

Research on the Impact of the Digital Economy on the Efficiency of Agricultural Resource Allocation

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Abstract: Based on panel data from 31 provinces in China spanning 2011–2023, this paper employs the DEASBM model, the Malmquist index, and the Tobit model to measure agricultural resource allocation efficiency across provinces, and uses the entropy method to construct a comprehensive digital economy index to examine the impact of the digital economy on agricultural efficiency. On this basis, a mediating effect model is further constructed to identify the pathways through which the digital economy operates. The findings are threefold. First, China’s agricultural efficiency demonstrates an overall upward trend, with total factor productivity growing at an average annual rate of 3.5%, driven primarily by technological progress. Second, the comprehensive digital economy index exerts a significantly positive effect on agricultural efficiency at the 1% level, a conclusion that remains robust after multiple robustness checks. Heterogeneity analysis reveals that this effect is significantly stronger in nonmajor grainproducing areas (coefficient 1.171) than in major grainproducing areas (coefficient 0.556), confirming the “latemover advantage” of the digital economy in regions with weaker foundational conditions. Third, the mediating effect test indicates that per capita telecommunications business volume plays a partial mediating role between the digital economy and agricultural efficiency, with the mediating effect accounting for approximately 10.9%, implying that the digital economy indirectly improves agricultural efficiency by enhancing telecommunications infrastructure. Accordingly, policy recommendations are proposed: strengthening rural telecommunications infrastructure, implementing differentiated strategies based on the distinction between major and nonmajor grainproducing areas, guiding consumption expenditure toward productive investment, and facilitating the transition of agricultural mechanization from quantitative expansion to qualitative upgrading.

Keywords: Digital economy; Agricultural resource allocation efficiency; DEA model; Malmquist index; Tobit; Mediating effect

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1. Introduction

In the context of the global digital economic transformation, the digital economy has become an important force driving agricultural modernization. For a long time, Chinese agriculture has faced problems such as unbalanced allocation and inadequate utilization of resources, and traditional resource allocation models

have struggled to break the “efficiency lockin.” Digital technology, through the flow of data elements and the embedding of intelligent technologies, is bringing a paradigm shift to agricultural resource allocation ^[1]. At the policy level, the *15th Five Year Plan for National Agricultural and Rural Informatization* explicitly proposes that by 2025, agricultural resource utilization efficiency will increase by 20%, the coverage rate of agricultural informatization infrastructure will reach 95%, and the digitalization rate of agricultural production and operation will reach 50%. At present, although China’s agricultural digitalization process is accelerating, overall, the digitalization of the service sector is still more advanced, and there remains considerable room for improvement in industrial and agricultural digitalization ^[2]. Digital technology is moving from pilot projects to fullscale penetration.

2. Literature review

Agricultural resource allocation efficiency is a core issue in agricultural economics. Traditional studies mostly explore optimization paths from the perspective of factor input/output, while the digital economy is regarded as a key force to break the “efficiency lockin” of traditional agriculture ^[3]. From the research progress, academic research on the relationship between the digital economy and agricultural development has shifted from “macroeffect verification” to “mechanism analysis”: early studies mainly focused on the overall impact of the digital economy on agricultural output and labor productivity, basically reaching a consensus that “the digital economy promotes agricultural development.” Therefore, how to scientifically and effectively further supplement the analysis of the impact of the digital economy on agricultural resource allocation efficiency still holds significant importance for the healthy development of agriculture.

Combining existing research findings, the digital economy effectively solves the problems of insufficient agricultural capital input, low efficiency, and high risk by optimizing capital factor allocation, broadening financing channels, reducing transaction costs, and strengthening risk control, thereby injecting strong momentum into the highquality development of agriculture and rural areas ^[4], and has significant impacts on rural economic development ^[5], relative poverty governance ^[6], rural industrial transformation ^[7], rural revitalization, and farmer income increase ^[8]. In terms of highquality development, Yan *et al.* ^[9], by constructing fixedeffects and mediation effect models, revealed that rural digital construction promotes highquality economic development, with the improvement of agricultural resource allocation efficiency being a key transmission path. The research team of Li ^[10] particularly emphasized that the digital economy, through reconstructing agricultural industry chains, fostering new business forms, and promoting technological and organizational change, effectively enhances the allocation and utilization efficiency of agricultural production factors, providing new momentum for the highquality development of rural industries. Regarding poverty governance, Wang and Ji ^[11], based on provincial panel data from 2013 to 2020, showed that the rural digital economy significantly alleviates multidimensional relative poverty by improving information symmetry and liquidity in agricultural factor markets, with this effect partly achieved through enhancing agricultural resource allocation efficiency. At the level of rural revitalization, Sun *et al.* ^[12] revealed the coupling coordination relationship between the rural digital economy and rural revitalization, pointing out that dimensions such as digital infrastructure construction, industrial digital upgrading, and digital industrialization all promote rural revitalization by optimizing the spatiotemporal allocation efficiency of agricultural resources. With respect to farmer income increase, Chen and Cheng ^[13] found that the digital economy affects farmers’ income through multiple pathways such as raising

agricultural labor productivity, enhancing human capital, and promoting employment and entrepreneurship, among which the improvement of agricultural resource allocation efficiency is a core mediating variable. Zhang *et al.* ^[14] further noted that new economic models and digital financial services spawned by the rural digital economy significantly improve the factor allocation capacity of smallholder farmers by alleviating their capital and information constraints. These studies collectively indicate that there exists a multidimensional interactive relationship between the digital economy and agriculture, rural areas, and farmers, with the improvement of agricultural resource allocation efficiency as the core. Future research could further explore the differentiated mechanisms by which the digital economy affects the allocation efficiency of different agricultural factors, as well as the specific pathways of digital technology in optimizing the spatiotemporal allocation of agricultural resources ^[15].

To this end, based on China's provincial panel data from 2011 to 2023, this study comprehensively employs the DEASBM model, Malmquist index ^[16], and Tobit regression methods to systematically analyze the pathways and effects of the digital economy on agricultural resource allocation efficiency, aiming to fill the gaps in existing research and enrich the theoretical framework in the interdisciplinary field of digital economy and agricultural economics.

3. Research hypotheses

Based on the research gaps identified in the literature review and existing theories, this section further examines the mechanisms through which various dimensions of the digital economy affect agricultural resource allocation efficiency and proposes corresponding research hypotheses.

3.1. Optimization effect on agricultural resource allocation efficiency

The digital economy can enhance agricultural production efficiency by optimizing factor allocation, reducing transaction costs, and promoting technology diffusion. The comprehensive index of the digital economy synthesized by the entropy method reflects multidimensional information such as digital infrastructure, digital inclusive finance, and digital logistics. The higher the value, the higher the development level of the digital economy, and the stronger its promoting effect on agricultural resource allocation efficiency. Based on this, the following hypothesis is proposed. H1: The comprehensive index of the digital economy has a significant positive impact on agricultural resource allocation efficiency.

3.2. Heterogeneity effects of the digital economy on agricultural resource allocation efficiency

There are significant differences between major grainproducing areas and nonmajor grainproducing areas in China in terms of agricultural scale, production structure, infrastructure, etc., and the empowering effects of the digital economy may differ across regions. Major production areas have a higher degree of agricultural intensification and may have stronger capacity to absorb digital technologies; nonmajor production areas have weaker foundations, and the digital economy may exhibit a “latemover advantage” ^[17] or more pronounced marginal effects. Therefore, the impact of the digital economy may show significant differences between the two types of regions. Based on this, the following hypothesis is proposed. H2: The impact of the comprehensive index of the digital economy on agricultural resource allocation efficiency exhibits regional heterogeneity.

3.3. The digital economy indirectly enhances agricultural resource allocation efficiency by improving telecommunications infrastructure

The impact of the digital economy on agricultural efficiency may have an indirect transmission path. If the total effect of the digital economy (x) on agricultural efficiency (crt_s) is significant, the effect of the digital economy on telecommunications infrastructure ($ln_telecom$) is significant, and after introducing telecommunications infrastructure, the coefficient of the digital economy decreases significantly while the coefficient of telecommunications infrastructure is significant, then telecommunications infrastructure plays a mediating role. It is expected that telecommunications infrastructure plays a partial mediating role between the digital economy and agricultural efficiency, meaning that the digital economy indirectly enhances resource allocation efficiency by improving the level of telecommunications infrastructure. Accordingly, the following hypothesis is proposed: H3: The digital economy indirectly enhances agricultural resource allocation efficiency by improving telecommunications infrastructure; that is, telecommunications infrastructure plays a mediating role between the digital economy and agricultural efficiency.

4. Research design and methodology

4.1. Model construction and measurement approach

The construction of an evaluation indicator system for agricultural resource allocation efficiency needs to balance scientific rigor and operational feasibility. In measuring agricultural resource allocation efficiency in China, this study employs the SBM model within the DEA framework and the Malmquist index to assess resource allocation efficiency from both static and dynamic dimensions. Drawing on existing studies by relevant scholars^[18], the design adopts an “input–output” framework. The input indicators are mainly constructed from three aspects: human resources, financial resources, and material resources. A comprehensive analysis yields the indicator system for measuring agricultural resource allocation efficiency, as presented in **Table 1**.

Table 1. Indicator system for agricultural resource allocation efficiency

Indicator category	Indicator	Indicator name (element)
Input Indicators	x1	Effective irrigated area (1,000 hectares)
	x2	Grain sown area (1,000 hectares)
	x3	Rural electricity consumption (100 million kWh)
	x4	Total power of agricultural machinery (10,000 kW)
	x5	Employment in primary industry (10,000 persons)
	x6	Agricultural fertilizer application (tons)
Output Indicators	y1	Gross output value of farming, forestry, animal husbandry and fishery (100 million yuan)
	y2	Total grain output (10,000 tons)
	y3	Total carbon emissions (10,000 tons) (undesirable)

This paper takes the agricultural resource allocation efficiency of 31 provinces in China as its research subject. The data are sourced from the China Rural Statistical Yearbook and the China Statistical Yearbook, and relevant data on agricultural resource allocation for 31 provinces (municipalities and autonomous regions) from 2011 to 2023 are selected for analysis (due to data availability, Hong Kong, Macao, and Taiwan are not included).

4.2. Measurement and analysis of agricultural resource allocation efficiency

4.2.1. Static analysis under the SBM model

Using the input-oriented SBM model, this study examines the data of 31 provinces from 2011 to 2023 and comprehensively analyzes the allocation efficiency of agricultural resources from the perspectives of comprehensive technical efficiency (crste), pure technical efficiency (vrste), and scale efficiency (scale).

In 2023, the mean comprehensive efficiency of agricultural resource allocation in China was 0.927, indicating a relatively high overall level, yet with significant interprovincial disparities. Based on the efficiency values and the status of returns to scale, the 31 provinces can be categorized into three types, as shown in **Table 2**.

Table 2. SBM efficiency classification of agricultural resource allocation efficiency in 2023

Category	Feature	Province	Number
Type I: Fully Effective Area	crste=1: both technology and management are at the frontier	Tianjin, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Fujian, Hunan, Hainan, Chongqing, Sichuan, Guizhou, Tibet, Qinghai	15
Type II: Technologically Effective but Scale Insufficient Area	vrste=1, scale<1, rts=irs (increasing returns to scale)	Beijing, Shandong, Henan, Hubei, Guangdong, Guangxi, Yunnan, Xinjiang	8
Type III: Technologically Ineffective and Overscale Area	vrste<1, scale<1, rts=drs (decreasing returns to scale)	Hebei, Shanxi, Inner Mongolia, Anhui, Jiangxi, Shaanxi, Gansu, Ningxia	8

The efficiency pattern presented in **Table 2** profoundly reflects the regional imbalances and stagespecific characteristics of China's agricultural development. In terms of efficiency classification, Type I fully efficient provinces are predominantly concentrated in the Northeast blacksoil region and the developed eastern coastal areas; Type II provinces face the encroachment of urbanization on agricultural space; and Type III provinces are mainly traditional major agricultural provinces, which exhibit a structural contradiction of excessive scale coupled with technological lag. These observations indicate that there is significant regional differentiation in China's agricultural efficiency.

4.2.2. Dynamic analysis based on the Malmquist index

Using DEAP 2.1 software, the Malmquist productivity index for China's agricultural resource allocation efficiency from 2011 to 2023 was calculated and decomposed, yielding the dynamic changes in agricultural resource allocation efficiency. The specific results are presented in **Table 3**, and the trends of total factor productivity and its decomposed components are shown in **Figure 1**.

Table 3. Malmquist index and its decomposition for China's agricultural resource allocation efficiency, 2011–2023

Period	effch	techch	pech	sech	Tfpch
2011–2012	1.000	1.037	1.008	0.993	1.038
2012–2013	0.996	1.057	1.004	0.991	1.052
2013–2014	1.020	1.006	1.012	1.008	1.026
2014–2015	0.999	1.018	0.996	1.003	1.018
2015–2016	1.000	1.044	1.012	0.988	1.043
2016–2017	1.019	1.017	1.010	1.010	1.037
2017–2018	1.028	1.015	1.010	1.018	1.044

Period	effch	techch	pech	sech	Tfpch
2018–2019	0.989	1.078	0.999	0.990	1.066
2019–2020	1.009	1.031	0.997	1.012	1.040
2020–2021	0.995	1.047	0.998	0.997	1.042
2021–2022	0.994	1.056	1.003	0.991	1.049
2022–2023	0.995	0.976	1.000	0.995	0.971
Mean	1.004	1.032	1.004	1.000	1.035

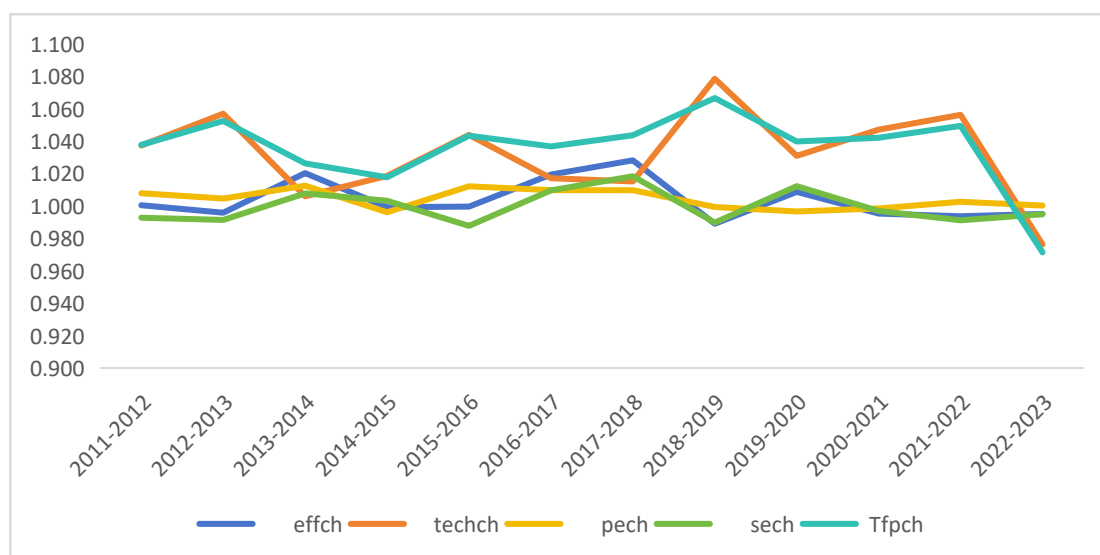


Figure 1. Trends of total factor productivity and its decomposition indicators from 2011 to 2023

The results in **Table 3** present the Malmquist index and its decomposition for China's agricultural resource allocation efficiency from 2011 to 2023. The analysis indicates that the total factor productivity (Tfpch) of agriculture in China exhibited an overall upward trend during the study period, with an average annual growth rate of 3.5%, suggesting that agricultural resource allocation efficiency improved steadily over this timeframe. In terms of decomposition indicators, technological progress (techch) emerged as the primary driver of total factor productivity growth, with an average annual increase of 3.2%, peaking in 2018–2019 (techch = 1.078), reflecting the significant contribution of the introduction, innovation, and diffusion of agricultural technologies to production efficiency. In contrast, improvements in technical efficiency (effch) and scale efficiency (sech) were relatively modest, with average annual growth rates of 0.4% and 0%, respectively, indicating that under existing technological conditions, there remains considerable scope for further enhancement in management and organizational capabilities, factor allocation structures, and economies of scale in agricultural production and operation. However, total factor productivity declined in 2022–2023 (Tfpch = 0.971), mainly attributable to the slowdown in technological progress (techch = 0.976). In summary, the current growth of agricultural total factor productivity in China is predominantly driven by technological progress. Going forward, while continuing to promote agricultural technological innovation, it is essential to optimize resource allocation structures and improve management and operational levels, so as to ensure sustained and steady improvement in agricultural resource allocation efficiency.

5. Analysis of factors influencing the efficiency of agricultural resource allocation in the digital economy

5.1. Model selection and data description

Based on the measurement results above, it can be observed that agricultural resource allocation efficiency is not uniformly effective across all cases. To further examine the factors through which the digital economy influences agricultural resource allocation, this study constructs the following econometric model.

5.1.1. Dependent variable

This paper takes the comprehensive technical efficiency of agricultural resource allocation (hereinafter simplified as *Crs*, representing comprehensive technical efficiency) from 2011 to 2023 as the dependent variable to analyze the factors affecting this value.

5.1.2. Core explanatory variable

In selecting explanatory variables, with reference to the choice of influencing factors in efficiency measurement from other literature, the level of digital economy development is taken as the core explanatory variable. Drawing on previous studies and combined with the *China Digital Economy Development Report (2023)*, an evaluation indicator system for digital economy development level is constructed from three dimensions: digital infrastructure, digital competence of rural subjects, and digital rural financial infrastructure. Digital infrastructure includes: rural internet penetration rate (%), measured by rural broadband access subscribers divided by the total rural population; and rural delivery routes (km). Digital competence of rural subjects includes: rural residents' digital level, measured by per capita transportation and communication consumption expenditure of rural households divided by per capita consumption expenditure of rural residents. Digital rural financial infrastructure includes: breadth of coverage of digital inclusive finance and depth of usage of digital inclusive finance, sourced from the Peking University Digital Financial Inclusion Index. The entropy method is used to calculate the composite indicator value of digital economy development level.

5.1.3. Control variables

The control variables selected include land transfer rate (measured by total area of contracted arable land transferred divided by the area of contracted arable land managed by households), rural electricity level [rural electricity consumption (100 million kWh)], and rural per capita income (total rural income divided by total rural population).

5.1.4. Data sources

This paper uses panel data from 31 provinces (autonomous regions and municipalities) in China (excluding Hong Kong, Macao, and Taiwan) as the analytical basis. Given the emergence of the digital economy, the study period is selected from 2011 to 2023. The data are mainly sourced from the China Statistical Yearbook and provincial statistical yearbooks, among which the digital inclusive finance index is derived from the Peking University Digital Financial Inclusion Index report. Linear interpolation is applied to some variables with missing values, resulting in the final research dataset.

5.2. Tobit model regression analysis

This study employs the DEASBM model to measure agricultural resource allocation efficiency across provinces

from 2011 to 2023, and finds that the efficiency values are strictly between 0 and 1, with a large number of provinces having efficiency values equal to 1 (lying on the frontier), exhibiting typical “limited dependent variable” characteristics. If ordinary least squares were directly applied, parameter estimates would be biased due to the failure to handle the truncated distribution of the dependent variable. Therefore, this paper adopts the Tobit model ^[19] (i.e., the censored regression model) for estimation, with the model specified as follows:

$$y_{it}^* = \beta_0 + \beta_1 x_{it} + \gamma_1 k1_{it} + \gamma_2 k2_{it} + \gamma_3 k3_{it} + \mu_i + \varepsilon_{it}$$

$$y_{it} = \min(1, \max(0, y_{it}^*))$$

where: y_{it} is the actually observed agricultural resource allocation efficiency (measured by the DEASBM model, with values between 0 and 1); y_{it}^* is the unobserved latent variable; x_{it} is the comprehensive digital economy index (synthesized by the entropy method); $k1_{it}$, $k2_{it}$, and $k3_{it}$ denote land transfer rate, rural electricity consumption, and rural per capita income, respectively; μ_i is the provincial random effect, capturing timeinvariant provincial heterogeneity; and ε_{it} is the independently and identically distributed random error term, assumed to follow $N(0, \sigma^2)$. The dependent variable y_{it} is leftcensored at 0 and rightcensored at 1; using ordinary least squares would lead to biased parameter estimates. Therefore, this paper uses the randomeffects panel Tobit model for estimation, assuming that $\mu_i \sim N(0, \sigma_{\mu}^2)$ and is independent of ε_{it} . The likelihood ratio (LR) test is used to determine whether individual effects exist (with the null hypothesis $\sigma_{\mu} = 0$). The model is estimated using Stata 18.0’s `xttobit` command. The regression results are presented in **Table 4**.

Table 4. Empirical results

Variable	Coefficient	Std. Err.	z	P
x	1.147***	0.168	6.85	0.000
k1	-0.334**	0.148	-2.25	0.024
k2	0.000***	0.000	3.43	0.001
k3	-0.000***	0.000	-2.69	0.007
Constant	0.8264***	0.084	9.78	0.000
Observations = 156				
Prob > chi2 = 0.0000				
Log likelihood = 9.00111				
Wald chi2 = 86.65				

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to the regression results, the comprehensive digital economy index is significantly positive at the 1% level, indicating that the development level of the digital economy has a significant enhancing effect on agricultural resource allocation efficiency. The coefficient of land transfer rate is significantly negative at the 5% level, which may reflect that current land transfer still suffers from the problem of “emphasizing scale over quality”; rural electricity consumption is significantly positive at the 1% level, suggesting that electricity input exerts a positive promoting effect on agricultural efficiency improvement; and rural per capita income is significantly negative at the 1% level, indicating that, given unchanged technology and organizational modes, income growth is more channeled into consumption rather than productive investment, thereby hindering efficiency gains. In summary, the digital economy has become a key driving force for optimizing agricultural factor allocation and promoting efficiency growth, yet issues concerning the quality of land transfer and income conversion still warrant attention. Hypothesis 1 is thereby validated.

5.3. Robustness checks

To ensure the reliability of the above conclusions, this paper conducts the following robustness checks:

(1) Individual fixed effects: To control for provincial fixed effects, this paper further adopts a pooled Tobit model and incorporates provincial dummy variables (i.id) in the estimation^[20]. The results indicate that the coefficient of the comprehensive digital economy index (x) remains significantly positive (see **Table 5**), consistent with the baseline regression results, thereby confirming the robustness of the core conclusions.

Table 5. Empirical analysis results

Variable	Coefficient	Std. Err.	z	P> z
x	1.186***	0.165	7.17	0.000
k1	-0.336**	0.147	-2.29	0.023
k2	0.000***	0.000043	4.00	0.000
k3	-0.000**	0.00000246	-2.84	0.005
Constant	1.124	0.117	9.59	0.000
Observations 403				
Prob > chi2 0.0000				
Log likelihood =80				
389004				

(2) Replacement of the dependent variable with pure technical efficiency. To avoid potential interference from scale factors in the measurement of overall efficiency, this paper further employs the pure technical efficiency (VRSTE) decomposed from the SBM model as the dependent variable and conducts a randomeffects panel Tobit regression. The results (**Table 6**) show that the comprehensive digital economy index (x) is significantly positive at the 1% level, consistent with the baseline regression findings, indicating that the digital economy also exerts a significant enhancing effect on agricultural pure technical efficiency, thereby further confirming the robustness of the core conclusions.

Table 6. Empirical analysis results

Variable	Coefficient	Std. Err.	z	P> z
x	0.648***	0.199	3.25	0.001
k1	-0.465***	0.181	-2.56	0.010
k2	0.000	0.0000809	1.04	0.296
k3	0.000	0.00000526	1.41	0.157
Constant	1.303***	0.075	17.43	0.000
Observations 156				
Prob > chi2 = 0.0000				
Log likelihood = 9.00111				
Wald chi2 = 86.65				

(3) Exclusion of municipalities directly under the central government. Considering that the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing differ considerably from other provinces in terms of administrative level, economic structure, agricultural scale, and development stage—with minimal agricultural shares and extremely high urbanization rates—they may potentially bias the regression results. To eliminate the influence of this factor on the core conclusions, this paper reestimates the randomeffects panel Tobit model after excluding the samples from these four municipalities.

The results show that after excluding the municipality samples, the coefficient of the comprehensive digital economy index (x) remains 0.957 and is still significantly positive at the 1% level, consistent with the baseline regression findings. This indicates that the promoting effect of the digital economy on agricultural resource allocation efficiency is not driven by the municipality samples, and the core conclusion is robust. The coefficient of land transfer rate (k1) is -0.338 , significantly negative at the 5% level, aligning with the baseline results. The significance levels of rural electricity consumption (k2) and rural per capita income (k3) have declined to some extent, which may be attributable to the reduced sample variation after excluding the municipalities; however, the direction and significance of the core explanatory variables have not fundamentally changed.

5.4. Heterogeneity analysis

Given the marked differences between major grainproducing regions and nonmajor grainproducing regions in terms of agricultural scale, production structure, infrastructure, and policy support, the impact of the digital economy on agricultural resource allocation efficiency may exhibit regional heterogeneity. This paper further divides the sample into major grainproducing regions (13 provinces) and nonmajor grainproducing regions (18 provinces) for subgroup regressions, with the results presented in **Table 7**.

As shown in **Table 7**, the comprehensive digital economy index (x) is significantly positive in both groups. Specifically, the coefficient of the digital economy in major grainproducing regions is 0.556, significant at the 5% level; while in nonmajor grainproducing regions, the coefficient is 1.171, significant at the 1% level. In terms of coefficient magnitude, the promoting effect of the digital economy in nonmajor grainproducing regions is notably larger than that in major grainproducing regions ($1.171 > 0.556$), indicating that the digital economy exerts a more pronounced efficiencyenhancing effect in nonmajor grainproducing areas. This finding is consistent with theoretical expectations and validates the hypothesis of “latemover advantage” of the digital economy in the agricultural sector.

Regarding control variables, the land transfer rate (k1) is not significant in either group, although its coefficient is negative in the nonmajor region; rural electricity consumption (k2) is insignificant in the major region but significantly positive in the nonmajor region; and rural per capita income (k3) is significantly negative in the nonmajor region, suggesting that the crowdingout effect of income growth on efficiency is more pronounced in nonmajor grainproducing areas.

In summary, the enabling effect of the digital economy on agricultural efficiency exhibits significant regional heterogeneity, with nonmajor grainproducing regions benefiting more. This provides empirical evidence for the differentiated promotion of digital rural construction.

Table 7. Subgroup regression results for major and nonmajor grainproducing regions

Variable	(1) Major production area		(2) Non-major production area	
	Coefficient	Standard error	Coefficient	Standard error
x	0.556**	0.249	01.171***	0.240
k1	-0.181	0.155	-0.410	0.262
k2	-0.000564	0.0000352	0.004403	-0.000
k3	0.000	0.000	-0.0000106***	0.106
Constant	0.807***	0.076	0.7957894***	0.111
Observations	169		234	

(1) Major production area			(2) Non-major production area	
Variable	Coefficient	Standard error	Coefficient	Standard error
Prob > chi2		0.0000		0.0000
Log likelihood		54.645986		-19.420369
Wald chi2		46.96		59.54

5.5. Mediation effect analysis: Transmission pathways of the digital economy

To further reveal the mechanism through which the digital economy affects agricultural resource allocation efficiency, this study draws on the threestep method proposed by Wen *et al.* to construct a mediation effect model ^[21]. The comprehensive digital economy index (x) is taken as the independent variable, agricultural resource allocation efficiency (crt) as the dependent variable, and per capita total telecommunications business volume (ln_telecom) is introduced as the mediator variable to capture the transmission pathway through which the digital economy influences agricultural efficiency by improving telecommunications infrastructure. Given the significant individual effects in the panel data ($\rho > 0.8$), all regressions employ a provincial fixedeffects model, with control variables consistent with the baseline regression. The results are presented in **Table 8**.

Table 8. Mediation effect test results

Variable	(1) Total effect	(2) Digital economy → Telecom infrastructure	(3) Direct effect (including telecom)
	CRSTE	ln_patent	CRSTE
Digital economy (x)	0.525*** (0.0967)	1.3549*** (0.3047)	0.468*** (0.0499)
Technological innovation (ln_patent)			0.0424** (0.0164)
Control variables	Controlled	Controlled	Controlled
Province fixed effects	Yes	Yes	Yes
R ² (within)	0.1798	0.1443	0.1944
Observations	403	403	403

Note: * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$; standard errors in parentheses; control variables include land transfer rate, rural electricity consumption, and rural per capita income, not reported.

Mediating effect of telecommunications infrastructure: Model (1) in **Table 8** shows that the total effect of the digital economy on agricultural efficiency is significantly positive (coefficient 0.5254, $P < 0.01$). In Model (2), the effect of the digital economy on per capita telecommunications business volume is significantly positive at the 1% level (coefficient 1.3549, $P < 0.01$), indicating that the development of the digital economy has significantly improved the service level of telecommunications infrastructure. In Model (3), after including per capita telecommunications business volume, its effect on agricultural efficiency is significantly positive at the 5% level (coefficient 0.0424, $P < 0.05$), while the absolute value of the digital economy coefficient decreases from 0.5254 to 0.4680. According to the criteria of the threestep method, the above results suggest that per capita telecommunications business volume plays a partial mediating role between the digital economy and agricultural efficiency, with the mediating effect accounting for approximately 10.9% of the total effect. In other words, the digital economy not only directly improves agricultural efficiency but also indirectly promotes efficiency growth through the enhancement of telecommunications infrastructure. This finding indicates that

advancing rural communication infrastructure construction is an important transmission pathway for unleashing the dividends of the digital economy. Hypothesis 3 is thereby validated.

6. Conclusion and policy implications

6.1. Research conclusions

Based on panel data from 31 Chinese provinces spanning 2011–2023, this paper employs the DEASBM model and the Malmquist index to measure agricultural resource allocation efficiency, synthesizes a comprehensive digital economy index using the entropy method, and examines the impact of the digital economy on agricultural efficiency through a panel Tobit model. The main conclusions are as follows:

First, agricultural efficiency in China exhibits an overall upward trend, yet with significant interprovincial disparities. In static terms, in 2023, 15 provinces were on the fully efficient frontier, 8 provinces showed insufficient scale, and 8 provinces exhibited excessive scale with technological lag; in dynamic terms, total factor productivity grew at an average annual rate of 3.5%, with technological progress serving as the primary driving force.

Second, the digital economy exerts a significant positive effect on agricultural efficiency. The comprehensive digital economy index is significantly positive at the 1% level, and this conclusion remains robust after a series of robustness checks, including replacement of the dependent variable, control for fixed effects, and exclusion of municipalities directly under the central government, indicating that the enhancing effect of the digital economy on agricultural resource allocation efficiency is highly robust. Heterogeneity analysis reveals that this effect is significantly stronger in nonmajor grainproducing areas (coefficient 1.171) than in major grainproducing areas (coefficient 0.556), validating the “latemover advantage” hypothesis that the digital economy yields greater marginal contributions in regions with weaker foundational conditions.

Third, the mediation effect test uncovers the core transmission pathway through which the digital economy empowers agriculture. Per capita telecommunications business volume plays a partial mediating role between the digital economy and agricultural efficiency, with the mediating effect accounting for approximately 10.9%, indicating that the digital economy indirectly improves agricultural efficiency through enhancing telecommunications infrastructure—that is, the transmission pathway of “digital economy → telecommunications infrastructure improvement → agricultural efficiency enhancement” is supported. In contrast, agricultural mechanization has not yet become an effective mediating pathway, and even exhibits a negative association (coefficient -0.1644, $P < 0.01$), suggesting that in some regions, agricultural machinery investment suffers from a structural problem of “emphasizing quantity over quality,” which fails to translate into actual efficiency gains under the green efficiency framework. This finding clarifies the microlevel pathway through which the digital economy operates on agricultural efficiency: the digital economy first improves the level of information and communication infrastructure, thereby enhancing information acquisition and resource allocation efficiency in agricultural production, and subsequently drives agricultural efficiency growth, providing a theoretical basis for differentiated policy design.

6.2. Policy implications

The above conclusions provide clear directions for empowering agricultural efficiency through the digital economy. First, efforts should be continuously strengthened to develop rural telecommunications infrastructure, enhance communication network coverage and service capacity, and consolidate the hardware foundation for

the implementation of the digital economy in the agricultural sector, ensuring that the information dividend benefits all farmers. Second, given that the marginal effect of the digital economy is more pronounced in nonmajor producing areas, priority should be given to advancing digital inclusive finance and ecommerce logistics systems in regions with weaker foundational conditions; meanwhile, major producing areas should focus on improving the quality of land transfer and promoting the transition from scalebased operation to intensive operation. Third, incremental rural income should be channeled toward productive investment through production subsidies and technical training, avoiding excessive diversion of income growth into consumption, and reinforcing agricultural reproductive capacity. Fourth, agricultural mechanization should be steered from “quantity expansion” toward “quality improvement,” supporting the development of smart agricultural machinery and shared machinery platforms, linking purchase subsidies to operational efficiency, and effectively translating machinery investment into efficiency growth momentum. The core of empowering agriculture through the digital economy lies in unblocking the transmission chain among infrastructure, human capital, and technology application, thereby achieving precise implementation of policy resources.

Disclosure statement

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References

- [1] Yao XB, Duan ZY, Che SF, et al., 2026, Spatiotemporal Evolution and Driving Factors of the Coupling Coordination Degree Between Digital Rural Construction and Agricultural Carbon Emissions. *Environmental Science*, 1–25.
- [2] Liu ZY, Wang Z, 2026, The Impact of Digital Economy on Regional Carbon Emission TradeOut Rate. *China Business and Market*, 1–16.
- [3] Liu M, 2025, Research on the Impact of Digital Inclusive Finance Development on Farmers’ Production and Operation in Shandong Province, Master’s thesis, Shandong University of Technology.
- [4] Li CD, Li NJ, 2025, Development of Applied Economics Disciplines at China Agricultural University: Review and Comparison. *Journal of China Agricultural University (Social Sciences Edition)*, 42(05): 32–50.
- [5] Li ML, Song DD, Zeng WT, et al., 2026, Digital New Quality Productive Forces and Agricultural and Rural Modernization Development—Based on the Mediating Effects of Regional Industrial Division and UrbanRural Digital Divide. *Journal of Southwest University (Natural Science Edition)*, 48(03): 119–131.
- [6] Han G, Li C, 2023, Digital Economy, Spatial Effects, and UrbanRural Income Gap. *Journal of Southwest University of Science and Technology (Philosophy and Social Sciences Edition)*, 40(06): 25–33.
- [7] Gao SM, 2026, Digital Economy Empowers Rural Industrial Revitalization. *Chongqing Science and Technology News*, March 27, 2026, 005.
- [8] Zhen SS, 2025, Research on the Digital Economy Enhancing the Benefits of Leading Enterprises in Driving Farmers’ Income from the Perspective of Transaction Costs, Master’s thesis, Sichuan Agricultural University.
- [9] Yan M, Jingyi M, Yuhui L, 2022, Digital Villages Construction Accelerates HighQuality Economic Development in Rural China Through Promoting Digital Entrepreneurship. *Sustainability*, 14(21): 14224.
- [10] Li Y, Cong HB, Zou DL, 2022, Research on the Impact of Digital Economy on the HighQuality Development of Rural Industry—Based on the Mediating Effect of Technological Innovation. *Science and Technology Management*, 24(05): 23–35 + 69.

- [11] Wang YJ, Ji YY, 2023, Theoretical Analysis and Mechanism Testing of Rural Digital Economy Alleviating Multidimensional Relative Poverty. *Statistics Decision*, 39(15): 57–63.
- [12] Sun YF, Du GF, Li JC, 2023, Analysis of Influencing Factors of Rural Digital Economy Development in Hunan Province. *Times Economy and Trade*, 20(02): 132–136.
- [13] Chen LL, Cheng WX, 2023, Research on the Impact of Rural Digital Economy Development on Farmers' Income Increase. *Journal of Chengdu Normal University*, 39(09): 105–115.
- [14] Zhang L, Xu ZM, Li CL, 2023, Impact of Rural Digital Economy Development on Farmers' Income Growth. *Journal of Jiangxi University of Finance and Economics*, (03): 82–94.
- [15] Zhou H, Liu Y, 2026, Mechanisms, Spatial Spillover and Threshold Effects of Digital Economy Alleviating UrbanRural Factor Misallocation. *Journal of Chongqing University (Social Sciences Edition)*, 32(01): 95–114.
- [16] Li PZ, Jian LR, Liu Y, 2019, Research on Innovation Efficiency Evaluation of Regional HighTech Industries Based on DEA and Malmquist Index. *Industrial Technology Economy*, 38(01): 27–34.
- [17] Dong K, Sun KK, 2026, Digital Economy, Technological Progress and Balanced Economic Development—An Empirical Analysis Based on Nighttime Light Data. *Industrial Organization Review*, 1–23.
- [18] Yang Q, Zhu HH, 2024, Spatial Differences and Driving Factors of Agricultural Resource Allocation Efficiency in China. *Statistics Decision*, 2024.
- [19] Shu XL, Min ZS, Guo XY, et al., 2024, Coupling Coordination and Driving Factors of Provincial Digital Economy and HighQuality Development of Tourism. *Economic Geography*, 44(01): 197–208.
- [20] Dong, Q, 2026, Research on the Supply Chain Spillover Effect of HighQuality Innovation of “ChainMaster” Enterprises. *Technical Economics and Management Research*, (03): 108–115.
- [21] Wen ZL, Ye BJ, 2014, Mediation Effect Analysis: Methods and Model Development. *Advances in Psychological Science*, 22(05): 731–745.

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