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Impact of rural digital economy development on agricultural eco-efficiency: evidence from mainland China

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The integration of the digital economy with rural development is of great significance as it plays a pivotal role in mitigating carbon emissions and environmental pollution in agriculture, thereby contributing to the evolution of agriculture in a green and sustainable manner. This study aims to examine the impact and mechanisms of rural digital economy development (RDED) on agricultural eco-efficiency (AEE). Specifically, based on provincial-level panel data from China spanning from 2011 to 2021, we evaluate China's AEE by employing the super-efficiency slacks-based measure (Super SBM) model, taking into account the positive externality of agricultural carbon sinks. Then we analyze the impact and mechanisms of RDED on AEE using the two-way fixed effects model. The findings indicate that: (1) RDED significantly promotes AEE, and this conclusion remains robust even after being tested by replacing the explained variable, altering the sample interval, and including more control variables; (2) RDED can significantly drive AEE in the midwestern regions of China, but the promotion effect on the eastern region has not been fully demonstrated. Additionally, the promotion effect in southern China is greater than that in northern China; (3) agricultural science and technology investment partially mediates the impact of RDED on AEE. Moreover, agricultural science and technology innovation has a positive moderating effect on the relationship between RDED and AEE. Lastly, this study provides new evidence and policy recommendations for developing countries, such as China, to proactively facilitate the coordinated development of the rural digital economy and agricultural ecology, and attain green and sustainable ecological agriculture.

KEYWORDS

rural digital economy development, agricultural eco-efficiency, agricultural science and technology input, agricultural science and technology innovation, sustainable agricultural development

1 Introduction

The growing trend of global warming, primarily attributed to the release of greenhouse gases, has generated worldwide apprehension and expedited the global shift towards environmentally friendly and low-carbon practices in both production and lifestyle. Agriculture, being a key sector in driving economic development, has been identified as a substantial contributor to the overall increase in global carbon emissions (Cui et al., 2022).

China, as one of the major agricultural countries, has paid a huge price in terms of resources and the environment during its development process, despite achieving sustained rapid growth in the agricultural economy at a rate of nearly 6% over the past three decades. With the swift advance of urbanization and industrialization, an increasing amount of arable land has been occupied and converted into construction land. In order to increase agricultural yields, there has been extensive utilization of pesticides, fertilizers, agricultural film, machinery, and other production factors, leading to carbon emissions and non-point source pollution in agriculture (West and Marland, 2002; Yan and Neng, 2016). Such a crude mode of agricultural development not only hampers agricultural production efficiency and resource allocation, but also poses severe constraints on the low-carbon and sustainable development of agriculture, placing immense pressure on China's resources and environment (Liu et al., 2020; Zou et al., 2020; Zhang C. et al., 2022). Consequently, it is imperative to prioritize the promotion of green agriculture development and address the urgent need for coordinated development of the economy, resources, and environment in China.

Agricultural eco-efficiency mainly refers to the reduction of inputs and resource consumption in agriculture, as well as the mitigation of pollution and ecosystem damage, while simultaneously promoting agricultural economic development (Fang and Zeng, 2021). It serves as a scientific assessment tool for evaluating the interplay between the agricultural economy, environment, and resources (Sun et al., 2014; Wang and Chen, 2020).

In recent years, the digital economy, centered on digital technology and data elements, has become an essential part of the global and Chinese economies by virtue of its high proliferation, scale effect, and network effect (Kong and Li, 2023). Moreover, the application of information technology in rural areas has facilitated the expansion of the digital economy into the countryside, thereby contributing to the advancement of agricultural modernization and rural development. Digitalization, networking, and intelligence are accelerating the penetration of the system of rural agricultural industry, production, and management, which will bring new opportunities for green agricultural development (Yan et al., 2022).

In this context, this paper takes China as an example to comprehensively measure the rural digital economy development (RDED) and agricultural eco-efficiency (AEE) respectively, and deeply explores the intrinsic connection and influence mechanism between the two from the empirical level. Not only does this help to supplement and enrich the rural digital economy literature, provide new ideas and methods for improving agricultural eco-efficiency, but also has vital practical significance and pragmatic value to facilitate the coordinated development of the agricultural economy and ecological environmental protection, and to fulfill the sustainable development of green and low-carbon agriculture.

2 Literature review

2.1 Agricultural eco-efficiency

The concept of eco-efficiency was initially proposed by German scholars (Schaltegger and Sturm, 1990), which encompasses the idea of economic and ecological efficiency (Baum and Bieńkowski, 2020). Agricultural eco-efficiency, an extension of eco-efficiency within the agricultural domain, emphasizes the sustainable utilization of agricultural resources (Wang et al., 2022). It advocates a contemporary eco-agricultural development model that highlights appropriate quantity, high quality, pollution reduction, and resource conservation. Existing research on agricultural eco-efficiency primarily concentrates on measurement methods, influencing factors, and spatial and temporal variations.

The evaluation methods for assessing agricultural eco-efficiency have undergone a progression from the ratio method, life cycle assessment method (Soteriades et al., 2016), ecological footprint analysis method (Passeri et al., 2013), to more advanced techniques such as the stochastic Frontier method (Lio and Hu, 2009), and data envelopment analysis method (Liu et al., 2020). These advancements reflect the continuous efforts of scholars to put forward more accurate measurements in response to changing ecosystem requirements and to boost sustainable agricultural development. In existing research, the indicator systems of agricultural eco-efficiency pay more attention to the negative externalities on the environment, such as agricultural carbon emissions and non-point source pollution (Liu et al., 2020; Ma and Li, 2021; Zhuang et al., 2021; Ji and Hoti, 2022), while ignoring the positive environmental output of agricultural production, the agricultural carbon sink (Li et al., 2022). Agricultural carbon sink usually refers to the carbon fixed by crops from the atmosphere in agricultural industry (Li and Wang, 2023), which has been recognized as an important part of the low-carbon agricultural development. Indicator systems that only consider negative environmental externalities degrade the comprehensiveness and accuracy of AEE evaluations and are not effective in assessing the sustainability of the agricultural system (Zhang C. et al., 2022).

In terms of influencing factors, scholars have analyzed various factors, including the level of urbanization (Li et al., 2022), the degree of financial support for agriculture (Liu et al., 2020), the structure of crop planting (Akbar et al., 2021), the rate of agricultural disaster (Ji and Hoti, 2022), and the density of machinery (Pang et al., 2016). Additionally, scholars have employed spatial econometric models and geographical detectors to examine the spatial and temporal patterns, spatial aggregation degree, spatial spillover effects, and spatial and temporal heterogeneity of agricultural eco-efficiency (Liu et al., 2020; Liao et al., 2021; Zhang C. et al., 2022; Cui et al., 2022; Li et al., 2022; Wang et al., 2022). Their findings indicate significant disparities in agricultural eco-efficiency and uneven agricultural green development across different regions.

2.2 Rural digital economy and green development of agriculture

The rural digital economy refers to a series of economic activities based on the upgraded digital infrastructure in rural areas, utilizing digital information technologies such as the Internet, cloud computing, and blockchain to empower the digital transformation of agricultural development and the digital enhancement of farmers' lives (Mu and Ma, 2021). By optimizing the allocation of agricultural production factors and adopting green technologies, the digital economy can ensure scientific agricultural production and efficient management systems (Jiang et al., 2022). Meanwhile, it can also reduce resource wastage and environmental pressure by minimizing inputs that might hinder nutrient cycling, carbon sequestration, and pest control (Lajoie-O'Malley et al., 2020), thus significantly increasing the green total factor productivity of agriculture (Hong et al., 2023) and realizing the green development of agriculture. The construction of digital villages, which involves the integration of the digital economy and traditional agriculture, has become the core driving force for high-quality agricultural development by fully leveraging the innovation diffusion effect of networking, the spillover effect of information and knowledge, as well as the technological universality effect of digitization (Sun et al., 2022). The development of digital villages is also conducive to the acceleration of rural digital transformation, the activation of new rural industries and formats featured with digitalization (Cui and Feng, 2020), and a significant reduction in agricultural carbon emission intensity through the effects of scale operation, structural optimization, and technological progress (Yang et al., 2023). Overall, it is evident that the progress of rural digital economy will stimulate rural sustainable development.

To sum up, whereas many scholars have conducted sufficient research on agricultural eco-efficiency and the impact of the digital economy on high-quality agricultural development, there is a lack of literature that specifically addresses the relationship between rural digital economy development and agricultural eco-efficiency, as well as the underlying mechanisms of this relationship. In addition, the existing literature rarely considers the integration of agricultural net carbon sink into the evaluation index system of AEE, neglecting the positive impact of agricultural production on the environment. This not only decreases the comprehensiveness and accuracy of the evaluation results, but also underestimates the sustainability potential of the agricultural system. Consequently, this paper will incorporate agricultural net carbon sinks into the agricultural eco-efficiency evaluation system, and investigate the intrinsic connection between the rural digital economy development and agricultural eco-efficiency, and empirically test the influence mechanisms. Besides, based on the findings, suggestions will be offered to unleash the development potential of the rural digital economy, enhance agricultural ecoefficiency, promote the green development of agriculture, and facilitate the construction of eco-civilization.

3 Theoretical analysis

3.1 Impact of rural digital economy development on agricultural eco-efficiency

In the digital information era, the integration of digital technology with modern agriculture and rural society has facilitated the emergence of the rural digital economy and the transformation of the agricultural industry chain to informatization. By implementing environmental monitoring systems in agriculture prior to and during production, as well as cultivating new rural e-commerce businesses post-production, it is possible to enhance agricultural production efficiency and the carbon sequestration capacity of farmland (Zhang and Xiu, 2022), thus stimulating the advancement of precise, eco-friendly, and sustainable agriculture and ultimately leading to improved agricultural eco-efficiency. Specifically, the impact of rural digital economy development on agricultural eco-efficiency can be reflected in the following aspects:

Firstly, the development of the rural digital economy fuels the formation of new businesses in agriculture and rural areas. The rural digital economy, with data and information elements, drives the digital transformation of the entire process of agricultural production and operation and the extension of the agricultural value chain (Wen and Chen, 2020). The application of digital technology has given rise to innovative development modes such as precision agriculture, digital agriculture, and smart agriculture. These cutting-edge approaches can effectively mitigate risks and costs associated with agricultural production, which enables scaled-up production and enhanced efficiency of agricultural practices (Mu and Ma, 2021), thereby contributing to the sustainable development of agriculture.

Secondly, the development of rural digital economy plays a crucial role in mitigating agricultural carbon emissions and improving carbon sequestration. It has been indicated that the digital economy development is beneficial for promoting the utilization of arable land to reduce agricultural carbon emissions, with green technological innovation playing a significant mediating role in this regard (Li J. et al., 2023). Improving and adjusting agricultural land use management through digital technologies can further increase agricultural carbon sinks (Wang et al., 2011). Additionally, real-time monitoring of farmland soil and emissions contributes to decision-making processes concerning ecological environment restoration and pollution prevention, thereby bolstering the capacity for agricultural carbon sequestration (Yang et al., 2023).

Thirdly, the rural digital economy development is conducive to promoting green and low-carbon consumption. The application of digital technology enables the traceability of agricultural products, catering to the increasing demand for environmentally friendly and low-carbon goods among consumers (Wan and Tang, 2022). Moreover, it facilitates the stimulation of demand-induced effects through network media and consumption platforms, effectively breaking down information barriers between producers and consumers (Su et al., 2021; Li and Fan, 2022). In that case, agricultural producers can establish accurate connections with the market, compelling agricultural business entities to adopt low-carbon production practices from a demand-driven perspective while expanding the supply of green and low-carbon agricultural products (Yang et al., 2023).

Fourthly, with the deep integration of the digital economy and rural areas, the practice mode of digital financial services for agriculture, rural areas, and farmers has been created. It has been demonstrated that digital finance can significantly reduce agricultural carbon emissions (Chang, 2022; Ma et al., 2022). By fully leveraging the core functions of finance, such as capital formation, capital allocation, and innovation incentives, digital finance markedly expands the scope of green investment in the agricultural sector. It optimizes the allocation of green capital in agriculture and provides financial support for research, development, and innovation in the agricultural green industry (Yang et al., 2022). Consequently, it promotes the organic coordination between agricultural technology development, environmental governance in agriculture, and economic transformation within this sector. This approach facilitates balanced development of the agricultural ecological environment while ultimately enhancing agricultural ecological efficiency (Li et al., 2023b). Based on the above analysis, the following hypothesis is proposed:

Hypothesis 1. Rural digital economy development can promote agricultural eco-efficiency.

3.2 Mediating effect of agricultural science and technology investment

Due to geographical limitations, it is more difficult to raise funds in rural areas compared with urban areas. Moreover, the primary industry is vulnerable to natural disasters and other factors, making it inherently characterized by high risk and low return. All this makes the allocation of financial resources more tilted to other industries, resulting in agricultural science and technology can not get enough capital investment support. With the increasing importance attached to the digital economy development in various regions, especially the rapid development of digital industrialization, the pillar of the digital economy, will accelerate the promotion of science and technology investment and industrialization (Xiao and Xu, 2022). Guiding the flow of social capital to the agricultural industry through increased investment in agricultural science and technology will help to motivate social talents to cluster for research and promote the modernization of agriculture (Ge et al., 2022). Thus, the development of a rural digital economy will inevitably drive an increase in agricultural science and technology input.

Agricultural science and technology investment is the basis and guarantee of agricultural industry digitalization, which can accelerate the transformation of sustainable agricultural production mode, and then improve agricultural eco-efficiency. On the one hand, the increased investment is conducive to accelerating the research and application of green agricultural production technologies, such as agricultural waste recycling, green prevention and control of harmful organisms and efficient water-saving irrigation (Yin, 2017; Yi et al., 2021). On the other hand, agricultural research input can further contribute to the growth of agroecological efficiency by digitalizing agriculture (Wu et al., 2019), improving human capital (Li et al., 2023b), promoting labor transfer (Fang et al., 2020), and providing public infrastructure (Zhuo and Zeng, 2018). Thus, it can be argued that RDED can ultimately contribute to AEE by having a positive effect on agricultural science and technology input. Based on this, we put forward the following hypothesis:

Hypothesis 2. The RDED acts on AEE through agricultural science and technology investment.

3.3 Moderating effect of agricultural science and technology innovation

The level of agricultural science and technology innovation reflects the extent of technological change and progress utilized in agricultural production. It has been revealed that the rate of technological progress dominants the change of agriculture TFP (Chen and Mu, 2022). To be specific, the application of various green innovative technologies such as clean or energy-saving equipment can curb carbon emissions (Hu, 2018), and reduce the consumption of natural resources and ecological environment damage in the process of agricultural production and operation. Besides, the efficiency of scientific and technological innovation can also achieve the effect of agricultural carbon emission reduction through the agglomeration of agricultural industries and the upgrading of agricultural industrial structure (Zhao and Zhao, 2023). It is believed that agricultural science and technology innovation will accelerate the green transformation of agriculture and is an effective measure to enhance agricultural eco-efficiency (Zhang F. et al., 2022).

A study has found that the digital economy exhibits non-linear characteristics in driving green transformation of industries, contingent upon the level of science and technology innovation (Li Z. et al., 2023). The promoting effect of digital economy on the integrated development of rural industries is continuously enhanced by the improvement of the agricultural scientific and technological innovation degree (Huang W et al., 2023). As the extent of agricultural science and technology innovation improves, the development of digital economy will overcome the technological bottleneck, and then attract a large number of talents and capital inflow, which in turn will stimulate innovation vitality (Yan and Chen, 2022). Based on the above discussion, this paper argues that when the level of agricultural science and technology innovation is high, RDED can expedite the commercialization of agricultural research findings and agricultural green transformation, thus further enhancing AEE. Therefore, this paper sets forth the following hypothesis:

Hypothesis 3. Agricultural scientific and technological innovation plays a positive moderating role in the impact of RDED on AEE.

4 Methodologies

4.1 Two-way fixed effect model

The two-way fixed effect model can simultaneously address the problem of omitted variables that do not change with time, but change with individuals, and those which do not change with individuals, but change with time (Halder and Malikov, 2020). Thus, to verify the proposed hypothesis, we construct a two-way fixed effect model of the impact of the rural digital economy development on agricultural eco-efficiency. Referring to existing research (He et al., 2022), the logarithm transformation of each indicator is carried out to alleviate the potential heteroscedasticity problem, and the formula is constructed as follows:

$$lnAEE_{it} = \beta_0 + \beta_1 lnRDED_{it} + \beta_2 lnControl_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{1}$$

In Equation 1, $lnAEE_{it}$ and $lnRDED_{it}$ represent the agricultural eco-efficiency and the rural digital economy development of the province i in the period t. The vector $lnControl_{it}$ encompasses all the control variables, containing the level of urbanization (UR), level of agricultural mechanization (AMI), crops planting structure (CPS), financial support for agriculture (FSA) and agricultural industry development (AID). Besides, β_0 is the intercept term, β_1 and β_2 are the coefficient parameters corresponding to the explanatory variables. The time effect, λ_t, remains constant across individuals, while the individual effect, μ_i remains constant over time. Lastly, ε_{it} denotes the random disturbance term.

4.2 Mediating effect model

In order to explore the possible internal mechanism of rural digital economy development on agricultural eco-efficiency, this study further verifies the intermediary role of agricultural science and technology investment between the two. The mediating effect model is established as follows:

$$lnARD_{it} = \alpha_0 + \alpha_1 lnRDED_{it} + \alpha_2 lnControl_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (2)$$

$$lnAEE_{it} = \beta_0 + \beta_1 lnRDED_{it} + \beta_2 lnARD + \beta_3 lnControl_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (3)$$

Equation 2 tests whether the development of rural digital economy has an impact on the intermediary variable agricultural science and technology investment. Eq. 3 uses the overall regression model. If α_1 in Eq. 2 and β_1 in Eq. 3 are significant, and β_2 is also significant, indicating a partial mediating effect, otherwise there is a complete mediating effect.

4.3 Moderating effect model

To gain a better grasp of the moderating mechanism of agricultural science and technology innovation (ASTI) at various levels in the impact of RDED to agricultural eco-efficiency, this study incorporates the interaction term between ASTI and RDED to Eq. 1. Then construct the following model to examine the moderating effect.

$$lnAEE_{it} = \beta_0 + \beta_1 lnRDED_{it} + \beta_2 lnASTI_{it} + \beta_3 lnRDED_{it} \cdot lnASTI_{it} + \beta_4 lnControl_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (4)$$

In Equation 4, $lnASTI_{it}$ denotes the level of agricultural science and technology innovation of province i in the period t.

5 Varibles and data

5.1 Explained variable: Agricultural eco-efficiency

5.1.1 Measurement method: Super-SBM

There are several commonly used methods for measuring agricultural eco-efficiency, including Data Envelopment Analysis (DEA), Slack-Based Measure (SBM), and other DEA expansion models (Falavigna et al., 2013; Bai et al., 2018; Zhou et al., 2018; Angulo-Meza et al., 2019). Tone improved the DEA model by incorporating slack variables (Tone, 2001), overcoming the bias in traditional models caused by radial and angular factors. Moreover, he proposed the super-efficiency SBM model next year, which effectively distinguishes multiple decision units that are simultaneously efficient (Tone, 2002), leading to more comprehensive and scientifically sound research findings. This model has been widely applied and has become the mainstream approach for estimating ecological efficiency. Therefore, this study chooses the Super-SBM model to evaluate agricultural eco-efficiency, and the specific model is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1}\frac{s_r{}^g}{y_{rk}{}^g} + \sum_{r=1}^{S_2}\frac{s_r{}^b}{y_{rk}{}^g}\right)} \quad (5)$$

$$\text{s.t}\begin{cases} x_k = X\lambda + s^-, \\ y_k^g = Y^g\lambda - s^g, \\ y_k^b = Y^b\lambda + s^b, \\ s^- \geqslant 0, s^g \geqslant 0, s^b \geqslant 0, \lambda \geqslant 0 \end{cases} \quad (6)$$

In Equations 5, 6, ρ^* denotes the value of agricultural eco-efficiency. m, s_1 and s_2 respectively denote the number of inputs, desired outputs and non-desired output indicators. s^-, s^g and s^b denote the input redundancy, desired output insufficiency and non-desired output excess. λ denotes the weight vector. When $\rho^* \geq 1$, it means that the decision-making unit is effcient. When $\rho^* < 1$, it means that the decision-making unit has efficiency loss, and the input-output structure should be optimized and adjusted.

5.1.2 Input and output indicators

The existing research on the evaluation of agricultural eco-efficiency points out that agricultural production has the dual function of emitting and sinking carbon. Therefore, it is suggested that agricultural carbon sinks be incorporated into the comprehensive evaluation system of agricultural eco-efficiency, which ensures the assessment more systematic and sound. Therefore, based on the actual situation in the process of agricultural production, this paper characterizes agricultural eco-efficiency from three aspects: resource input, economic and ecological development (desirable output), and environmental pollution (undesirable output). The specific evaluation indicators are presented in Table 1.

This study uses labor, natural resources, energy, and chemicals as input indicators (Han and Sun, 2018; Shen et al., 2018). (1) Labor input is characterized by the number of agricultural workers. It is derived by multiplying the ratio of the gross value of agricultural output to the gross value of agricultural, forestry, animal husbandry and fishery output by the number of persons employed in the primary sector. (2) Natural resource input is based on land and irrigation. The total area of sown crops and effective irrigation area are selected to characterize them respectively. (3) Energy input is represented by the total power of agricultural machinery and rural electricity consumption. (4) Chemical input includes the use of fertilizers, pesticides, and agricultural plastic films.

Desired output is characterized by the gross agricultural output value (converted using 2014 as the base period) and the agricultural net carbon sink. Agricultural net carbon sink is the amount of crop carbon absorption that excludes carbon emissions from agricultural materials input in the process of agricultural production. The formula for calculating the total carbon sink of agriculture (Tian and Zhang, 2013) is as follows:

$$S = \sum_{i=1}^{k} S_i = \sum_{i=1}^{k} s_i Y_i (1-r) \Big/ HI_i \quad (7)$$

TABLE 1 The input and output indicators of agricultural eco-efficiency.

Primary indicators	Secondary indicators	Specific defination
Input	Labor	Agricultural employees (10,000 people)
	Natural resources	The total area of sown crops (10,000 hm^2)
		Effective irrigation area (10,000 hm^2)
	Energy	The total power of agricultural machinery (10,000 *kw*)
		Rural electricity consumption (billion *kw*)
	Chemicals	Fertilizer consumption (10,000 *t*)
		Agricultural plastic film usage (10,000 *t*)
		Pesticide usage (10,000 *t*)
Desirable output	Agricultural economic development	Gross agricultural output value (yuan)
	Agricultural ecological development	Total agricultural net carbon sinks (10,000 *t*)
Undesirable output	Environmental pollution	Total agricultural carbon emissions (10,000 *t*)
		Agricultural non-point source pollution (10,000 *t*)

TABLE 2 The coefficients of major crops.

Crops	Economic coefficient	Water content (%)	Carbon absorption	Crops	Economic coefficient	Water content (%)	Carbon absorption
Rice	0.45	12	0.414	Manioc	0.70	70	0.423
Wheat	0.40	12	0.485	Beet	0.70	75	0.407
Corn	0.40	13	0.471	Cotton	0.10	8	0.450
Beans	0.34	13	0.450	Tobacco	0.55	85	0.450
Millet	0.42	12	0.450	Vegetables	0.60	90	0.450
Sorghum	0.35	12	0.450	Melons	0.70	90	0.450
Cane	0.50	50	0.450				

In Equation 7, S represents the carbon absorption of crops, S_i represents the carbon absorption of a specific crop, k represents the type of crops, s_i represents the carbon absorption rate of crops, Y_i represents the economic yield of crops, r represents the moisture content of the crops, and HI_i represents the economic coefficient of crops. The coefficients of the major crops are shown in Table 2.

Agricultural carbon emissions are calculated by multiplying the carbon emission index by the corresponding carbon emission coefficient (Li et al., 2011). The estimation formula is as Eq. 8, then use Eq. 9 to calculate the agricultural net carbon sink.

$$E = \sum E_i = \sum T_i Q_i \tag{8}$$

$$C = S - E \tag{9}$$

In Equation 8, E represents the total amount of agricultural carbon emissions, E_i represents the total amount of agricultural carbon emissions from various carbon sources, T_i represents the total amount of agricultural carbon emissions from the i th carbon source, and Q_i represents the carbon emissions coefficient of the i th carbon source. The agricultural carbon emissions coefficients are: agricultural film 5.18 kg/kg, pesticide 4.9341 kg/kg, fertilizer 0.8956 kg/kg, diesel 0.5927 kg/kg, agricultural irrigation 20.476 kg/hm^2, tillage 312.6 kg/km^2. In Equation 9, C is the agricultural net carbon sink.

Undesirable output includes agricultural carbon emissions and agricultural non-point source pollution. Referring to the existing literature (Pan and Ying, 2013; Zhang et al., 2021), non-point source pollution in agriculture is a term to describe environmental pollution primarily resulting from the use of fertilizers, pesticides, and agricultural plastic films. The volume of agricultural non-point source pollution is calculated as the application amount multiplied by the respective loss rate, with loss rates of 65% for fertilizer, 50% for pesticides, and 10% for plastic film residue.

China's national and regional agricultural eco-efficiency from 2011 to 2021 is depicted in Figure 1. Overall, China's agricultural eco-efficiency showed a fluctuating upward trend during the study period, peaking at 0.78 in 2021. This positive trend can be attributed to the prioritization of green development outlined in China's Twelfth Five-Year Plan, which was introduced in 2011. Since then, various regions within China have endeavored to implement the national green development requirements and strengthen the management of agricultural resources and environmental conservation.

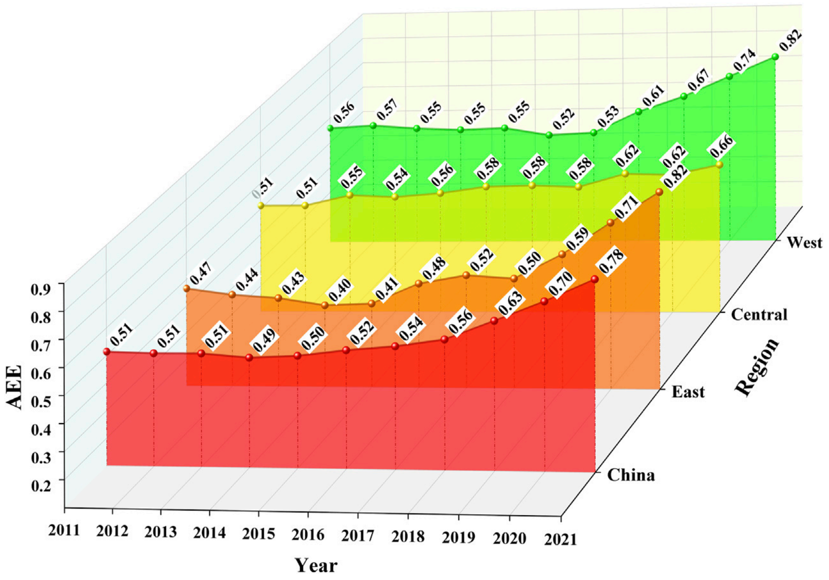

FIGURE 1
China's national and regional agricultural eco-efficiency.

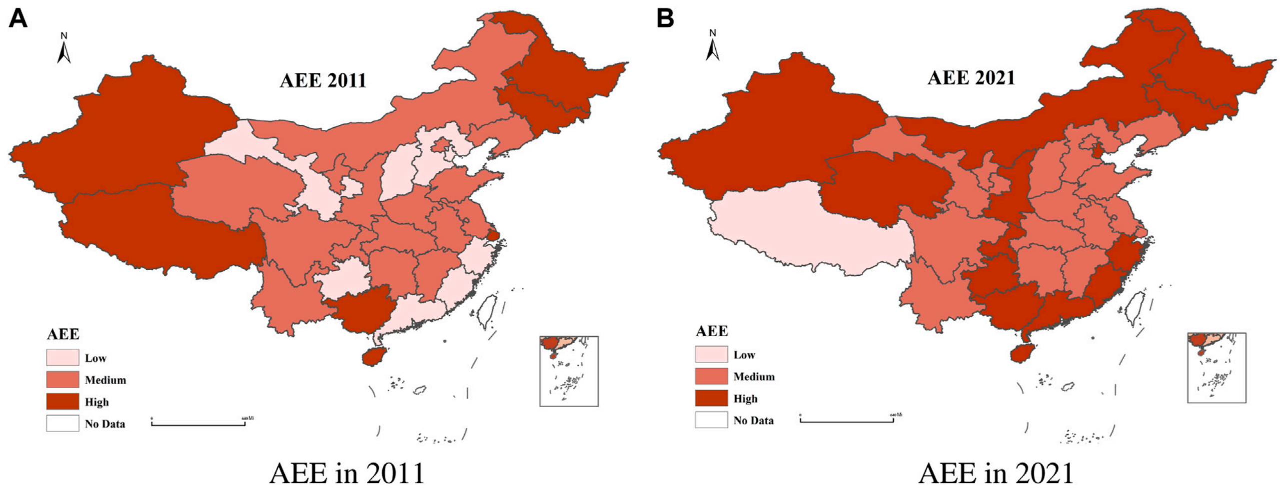

FIGURE 2
China's provincial agricultural eco-efficiency.

In terms of spatial distribution, there are evident differences in agricultural eco-efficiency among the three major economic zones in China. In most years, the central and western regions have shown higher levels of eco-efficiency compared to the national average. Conversely, the eastern region only caught up with the average after 2020. Notably, none of the regions have reached an effective state, thus indicating substantial potential for improvement of agricultural eco-efficiency throughout the country.

The reasons behind these differences can be attributed to various factors. In the eastern region, early agricultural modernization has resulted in a stronger intensity of agricultural development, leading to greater damage to the ecological environment. Nonetheless, efforts in green agriculture and pollution control have been initiated in recent years, resulting in increased farmers' environmental awareness and a significant rise in agricultural eco-efficiency. In contrast, the growth of agricultural eco-efficiency in the central region has been relatively slow. Both the level of agricultural modernization and the degree of intensification are weaker compared to the eastern region. Thus, the control of agricultural pollution remains feeble, limiting its potential for agricultural green development. Despite the poorer endowment of natural resources in the western region, the intensity of agricultural development is also comparatively low. Consequently, the damage to the ecological environment is less severe, resulting in a somewhat higher agricultural eco-efficiency than the national average.

Figure 2 illustrates the inter-provincial comparison of China's agricultural eco-efficiency in 2011 and 2021. The 31 provinces have

TABLE 3 Evaluation index system of rural digital economy development.

Core indicator	Primary indicators	Secondary indicators	Specific defination	Type
Rural digital economy development level	Rural digital Infrastructure construction	Rural Internet penetration rate	Rural Internet broadband access users/rural resident population	+
		Rural smartphone penetration rate	Rural mobile phone ownership per million households at the end of the year	+
		Rural radio and television network coverage rate	Rural cable radio and television household rate	+
		Agricultural meteorological observation scale	Agricultural meteorological observation stations	+
	Argricultural digitization	Digital transaction of agricultural products	Agricultural products network retail sales	+
		Investment in agricultural production	Investment in fixed assets of agriculture	+
		Rural digital base	The number of Taobao villages	+
	Rural digital services	Rural information technology radiation range	Rural delivery route length	+
		Consumption level of digital services	Per capita transportation and communication expenditure of rural households	+
		Rural Internet Payment	Rural online payment index	+
		Rural information technology application	The average number of deliveries per week in rural areas	+

been categorized into three groups—low, medium, and high efficiency—using the natural breakpoint method, revealing noticeable differences among them. Over time, the distribution of China's agricultural eco-efficiency has evolved. Initially, there was high efficiency in marginal areas and low efficiency in certain central and southeastern coastal regions. However, the current distribution showcases high levels of agricultural eco-efficiency in some western, northeastern, and southeastern coastal regions. Despite the remarkable improvement across all regions in China, there still exist imbalances, which are likely related to the level of economic development in each region. Provinces in the eastern region are economically developed and possess the capacity to support agricultural modernization. Moreover, even though the southeastern coastal region has a relatively low proportion of agriculture, the concept of agroecology has been gradually strengthened, leading to a more significant increase in agricultural ecological efficiency. In contrast, some regions in the central and western areas continue to employ crude production and management practices in their agricultural development, resulting in significant resource wastage and environmental pollution. Consequently, these regions still maintain a medium level of agricultural eco-efficiency.

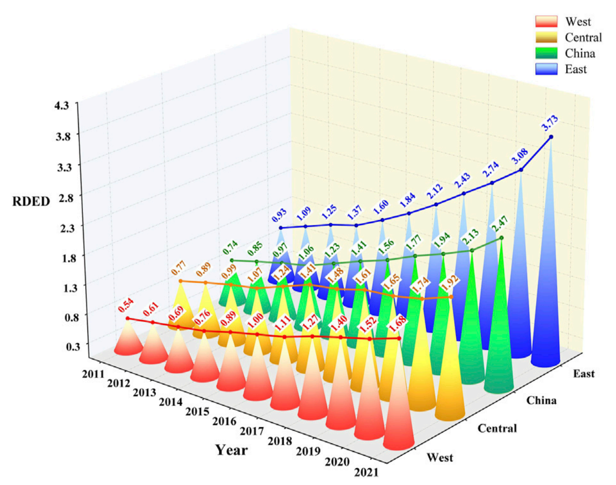

FIGURE 3
China's national and regional rural digital economy development.

5.2 Explanatory variable: Rural digital economy development

5.2.1 Construction of evaluation index system

Currently, there is no consensus on the definition of rural digital economy. Scholars have varying perspectives on the establishment of a rural digital economy index system. Based on a review of relevant literature (Cui and Feng, 2020; Mu and Ma, 2021; Aimin et al., 2022; Wu G. et al., 2022; Yue et al., 2023) and considering data availability, this study constructs an evaluation index system for the development of the rural digital economy from three dimensions: rural digital infrastructure construction, agricultural digitization, and rural digital services. The specific description of the evaluation index system is shown in Table 3.

5.2.2 Measurement method: Entropy method

In measuring the rural digital economy development, commonly used methods include the entropy method, the principal component analysis method (PCA), the analytic hierarchy process (AHP), etc. The entropy method, in particular, is well-suited for evaluating different research objects over multiple periods as it assigns weights to indicators based on their relative degree of change within the system. This approach has been utilized in previous studies (Maheswarappa et al., 2011; Ahmed, 2022). Consequently, this study will employ the entropy method to determine the weights of the comprehensive index for assessing the rural digital economy development in different regions and different years.

The development of China's rural digital economy at the national and regional levels from 2011 to 2021 is depicted in Figure 3. The level of rural digital economy development has shown a gradual increase year by year, with significant variations in growth rates among different regions. Overall, the growth of the rural digital economy development follows the trend of "eastern >national >central >western". This indicates that the eastern region, benefiting from its geographical location and economic progress, has surpassed the national average in the construction and advancement of smart villages and digital agriculture. Conversely, the central and western regions are experiencing slower development and should capitalize on their unique resource endowments to expedite digital transformation and tap into the potential for rural digital economy development.

5.3 Mediating variable: Agricultural science and technology investment

Based on the above theoretical analysis, it is known that the rapid development of rural digital construction can effectively improve the agro-ecological system. This improvement can be attained by promoting the development of sustainable agriculture, which is expected to be facilitated by increasing investment in agricultural science and technology. To measure the input of agricultural science and technology, this paper refers to the existing literature (Wang and Zuo, 2021; Huang Y et al., 2023) and proposes multiplying the provincial expenditure on research and experimental development (R&D) by the ratio of gross agricultural product to gross regional product.

5.4 Moderating variables: Agricultural science and technology innovation

Agricultural science and technology innovation plays a crucial role in enhancing the effectiveness of agricultural resource allocation and promoting the adjustment of agricultural structure. This, in turn, facilitates the sustainable development of agriculture and improves the efficiency of agricultural production. Furthermore, the acceleration of rural digital construction and the progress of technological innovation have led to the emergence and application of green agricultural technologies and production methods. These advancements further contribute to the improvement of agricultural ecological efficiency. Therefore, based on the existing literature (Wu L. et al., 2022; Lai et al., 2022; Huang Y et al., 2023), this paper proposes a measure of the agricultural science and technology innovation by dividing the number of patent applications for agriculture, forestry, animal husbandry, and fishery by the resident population.

5.5 Control variables

To mitigate the potential bias arising from omitted variables, this study draws upon the existing literature (Wu L. et al., 2022; Yan et al., 2022; Jin et al., 2023) and selects the following control variables: (1) the level of urbanization (UR) is measured by the ratio of the urban population to the total population at the end of the year; (2) the level of agricultural mechanization (AMI) is quantified as the total power of agricultural machinery divided by the sown area of crops; (3) the crops planting structure (CPS) is represented by the ratio of the grain sown area to the total sown area of crops; (4) financial support for agriculture (FSA) is assessed by comparing local agricultural and forestry expenditures to general government budget expenditures; (5) agricultural industry development (AID) is measured by dividing the added value of the primary industry by the gross regional product.

5.6 Data sources and descriptive statistics

The research samples in this paper consist of panel data from 31 provinces (municipalities and autonomous regions) in China spanning the years 2014–2021 (due to the availability of data, the research area does not include Hong Kong Special Administrative Region, Macao Special Administrative Region and Taiwan Region). The relevant data is sourced from various reputable publications and institutions, including the National Bureau of Statistics of China, China Statistical Yearbook, China Rural Statistical Yearbook, China Fixed Assets Statistical Yearbook, China Tertiary Industry Yearbook, statistical yearbooks of different provinces, the China Taobao Village Research Report by Ali Research Institute, Peking University Digital Inclusive Financial Index, China Human Resources Report by the Human Capital and Labor Economy Research Center of the Central University of Finance and Economics, and the China Patent Information Center website. To address missing data for certain indicators in specific years, multiple interpolation techniques are employed, and a 1% winsorization is applied. The descriptive statistics of each variable are presented in Table 4.

6 Empirical results

6.1 Fixed effects regression

Mixed regression, fixed effects model, or random effects model are commonly used for panel data analysis. In this paper, we conducted several tests to determine the most appropriate model. Firstly, an F-test was performed, yielding an F-value of 27.43 and a p-value of 0. This result indicates that the fixed effects model outperforms the mixed regression model. Subsequently, a Hausman test was conducted, which resulted in a p-value of 0, rejecting the initial hypothesis of choosing the random effects model. Thus, we adopted the fixed effects panel model. Additionally, we included annual dummy variables to examine individual time effects. The joint significance test of all year dummy variables yielded a p-value of 0, strongly rejecting the null hypothesis of no time effect. Consequently, we selected the

TABLE 4 Descriptive statistics.

Type	Variables	Codes	N	Mean	Std	Min	Max
Explained	Agricultural eco-efficiency	AEE	341	0.569	0.241	0.235	1.042
Explanatory	Rural digital economy development	RDED	341	0.146	0.091	0.027	0.526
Mediating	Agricultural science and technology investment	ARD	341	31.55	30.14	0.161	122.5
Moderating	Agricultural science and technology innovation	ASTI	341	1.488	1.857	0.057	9.873
Control	Level of urbanization	UR	341	0.581	0.130	0.258	0.893
	Level of agricultural mechanization	AMI	341	0.700	0.355	0.298	2.291
	Crops planting structure	CPS	341	0.661	0.145	0.371	0.966
	Financial support for agriculture	FSA	341	0.116	0.034	0.043	0.188
	Agricultural industry development	AID	341	9.777	5.209	0.282	24.08

TABLE 5 Fixed effect of RDED on agricultural eco-efficiency.

Variables	(1)	(2)	(3)	(4)
lnRDED	0.372***	0.492***	0.352***	0.330***
	(0.035)	(0.080)	(0.107)	(0.106)
lnUR		−0.322		−1.275***
		(0.322)		(0.377)
lnAMI		−0.322***		−0.360***
		(0.101)		(0.099)
lnCPS		0.312		0.518
		(0.327)		(0.320)
lnFSA		0.120		−0.420***
		(0.130)		(0.139)
lnAID		0.120		0.158
		(0.130)		(0.141)
Province FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	341	341	341	341
R^2	0.273	0.351	0.356	0.448
adj. R^2	0.200	0.274	0.268	0.362

Standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

two-way fixed effects model, incorporating fixed year and province effects. To ensure the robustness of the findings, we ran separate regression models with and without control variables. The regression results for the fixed effects model are presented in Table 5.

Table 5 clearly demonstrates that the regression coefficient of rural digital economy development is significantly positive at the 1% level across all models. This finding indicates that an increase in the level of rural digital economy development effectively contributes to the improvement of agricultural eco-efficiency, thus confirming Hypothesis 1.

The analysis primarily focuses on columns (3) and (4) for fixed years. Specifically, in column (3), it is evident that for every 1% increase in the level of rural digital economy development, agricultural eco-efficiency improves by 0.352%. There are several reasons for this:

Given the rapid development of the rural digital economy, digital technology empowers the entire process of agricultural production and operation by facilitating element aggregation, technological penetration, and institutional innovation (Wan and Tang, 2022). As a result, it not only enhances the efficiency of agricultural production but also expands the scale of agricultural operation. Furthermore, the integration and promotion of green and efficient technologies can help reduce the amount but increase the efficiency of chemical fertilizers and pesticides, and save energy and reduce emissions of agricultural machinery. Therefore, the development of the rural digital economy not only fosters the deep integration of new information technology and rural socio-economic development but also enables the green and low-carbon transformation within agriculture.

Moreover, in column (4) of Table 5, where control variables are included, the regression results remain generally consistent overall. To be specific, it is observed that every 1% increase in the level of rural digital economy development results in a 0.330% increase in agricultural eco-efficiency, further validating Hypothesis 1. In addition, the effects of the level of urbanization, the degree of agricultural mechanization, and the financial support for agriculture on agricultural eco-efficiency are found to be significantly negative at the 1% level of significance.

The increasing level of urbanization (UR) has a negative impact on the enhancement of agricultural eco-efficiency. On the one hand, rapid urbanization will result in a significant outflow of young and skilled talents from rural areas, leading to a severe aging of the agricultural labor force (Li and Xu, 2021). Consequently, there is an increased reliance on agricultural machinery to compensate for the reduced workforce, thereby diminishing agricultural eco-efficiency (Shang et al., 2020). On the other hand, as urbanization accelerates, agricultural producers often resort to excessive use of pesticides and chemical fertilizers in an attempt to improve crop yields, increase economic returns, and even narrow the income gap between urban and rural areas. However, this practice not only depletes natural resources but also causes immeasurable environmental pollution and ecological degradation, significantly impeding the improvement of agricultural eco-efficiency.

The level of agricultural mechanization (AMI) has a significant negative impact on agricultural eco-efficiency. This could be attributed to the increased input of agricultural mechanization, which leads to extensive use of fossil fuels in agriculture. Despite the benefits brought by improved labor efficiency, carbon dioxide and polluting gas emissions outweigh them, hindering the enhancement of agricultural eco-efficiency (Li et al., 2023c).

The regression coefficient of financial support for agriculture (FSA) is significantly negative at the 1% level, indicating that insufficient financial support for agriculture suppresses its positive effect on agricultural eco-efficiency. This is contrary to the existing research (Sun et al., 2022). It may caused by the failure to give full play to the positive guiding role of financial funds. Although the financial input to agriculture in each province has been increasing year by year, there are still some problems such as small scale of agricultural financial expenditure, unreasonable structure of capital expenditure and non-standard use of funds (Li et al., 2023b).

Although not statistically significant, both the crops planting structure (CPS) and agricultural industry development (AID) have a positive effect on agricultural eco-efficiency. The insignificant coefficient for CPS may be owing to the relatively small scale of food crop cultivation. While scaling up and specializing in food crop cultivation can lead to reduced agricultural carbon emissions (Sun et al., 2022), the higher benefits associated with cash crops align more closely with farmers' practical planting choices. Therefore, CPS fails to contribute significantly towards positive outcomes. As for the insignificant coefficient of agricultural industry development, it may be attributed to relatively slow pace of development in the agricultural economy, despite the continuous increase in the share of value added by the primary industry (He et al., 2022). The limited progress is insufficient to promote high agricultural yields and enhance agricultural eco-efficiency.

6.2 Robustness tests

In order to enhance the credibility of the regression findings regarding the relationship between rural digital economy development and agricultural eco-efficiency, this study conducts robustness tests across three dimensions:

6.2.1 Replace the explained variable

In the two-way fixed effects regression, agricultural eco-efficiency calculated based on total pollution emissions of fertilizers, pesticides, and agricultural films is used an explained variable. In an attempt to enhance the robustness of the results, this paper adopts a comprehensive index of agricultural non-point source pollution to re-measure agricultural eco-efficiency, drawing upon existing literature (Lei et al., 2020; Zhang et al., 2021). The result, presented in column (1) of Table 6, demonstrates that the regression coefficient for the rural digital economy development remains significantly positive at the 1% level. This indicates that the conclusion that rural digital economy development significantly boosts agricultural eco-efficiency still holds.

6.2.2 Change the sample interval

Since the development of the rural digital economy was limited by the epidemic in 2020, the data of 2020 is excluded from this paper for further validation. The regression result is presented in column (2) of Table 6, reveals a significant positive coefficient for the core explanatory variable at the 5% level of significance. This suggests that the results obtained from the two-way fixed effects model are credible.

TABLE 6 The robustness tests.

	(1)	(2)	(3)
lnRDED	0.373***	0.248**	0.340***
	(0.097)	(0.112)	(0.102)
ADR			−0.527***
			(0.146)
RHC			0.840***
			(0.191)
CV	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	341	310	341
R^2	0.514	0.417	0.500
adj.R^2	0.438	0.317	0.418

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

6.2.3 Add control variables

Two control variables are introduced - agricultural disaster rate (ADR) and rural human capital level (RHC). Referring to the existing literature (Li and Xu, 2021; Li et al., 2023b), the agricultural disaster rate is expressed as the ratio of the affected area of crops to the total sown area of crops, while the rural human capital is measured by the actual *per capita* rural labor force capital (in 10,000 yuan) estimated by the China Center for Human Capital and Labor Market Research of the Central University of Finance and Economics. The result presented in column (3) of Table 6 shows that, compared to the results of the former two-way fixed effects regression, the regression coefficient for the rural digital economy development remains significantly positive at the 5% significance level. This finding underscores the robustness and reliability of the study's conclusions.

Consistent with the existing literature, agricultural disaster rate has a significant negative impact on agricultural eco-efficiency. The higher the rate of agricultural disasters gets, the greater the loss of factor inputs will be, resulting in a reduction in desired outputs and consequently impeding agricultural eco-efficiency improvement. Furthermore, the rural human capital has a significant positive effect on agricultural eco-efficiency. To enhance agricultural eco-efficiency, it is recommended to upgrade the level of rural human capital and provide digital training to rural residents. This will assist in the penetration of the digital economy in agriculture, leading to the scaling up and modernization of agricultural production and operations. Consequently, agricultural production capacity and efficacy will increase, further enhancing agricultural eco-efficiency.

Based on the robustness test analysis, it is evident that the impact relationship in the fixed effects regression has a certain degree of reliability.

TABLE 7 The heterogeneity analysis.

	(1)	(2)	(3)	(4)
	East	Midwest	North	South
lnRDED	0.019	0.563***	0.496***	0.535***
	(0.193)	(0.152)	(0.110)	(0.195)
CV	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	121	220	165	176
R^2	0.601	0.385	0.690	0.473
adj.R^2	0.491	0.268	0.621	0.360

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

6.3 Heterogeneity tests

Given the vastness of China's territory and the complexity of its topography, the geographic locations and regional resource endowments vary from province to province. This variation may result in differences in the impact of rural digital economy development on agricultural eco-efficiency. Hence, this paper aims to analyze the heterogeneity in terms of geographic location characteristics.

6.3.1 Regional heterogeneity in the East and the Midwest

The division of China's eastern, central, and western regions is primarily characterized by their geographic location and level of economic development. The eastern part of China, being the first to implement the coastal opening policy, has achieved a relatively high level of economic development. In contrast, the central and western regions experience rather poor economic development. These differences in economic development also translate into variations in the degree of digital economy development, industrial structure, and infrastructure across regions. Consequently, the impact of rural digital economy development on agricultural eco-efficiency may exhibit heterogeneity. To address this, the study divides the sample into separate group regressions for the eastern and midwestern regions.

As indicated in columns (1) and (2) of Table 7, rural digital economy development has a significantly positive effect on agricultural eco-efficiency in the midwestern regions, while it is statistically insignificant in the eastern regions. This can be interpreted as follows:

In the midwestern region, the adoption of information technology has helped overcome spatial and temporal barriers in traditional agricultural practices. It has facilitated the emergence of new business models such as agricultural e-commerce, contract agriculture, and healthcare tourism, reducing dependence on chemical fertilizers, pesticides, machinery, and energy. As a result, there is a reduction in agricultural carbon emissions at the source, making the positive impact of rural digital economy development on agricultural eco-efficiency more evident in the midwestern regions. Conversely, the eastern region is already economically developed and has a more comprehensive digital infrastructure. The degree of integration and development of digital technology and agriculture is relatively high in these areas, leading to a relatively limited effect of rural digital economy development on the enhancement of agricultural eco-efficiency.

6.3.2 Regional heterogeneity in the North and the South

China's north and south exhibit significant differences in temperature, climate, precipitation, soil environment, and other natural conditions. These variations result in diverse agricultural resource endowments, farming systems, and production methods. Consequently, there are disparities in basic agricultural production conditions and the choice of policies for agricultural development planning and environmental management. To address this, this study divides the sample into southern and northern regions to examine the regional heterogeneity of the impact of rural digital economy development on agricultural eco-efficiency in each region.

As presented in columns (3) and (4) of Table 7, the regression coefficients of rural digital economy development are both positive at the 1% significance level in the northern and southern regions. This indicates a significantly positive promotion effect of rural digital economy development on agricultural eco-efficiency in both areas. Comparing the regression coefficients, it is evident that the promotion of the rural digital economy development in the South is more pronounced than in the North. This phenomenon can be attributed to the fact:

The northern regions mainly experience temperate monsoon and temperate continental climates, which are characterized by relatively low precipitation. This leads to water scarcity, to some extent, making it a major limiting factor for agricultural development. In comparison, the southern regions encompass more abundant natural resources, including soil and water, and face fewer constraints imposed by climates. These favorable conditions create better conditions for agricultural development. As a result, rural digital economy development has a more pronounced effect on increasing agricultural eco-efficiency in these areas.

6.4 Endogeneity test

The common endogeneity problems can be categorized into three main aspects: omitted variable bias, reverse causation, and data measurement error. For this paper, firstly, although multiple control variables are selected and two-way fixed effect model is adopted, it is inevitable that other explanatory variables may be omitted, resulting in biased parameter estimates. Secondly, RDED is calculated by the comprehensive index system, and the data itself may have problems such as observation factors and measurement errors. Lastly, there may be a bidirectional causality between RDED and AEE. Specifically, RDED helps to upgrade agricultural technology, transform agricultural production, and ultimately improve AEE. And the increased AEE also means higher comprehensive agricultural production capacity, including the reduction of agricultural machinery emissions and precise control of agricultural pollution, which cannot be separated from the support of digital technology.

Therefore, considering the possible problems above, referring to the available literature (Yang et al., 2023), we select the interaction term of the number of fixed telephones per 100 people in each

TABLE 8 The endogeneity test.

	2SLS	
	1st	2nd
lnRDED-iv	0.134***	
	(8.573)	
lnRDED		0.771***
		(0.237)
CV	Yes	Yes
N	341	341
R^2	0.970	0.749
LM	62.00 [0.000]	
Wald	73.50 {16.38}	

In [] is the *p*-value in Kleibergen-Paaprk LM underidentification test, and in {} is the critical value at the 10% level of Stock-Yogo test.
Standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

province in 1984 and the total social fixed asset investment in agriculture, forestry, animal husbandry and fishery in the previous year as the instrumental variable. On the one hand, the traditional post and telecommunications industry is the predecessor of the rural communication industry, while the development of rural digital economy cannot be separated from the construction of information infrastructure, which meets the relevance condition. On the other hand, with the development of emerging communication technologies such as big data and cloud computing, the influence of traditional telecom industry on contemporary economy and society is gradually declining, and it is even more difficult to affect agricultural production. So this satisfies the exogeneity constraint to some extent.

We use two-stage least square (2SLS) to test the model and the results are shown in Table 8 where lnRDED-iv is the instrumental variable. It is evident that the regression coefficient of RDED remains significantly positive at the level of 1%, which indicates that after considering the endogeneity problem, the conclusion that RDED promotes AEE is still robust and reliable. Meanwhile, the LM statistic value is 62.002, corresponding to a *p*-value of 0, suggesting that there is no under-recognition problem; the Wald statistic value is 73.503, which is greater than the threshold value at the 10% level, illustrating that there is no weak instrumental variable problem. Therefore, it can be considered that the instrumental variable is reasonable.

6.5 Impact mechanism tests

6.5.1 Mediating effect test

To further examine the intrinsic mechanism of rural digital economy development on agricultural eco-efficiency, this paper investigates the mediating effect of agricultural science and technology investment by applying Eqs 2, 3. The results of the mediating effect test are presented in Table 9.

In Table 9, column (2) reveals that the rural digital economy development has a significantly positive effect on agricultural science and technology investment (ARD) at the 1% level of significance. This suggests that the development of the rural digital economy has led to an increase in agricultural science and technology input. Column (3) shows the results of the fixed effects regression model when the agricultural science and technology input is included. The coefficients of RDED and ARD are both significantly positive at the level of 5%. In other words, all else being equal, not only does RDED drive a significant increase in ARD, but also the positive changes of both lead to an increase in AEE, albeit with a decrease in the absolute level of the impact of RDED on AEE. Combined with the results of Column (1) and (3) in Table 9 and after calculating, it can be seen that agricultural science and technology investment partially mediates the impact of rural digital economy development on AEE. The magnitude of the mediating effect is 7.2% (0.330–0.258=0.072), which accounts for 19.7% of the total effect (0.072/0.330=0.219).

TABLE 9 The mediating effect of agricultural science and technology investment.

	(1)	(2)	(3)
	lnAEE	lnARD	lnAEE
lnRDED	0.330***	0.333***	0.258**
	(0.106)	(0.061)	(0.110)
lnARD			0.217**
			(0.101)
CV	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	341	341	341
R^2	0.448	0.864	0.457
adj.R^2	0.362	0.843	0.370

Standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 10 The moderating effect of agricultural science and technology innovation.

	(1)	(2)
lnRDED	0.309***	0.284***
	(0.103)	(0.104)
lnASTI	0.297***	0.247***
	(0.087)	(0.093)
lnRDED × lnASTI	0.125***	0.115***
	(0.025)	(0.031)
CV	No	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
N	341	341
R^2	0.416	0.478
adj.R^2	0.331	0.392

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

The above conclusions verify the correctness of Hypothesis 2. Through the analysis of the above mediating effect model, not only the direct effect of RDED on AEE is tested, but also its mechanism and indirect effect are identified, which enables us to have a deeper understanding of the influencing process of RDED on AEE.

6.5.2 Moderating effect test

The previous sections discuss the influencing mechanism of rural digital economy development on agricultural eco-efficiency. However, is there a synergy between other factors and the development of rural digital economy that will further strengthen or inhibit the improvement of AEE? According to the theoretical analysis, under the condition of improved level of agricultural science and technology innovation (ASTI), RDED has an increasingly positive role in promoting AEE. Therefore, this paper applies Eq. 4 to further reveal the joint influence mechanism of RDED and ASTI on AEE. The estimation results are shown in Table 10.

In Table 10, both columns (1) and (2) illustrate that the coefficients of the interaction term between agricultural science and technology innovation and rural digital economy development are significantly positive at the 1% level, regardless of the inclusion of control variables. This suggests that agricultural science and technology innovation has a positive moderating effect. In other words, it strengthens the positive impact of rural digital economy development on agricultural eco-efficiency. Therefore, Hypothesis 3 is supported.

Futhermore, all this implies that while deepening the penetration of digital economy in agricultural fields, we should encourage the innovation of new green agricultural technology as well, such as improved seed breeding, energy saving and emission reduction. Only in this way can we better improve agricultural eco-efficiency and promote sustainable agricultural development.

7 Conclusion, policy recommendations and limitations

7.1 Conclusion

This paper utilizes the super-efficiency SBM model and introduces agricultural net carbon sink as one of the expected outputs to measure the agricultural eco-efficiency of 31 provinces in China from 2011 to 2021. Subsequently, the two-way fixed effects model is applied to investigate the impact of rural digital economy development on agricultural eco-efficiency. Additionally, the mediating effect of agricultural science and technology input and the moderating effect of agricultural science and technology innovation are further discussed. The conclusions are drawn as follows:

(1) The development of rural digital economy significantly promotes agricultural eco-efficiency. In accordance with the results of the two-way fixed effects regression, it is demonstrated that agricultural eco-efficiency tends to increase significantly with the development of the rural digital economy in China. This finding remains robust even after being verified by replacing the explained variable, changing the sample interval, adding control variables and introducing instrumental variables.
(2) There is significant regional heterogeneity in the impact of rural digital economy development on agricultural eco-efficiency. Specifically, the rural digital economy has a significant driving effect on improving agricultural eco-efficiency in the midwestern regions, while its impact on the eastern region is not fully demonstrated. Additionally, as far as the southern and northern regions are concerned, the positive impact of the rural digital economy development in the southern regions on agricultural eco-efficiency is stronger than that in the northern regions.
(3) The mediating effect analysis suggests that agricultural science and technology investment partially mediates the impact of rural digital economy development on agricultural eco-efficiency. Furthermore, the mechanism of moderating effect indicates that agricultural science and technology innovation strengthens the promoting effect of rural digital economy development on agricultural eco-efficiency.

7.2 Policy recommendations

Combining the aforementioned research findings with the practical background, this paper proposes the following suggestions to enhance agricultural eco-efficiency and futher facilitate the harmonious advancement of the agricultural economy and ecology:

(1) Consistently promote the construction of digital villages for high-quality agricultural development. The government ought to intensify investment in rural digital infrastructure and vigorously develop the digital industry to empower agricultural modernization. The penetration and integration of the digital economy into all aspects and

fields of agriculture is expected to transform the production, operation, and service systems of the agricultural industry. Consequently, this will give rise to novel models of modern agricultural industry, thereby effectively mitigating agricultural carbon emissions and enhancing agricultural eco-efficiency.

(2) Implement diversified green agricultural development strategies based on specific regional realities. It is imperative for the government to encourage localities to adopt differentiated policies depending on the distinctive natural resources and agricultural development levels in various regions. Only in this way can we effectively explore and develop innovative paradigms and approaches for green and sustainable agricultural development.

(3) Increase investment in agricultural science and technology and establish a sound mechanism for agricultural research funding. The government should take the priority of agricultural and rural development as the premise, and set up a mechanism that ensures stable growth in investment in agricultural science and technology. This aims to gradually increase the proportion of agricultural scientific and technological input in the gross agricultural product to a level that surpasses the industry average. Furthermore, authorities should attach great importance to the construction of agricultural basic and long-term scientific and technological facilities. The establishment of major scientific research platforms, such as national laboratories in the agricultural field, should be given priority. This will strengthen the leading and supporting role of science and technology in agricultural and rural modernization.

(4) Encourage agricultural science and technology innovation and reinforce basic research on green agriculture. Relevant administrations can use preferential policies, such as tax breaks and fiscal subsidies, to guide individuals and enterprises in strengthening agricultural green technology innovation. It is especially important to promote innovations in new green agricultural technologies, such as agricultural seed cultivation, energy conservation, and emission reduction. These innovations will help reduce the risk and cost of agricultural production, while simultaneously fostering energy conservation and environmental sustainability within the agricultural sector. Additionally, efforts should be made to fortify the transformation and application of scientific research achievements, as well as harness the full potential of science, technology, and digitization to facilitate the high-quality and sustainable development of agriculture, so as to enhance agricultural eco-efficiency.

7.3 Limitations

While this paper provides new empirical evidence on the relationship between rural digital economy development and agricultural eco-efficiency, as well as offers policy recommendations to stimulate the coordinated development of the agricultural economy and rural ecology, there are several limitations that should be acknowledged. Firstly, the measurements of rural digital economy development and agricultural eco-efficiency in this paper are based on China's provincial-level data. It would be beneficial for future research to incorporate more granular data at the county level for a more accurate analysis. Secondly, this paper only covers three dimensions to measure the level of rural digital economy development. To establish a more comprehensive measurement system, future studies could consider incorporating additional representative indicators that capture the nuances of the rural digital economy. Lastly, the transmission mechanisms between the rural digital economy development and agricultural eco-efficiency need to be further scrutinized to provide more holistic, concrete, and unique recommendations for policymaking.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

CC: Conceptualization, Formal Analysis, Methodology, Project administration, Supervision, Writing–original draft. QY: Data curation, Formal Analysis, Software, Validation, Visualization, Writing–original draft. QL: Conceptualization, Formal Analysis, Methodology, Writing–original draft. SL: Data curation, Formal Analysis, Validation, Writing–original draft. HZ: Project administration, Supervision, Validation, Writing–review and editing. XG: Funding acquisition, Project administration, Writing–review and editing. SZ: Data curation, Funding acquisition, Resources, Writing-review and editing.

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Conflict of interest

Author SZ was employed by Bank of Rizhao Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenef.2024.1292248/full#supplementary-material

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