. Additionally, Chen, Jinbiao, et al.[40] selected multiple indicators from aspects such as infrastructure, user base, and industry scale to measure the digital economy, but many of these indicators are derived from the secondary industry, which does not reflect the development level of the rural digital economy. Building on a systematic review of previous research, this study employs the entropy method, selecting multidimensional indicators from innovation development, infrastructure, digital penetration, and digital application to measure the development level of the rural digital economy. This approach not only provides reliable data support for calculating the rural digital economy but also offers a beneficial expansion of the existing measurement indicators for the rural digital economy. On this basis, this study analyzes the spatiotemporal evolution characteristics of agricultural ecological quality and the rural digital economy, contributing to a deeper understanding of the current development status of agricultural ecological quality and the rural digital economy.

Building on this foundation, this study explores how the rural digital economy empowers the development of agricultural ecological quality from the perspective of net carbon efficiency. Theoretical analysis and empirical tests reveal that the development of the rural digital economy can significantly enhance agricultural net carbon efficiency, which is logical. On one hand, the proliferation of new infrastructure in the course of rural digital economy development provides a solid foundation for the digital transformation of traditional agriculture, promoting the effective allocation of agricultural resources and improving the utilization rate of agricultural production factors. On the other hand, the innovative development of agricultural digital technologies offers intrinsic motivation for the green and low-carbon development of agriculture. The promotion of the digital economy can enhance farmers' awareness of both ecological and economic benefits[41], guiding them towards an ecological mindset and thereby enhancing agricultural net carbon efficiency.

However, this empowering effect exhibits significant heterogeneity. Firstly, for agricultural production functional areas, the digital economy has a significant positive impact on agricultural net carbon efficiency at the 1% level in major grain-producing areas, while non-grain-producing areas do not pass the significance test. The underlying reasons may be attributed to the well-developed planting industry in major grain-producing regions, which benefits from advantages in organization, large-scale operations, and intensive production. These factors provide a strong foundation for the rapid advancement of the digital economy within the agricultural sector. Moreover, as the digital economy becomes increasingly integrated with the planting industry, land management efficiency is significantly enhanced, while the optimized allocation of production inputs improves the utilization efficiency of fertilizers, pesticides, and other agricultural resources. Precision and intelligent agricultural production and operations not only enhance the efficiency of grain production and distribution but also reduce costs, thereby driving the growth of green total factor productivity in agriculture. For instance, the Beidahuang Agricultural Reclamation Group in Heilongjiang Province has implemented the "Unmanned Farm" pilot project, leveraging digital technologies such as Beidou navigation, drone-based crop protection, intelligent irrigation, and remote monitoring to improve land management efficiency and the precise application of agricultural inputs. Precision fertilization and intelligent irrigation have effectively reduced fertilizer and water resource waste, thereby lowering agricultural carbon emissions and enhancing agricultural net carbon efficiency. Therefore, the digital economy plays a particularly significant role in improving agricultural net carbon efficiency in major grain-producing regions.

Secondly, regarding agricultural industrial agglomeration, the digital economy significantly promotes agricultural net carbon efficiency at the 1% level in high agricultural industrial agglomeration areas, while it has no significant effect in low agricultural industrial agglomeration areas. This is because low agricultural industry agglomeration regions are typically economically developed areas, such as the Yangtze River Delta, the Pearl River Delta, and the core regions of Beijing-Tianjin-Hebei. These areas are primarily characterized by non-agricultural industrial structures. Although they exhibit a high level of digital economy development, the potential for applying digital technologies to agricultural ecological improvements is relatively limited, resulting in an insignificant impact of the digital economy on agricultural net carbon efficiency. In contrast, high agricultural industry agglomeration regions are often economically underdeveloped areas primarily engaged in agricultural production, such as the Northeast Plain and the Huaihai Plain. These regions generally have lower levels of digital economy development but exhibit a strong demand for the application of digital technologies in agriculture. Consequently, the rapid development of the digital economy in these low-level regions has a more pronounced impact on agricultural net carbon efficiency.

Finally, in terms of the degree of government intervention, the digital economy has a significant positive effect on agricultural net carbon efficiency in areas with low government intervention, but not in areas with high government intervention. A possible explanation lies in the fact that in regions with low government intervention, the market mechanism plays a dominant role, facilitating the rapid and smooth flow of various factors, thereby improving the efficiency and rationality of resource allocation. From the perspective of transaction cost theory in institutional economics, lower government intervention implies fewer administrative barriers and policy constraints. As a result, enterprises and farmers face lower institutional transaction costs when adopting new technologies, which promotes the widespread application of the digital economy in areas such as agricultural production. This, in turn, enhances the impact of the digital economy on agricultural net carbon efficiency and promotes the development of agricultural ecological quality. From the perspective of the policy crowding-out effect, regions with high levels of government intervention may result in a greater reliance on government-driven allocation of agricultural policy resources, rather than market demand. This reduces the autonomy of market entities and weakens the innovation drive of farmers and agricultural enterprises. For instance, if the government directly provides subsidies for agricultural machinery instead of supporting the application of digital technologies, farmers may prefer to adopt traditional farming methods over investing in digital agriculture technologies, thereby diminishing the impact of the digital economy on agricultural net carbon efficiency. Further consideration suggests that when government intervention is excessive and lacks transparency, policy resources may be captured by certain stakeholders, failing to truly foster the development of the digital economy. This may lead to a disconnect between government-driven agricultural green development policies and market needs, preventing the effective realization of the carbon reduction potential of the digital economy. Ultimately, this results in the insignificant impact of the digital economy on agricultural net carbon efficiency in high government intervention regions.

Previous studies have often conducted heterogeneity analyses based on regional differences within China. For instance, Zhang Hongsheng et al.[42] investigated the impact of the digital economy on agricultural carbon emissions, finding that the carbon reduction effects were more pronounced in the eastern and central regions compared to the western region. The eastern region of China, being coastal, benefits from a more developed environment for technological innovation and a higher degree of digitalization, thus exhibiting significant differences in the "digital carbon reduction" effects. However, substantial internal regional disparities make it difficult to capture local characteristics, thereby reducing the practical applicability of the results. This study, by analyzing heterogeneity from the perspectives of grain production areas, agricultural industrial agglomeration, and government intervention, aims to provide a more targeted analysis of policy effects. Consequently, it offers a more precise explanation of the mechanisms at play and provides differentiated, practically valuable policy recommendations.

Moreover, there are multiple pathways through which the development of the digital economy can enhance agricultural ecological quality. This study posits that human capital and technological innovation are important intermediary channels, and this hypothesis has been empirically validated. From the perspective of human capital effects, the development of the rural digital economy provides diversified education and training platforms for agricultural producers, offering channels for farmers to learn about agricultural production techniques, sustainable development, and the agricultural ecological environment. Agricultural producers can access agricultural knowledge, market information, weather forecasts, and other data through digital technologies. Moreover, highly skilled labor can comprehend the precise agricultural management schemes provided by digital technology, which helps to improve agricultural production efficiency and better adapt to agricultural environmental challenges. From the perspective of technological innovation effects: on one hand, the rural digital economy provides precise management tools for agricultural production through technological innovation. Using innovative technologies such as drones, satellite remote sensing, and sensors, farmers can obtain information on soil moisture, crop growth status, and climate change, enabling precise monitoring and management of the agricultural production process. On the other hand, the rural digital economy promotes the development of intelligent agricultural carbon reduction technologies through technological innovation[43]. With monitoring equipment and data analysis, farmers can monitor and assess the greenhouse gas emissions generated by agricultural activities in real-time, identify and locate emission sources, and take corresponding reduction measures. Technological innovation can improve resource utilization efficiency and reduce greenhouse gas emissions, thereby enhancing agricultural net carbon efficiency.

The limitations of this study are as follows. Firstly, in selecting the evaluation indicators for the development level of the rural digital economy, this study referred to excellent domestic and international journal articles and aimed to comprehensively and scientifically choose indicators widely recognized by scholars. However the inherent complexity and accessibility challenges of agricultural digitalization data impose measurement constraints. Specifically, the unavailability of sector-specific datasets on precision agriculture adoption rates and smart irrigation penetration indices – critical dimensions of agricultural technology application may result in systematic underestimation of digital economy development levels. Secondly, the empowering channels of the rural digital economy on agricultural ecological quality could be diverse. For feasibility reasons, this paper only selected human capital and technological innovation as intermediary mechanisms. Future research could analyze and verify other perspectives, such as agricultural planting structures. Thirdly, the data in this paper is sourced from provincial panel data in China, and analyses at the provincial level may mask the effects of heterogeneity at the county level. Meanwhile, the development of the digital economy has an international trend and can bring more ecological benefits to the international community, not limited to agriculture. The research ideas and methodological models of this paper can be applied to the issues of digital economy development and agricultural ecological quality in other countries and regions. Future research could extend the perspective to an international context.

Conclusions and policy implications
Conclusion
The rural digital economy is a key force in enhancing agricultural net carbon efficiency and plays a significant role in promoting agricultural ecological quality. This study examines how the rural digital economy empowers agricultural ecological quality development, incorporating human capital and agricultural technological progress into the analytical framework. Based on panel data from 30 provinces (municipalities, autonomous regions) in China from 2013 to 2020, the study conducts empirical tests and finds the following:

Agricultural Net Carbon Efficiency Trends: Agricultural net carbon efficiency shows a fluctuating upward trend, while the development level of the rural digital economy continues to grow, albeit with significant regional differences.

Positive Impact of Digital Economy: The development of the rural digital economy significantly enhances agricultural net carbon efficiency. This result remains robust even after introducing instrumental variable estimation, changing variables, excluding certain samples, and performing winsorization.

Heterogeneity in Impact: The impact of the digital economy on agricultural net carbon efficiency varies across different agricultural production functional zones, levels of agricultural industry clustering, and degrees of government intervention.

Indirect Enhancement through Human Capital and Technological Advancement: The rural digital economy can indirectly enhance agricultural net carbon efficiency through the effects of human capital and technological advancement.

Policy implications
Based on these findings, the following policy implications are proposed to improve the development of the rural digital economy, optimize the pathways to enhance agricultural net carbon efficiency and promote agricultural ecological quality development:

Firstly, based on the findings regarding the upward trend in agricultural net carbon efficiency fluctuations, a dynamic agricultural carbon monitoring mechanism should be established to enable real-time tracking of the agricultural carbon footprint. Simultaneously, efforts should be made to actively participate in the development of a global digital trading platform for agricultural carbon credits, facilitating cross-border digital carbon certification and mutual recognition pilot programs in collaboration with other countries.

Secondly, the research findings indicate that the development of the digital economy can effectively enhance agricultural net carbon efficiency. Therefore, the government should adopt a top-level design approach to formulate a comprehensive agricultural digitalization development strategy, leveraging the inclusive benefits of the digital economy while prioritizing agricultural ecological benefits. Additionally, it is crucial to mitigate the potential negative impacts and social risks associated with digital economic development, preventing the widening of the digital divide.

Thirdly, given the threshold effect observed in digital economy development, it is essential to strengthen rural digital infrastructure, expand internet coverage, and enhance network quality. Efforts should be made to promote the widespread application of digital technologies across the entire agricultural production value chain. This includes focusing on the development and optimization of digital platforms throughout the agricultural production process, accelerating the innovative integration of digital platforms and technologies in agriculture, and guiding small-scale farming toward a green, eco-friendly digital agricultural transformation.

Finally, research indicates that human capital and agricultural technological innovation serve as effective transmission mechanisms through which the digital economy enhances agricultural net carbon efficiency. On one hand, it is essential to establish a well-structured rural education system and develop high-quality agricultural skills training platforms. Strengthening education and training for farmers in the use of agricultural digital technologies will help improve their digital literacy, human capital, and capacity for digital innovation. Additionally, enhancing farmers' scientific production and management capabilities through knowledge-sharing platforms can facilitate experience exchange and technological collaboration among agricultural practitioners. On the other hand, efforts should be made to reinforce support for agricultural technological innovation by increasing fiscal investment in agricultural R&D and establishing dedicated funding programs to promote rural digital economy development. Providing targeted loans and financing channels for farmers, while encouraging agricultural enterprises to invest in digital agricultural technologies and equipment, will further drive innovation. Moreover, strengthening agricultural science and technology research and its application requires the creation of collaboration platforms between research institutions and agricultural enterprises. This will accelerate the integration of digital technologies into agricultural production, facilitating the rapid transformation of technological advancements into practical agricultural applications.

Building on this foundation, active participation in global digital agriculture governance is essential. On one hand, fostering cross-border technological collaboration and innovation is crucial. Drawing on the digital agriculture experiences of the European Union and other countries, efforts should focus on the development of climate-smart agricultural technologies. Additionally, advanced digital irrigation technologies from countries such as Israel should be introduced and localized for application in arid regions like Northwest China. On the other hand, leveraging the "Belt and Road" Initiative, China should promote its smart agriculture solutions to developing countries. For instance, the Chinese agricultural remote sensing monitoring system can be introduced to Southeast Asia, facilitating the establishment of a digital agriculture alliance to enhance global agricultural digitalization and cooperation.

In conclusion, enhancing agricultural net carbon efficiency from the perspective of rural digital economy development requires the cooperation and joint efforts of the government, research institutions, agricultural enterprises, and farmers. It is essential to strengthen the cross-regional flow of digital economy resources and the cultivation of digital talents, promote the research and dissemination of low-carbon agricultural technologies, comprehensively improve agricultural production efficiency, and advance agricultural ecological quality development.

Data availability

The Rural Digital Inclusive Finance Development Index is derived from the Peking University Digital Inclusive Finance Index Research Report, but the availability of data is restricted and its use in this research is authorised and therefore not publicly available. However, data is available at the reasonable request and permission of the Peking University Digital Finance Research Centre. Other data are available to the public under a Creative Commons licence at https://data.cnki.net/. Corresponding author may be contacted if data from this study are required.

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Rui Dong wrote the main manuscript, Qingkai Kong carried out the analysis of the article's data, Qiang Gao and Ligang Ren gave important instructions on the framework of the paper, and all the authors reviewed the manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

Additional information

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