

Agricultural digitalisation, farmland-scale management and agroecological efficiency: Evidence from China

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Abstract: This study examines how agricultural digitalisation affects agroecological efficiency, with the aim of informing the transition towards low-carbon, high-quality agricultural development. Using provincial panel data from China (2007–2022), we employ fixed-effects, spatial Durbin, and mediation models for empirical analysis. The results reveal three main findings: (i) The impact of agricultural digitalisation on agroecological efficiency presents a productivity paradox, characterised by a U-shaped relationship of initial suppression followed by promotion, a finding that remains robust after endogeneity is addressed and sensitivity checks are conducted. (ii) Agricultural digitalisation generates significant positive spatial spillover effects on neighbouring regions' agroecological efficiency. However, the realisation of these spillovers is contingent on the alignment between diffused technologies and local agricultural infrastructure. (iii) Farmland-scale management serves as a critical mediating channel. Furthermore, agricultural organisation – through stabilising profit expectations for scaled operators and facilitating land transfer through reduced tenure disputes – positively moderates the effective integration of digital technologies into agricultural practices. The findings suggest that digitally empowered sustainability goes beyond technological determinism. We recommend improving rural digital infrastructure, promoting land transfer, and reinforcing village-level collective economies to enhance agricultural organisation. Although it is geographically focused on China, this study offers theoretical and policy insights for advancing sustainable agriculture through digitalisation.

Keywords: digital technology applications in agriculture; agricultural production organisation; large-scale farming; agricultural sustainability; productivity paradox

China's 14th Five-Year Plan prioritises green agricultural transformation and high-quality development, yet significant challenges persist. These include the rapid expansion of digital agriculture, an ageing rural workforce, a heavy reliance on biochemical inputs, nonpoint source pollution, and continued carbon emissions.

Against this backdrop, leveraging agricultural digitalisation to reduce carbon emissions and improve agroecological efficiency has become a critical policy and research priority.

However, as noted in the literature on the 'productivity paradox' (Solow 1987), heavy investment in digital

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technologies did not automatically yield proportional gains in productivity – a caution that applies equally to agricultural digitalisation. The adoption of digital tools often entails significant upfront costs for producers, coupled with risks of low returns and poor adaptation to local resource endowments and geographical conditions – a phenomenon commonly termed the productivity paradox or Solow paradox (Zhang et al. 2023). This mismatch may lead to inefficient early-stage implementation, characterised by high investment, weak suitability, and limited effectiveness. These challenges raise a critical question: How can digital technologies be effectively leveraged to enhance agroecological efficiency?

While technological determinism has long influenced growth theory, institutional economists such as North and Thomas (1999) emphasise that institutions and organisational change – not technology alone – shape developmental trajectories. In the context of China, smallholder farming remains the dominant operational form (Beeson 1987), yet digital empowerment has thus far reached only a limited number of producers. Most smallholders cannot afford digital transition costs, and their livelihood strategies often conflict with state-led modernisation agendas. As Li et al. (2022) suggested, local governments, village collectives, and social capital can mediate tensions by facilitating land transfer and improving smallholders' market integration – thus reducing transaction costs and enabling scaled operations (Han 2020). This highlights the need to move beyond technological determinism and consider how digital tools are embedded within socioinstitutional systems.

In summary, while digitalisation offers the potential to improve agroecological efficiency, existing research remains limited, particularly regarding the role of farmland-scale management. This study contributes in two key ways. First, by adopting the perspective of farmland scale management within the broader framework of agricultural revitalisation, it clarifies the pathways through which digitalisation can enhance ecological efficiency and helps explain the related productivity paradox. Second, recognising that smallholders remain central to Chinese agriculture, this paper does not equate farmland-scale management with smallholders' marginalisation; rather, it emphasises integrating smallholders into digitalisation processes. The findings suggest that low-carbon agricultural advancement depends not on technological innovation alone but on synergies among technology, organisations, and institutions. Enhancing collective action and organisational capacity among smallholders can mitigate the constraints of small-scale operations, thereby offering

a fuller understanding of the dynamic interplay between technology, organisation, and institutional change.

MATERIAL AND METHODS

Theoretical analysis and research hypothesis

Direct impact of agricultural digitalisation on agro-ecological efficiency. The integration of digital technologies introduces advanced resources and information systems into agriculture, fostering practices that are greener, more productive, and more efficient. In production, data-driven decision-making enables precision, intelligence, and connectivity, facilitating the adoption of low-carbon techniques such as precision fertilisation and irrigation (Wang et al. 2023). In sales, digitalisation uses e-commerce platforms to reduce information asymmetry, providing producers with diversified market signals and channels, which lowers transaction costs and enhances operational efficiency (Luo 2022).

Furthermore, by standardising the production and branding of green agricultural products, digitalisation helps align output with consumer demand for sustainability, creating a market-driven incentive to adopt green technologies (Xie and Han 2022). However, the pathway from digitalisation to improved agroecological efficiency is not linear. Its effectiveness is moderated by contextual factors such as infrastructure, resource endowments, and geographical conditions. A misalignment between technology and the local context can trigger a productivity paradox, where early-stage investments result in high costs, poor adaptability, and low returns, thereby dampening ecological efficiency in the short term.

Given this complex interaction, studies suggest that the spatial spillover effects of agricultural digitalisation exhibit threshold characteristics (Tian and Yin 2021). Positive externalities for neighbouring regions may remain latent until a critical level of technological advancement is reached, overcoming the dual constraints of technological lock-in in lagging areas and siphon effects in advanced hubs.

On the basis of this reasoning, the following hypothesis is proposed:

H_1 : The impact of agricultural digitalisation on agro-ecological efficiency follows a productivity paradox, manifesting as an initial inhibitory effect that later transitions into a positive influence, thereby exhibiting a U-shaped relationship.

Mediating mechanism of farmland scale management. Academic consensus identifies farmland-scale

management as a critical mechanism for reducing average production costs. Empirical evidence highlights substantial disparities in average farm size between high- and low-income countries, with structural fragmentation and smallholder-oriented policies in poorer nations often introducing significant economic distortions (Adamopoulos and Restuccia 2014). In China, Luo (2017) reported that fragmented agricultural production struggles to meet the conditions required for the large-scale replication and promotion of digital technologies. Moreover, digital agricultural technologies can result in notable short-term yield improvements, which in turn accelerate land transfer. Practices such as joint cultivation models demonstrate that the concentration of farmland operations, combined with land consolidation and specialised production, has become an inevitable pathway. Zhao (2021) notes that adjustments to China's rural land transfer policy have actively promoted farmland scale management, thereby laying the necessary foundation for technology application and stimulating demand for technologies that support agricultural green and low-carbon transformation. This implies that the effective adoption of new digital technologies imposes certain requirements on the scale of operations. Furthermore, Wen et al. (2024) emphasises that the precision, intelligence, and informatisation inherent in digital agricultural technologies are gradually transforming production methods, giving rise to new agricultural formats such as Internet Plus and platform economies. These developments are driving Chinese agriculture from fragmentation towards greater cooperation and scale, thereby reducing the per-unit cost of digital technology adoption, facilitating uptake, and ultimately enhancing agroecological efficiency. Thus, farmland-scale management serves not only as the carrier for applying and promoting digital agricultural technologies but also as an inherent requirement for large-scale agricultural production. Fostering deeper integration between digital technology and agriculture enables comprehensive digital empowerment across production, logistics, sales, and finance. In turn, this promotes regionalised, integrated, and cooperative production patterns that contribute to improved agroecological efficiency.

Moderating role of the agricultural organisation.

While countries such as the United States, France, and Brazil have pursued farm-scale enlargement policies since the 1960s, this pathway remains contested in China. Given China's land endowment, land transfer is essential for advancing farmland scale management. In practice, however, informality and tenure disputes

in land transfers present significant barriers, hindering both scale management and the diffusion of digital agricultural technologies. As Luo (2017) notes, long-term investments – including technology adoption and land improvement – depend on secure land rights and stable profit expectations. Insecure tenure may lead to short-termist practices, such as overreliance on chemical inputs and underinvestment in digital technologies (Ma et al. 2019). This underscores how fragmented operations constrain agricultural modernisation and emission reduction in China's smallholder system. According to the perspective of New Institutional Economics (North and Thomas 1999), informal institutions remain vital in regulating social behaviour. However, China's rural transition has eroded the traditional acquaintance society, weakening village-level mutual trust and hindering the marketisation and scaling of land transfers (Du 2020). Village collectives and cooperatives can counteract this social fragmentation. By increasing the level of organisation, they help overcome smallholders' market limitations, fill institutional voids, and align expectations around land transfer. As Chen et al. (2023) argue, these organisations establish shared rules and interest-linkage mechanisms, promoting contiguous land transfer and scale management. This organised approach standardises transactions, reduces disputes, and enhances profit expectations, thereby facilitating the adoption of smart agricultural technologies. The resulting gains in management efficiency contribute to lower energy use and carbon emissions, ultimately improving agroecological sustainability.

Thus, the following hypothesis is proposed:

H₂: Agricultural organisation positively moderates the relationship between farmland scale management and agroecological efficiency, strengthening the contribution of scale management to ecological sustainability.

Model selection

Baseline model. To verify the correlation between agricultural digitalisation and agroecological efficiency and test its direct impact, this study constructed a baseline regression model [Equation (1)]:

$$AGTFP_{it} = \alpha_0 + \alpha_1 Rdig_{it} + \alpha_2 Rdig_{it}^2 + \sum_k \alpha_k X_{it} + \varepsilon_{it} \quad (1)$$

where: *AGTFP* – agricultural green total factor productivity, given that *TFP* represents a growth rate, in this study, the cumulative product result is used as a proxy variable for evaluating China's provincial agroecological efficiency; *Rdig* – the level of agricultural digitalisation; *Rdig*² – used to test the nonlinearity of agricultural

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digitalisation; X – a vector of control variables; ε – the random disturbance term; i and t – region and time, respectively.

Spatial Durbin model (SDM). Given the enhanced interregional connectivity, which facilitates factor mobility and technology diffusion, this study employs a spatial panel model to examine the impact of agricultural digitalisation on agricultural green development. Among the commonly used spatial econometric models – the spatial autoregressive (SAR), spatial error (SEM), and spatial Durbin (SDM) models – their relative suitability is determined using Lagrange multiplier (LM), likelihood ratio (LR), and Wald tests. While the specifications of the SAR and SEMs are standard and are omitted here for brevity, the SDM is formally specified as Equation (2):

$$\begin{aligned} AGTFP_{it} = & \beta_0 + \rho \sum_{j=1}^n W_{ij} Rdig_{jt} + \beta_1 Rdig_{it} + \\ & + \beta_2 Rdig_{it}^2 + \beta_k \sum_k X_{it} + \theta_1 \sum_{j=1}^n W_{ij} Rdig_{jt} + \\ & + \theta_2 \sum_{j=1}^n W_{ij} Rdig_{jt}^2 + \theta_k \sum_k W_{ij} X_{jt} + c_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (2)$$

where: ρ – the spatial autocorrelation coefficient; ω – the spatial weight matrix; β – a coefficient; θ – the coefficient vector for spatial spillover effects; c – spatial fixed effects, μ – time fixed effects; ε – the random error term.

Mediation effect model. *i) Mediation effect.* To examine the underlying pathways through which agricultural digitalisation influences agroecological efficiency, this study draws on the approaches of Wen et al. (2004), Han et al. (2019), and Wang et al. (2021), adopting farmland-scale management ($Lscale$) as a mediating variable and constructing Equations (3 and 4) to test the mediating effect.

$$Lscale_{it} = \delta_0 + \delta_1 Rdig_{it} + \sum_k \delta_k X_{it} + \varepsilon_{it} \quad (3)$$

$$AGTFP_{it} = \phi_0 + \phi_1 Rdig_{it} + \phi_2 Lscale_{it} + \sum_k \phi_k X_{it} + \varepsilon_{it} \quad (4)$$

ii) Moderated mediation effect. Drawing on research by Li et al. (2022), this study builds a moderation effect model [Equation (5)] to test the moderating effect of agricultural organisation, revealing the underlying logic influencing farmland scale management.

$$\begin{aligned} AGTFP_{it} = & \gamma_0 + \gamma_1 Rdig_{it} + \gamma_2 Lscale_{it} + \gamma_3 DgreeOa_{it} + \\ & + \gamma_4 DgreeOa_{it} \times Lscale_{it} + \sum_k \gamma_k X_{it} + \varepsilon_{it} \end{aligned} \quad (5)$$

Variable description

Dependent variable. The dependent variable is agroecological efficiency. To comprehensively evaluate the environmental and economic benefits of provincial agricultural development in China from 2007 to 2022, this study draws on Xu and Yin (2021), Liu (2021), and Li et al. (2021) and uses agricultural green total factor productivity ($AGTFP$) as a proxy indicator. In the estimation of $AGTFP$, the SBM efficiency model incorporates undesirable outputs as slack variables into the objective function. The estimated $AGTFP$ is marked as the global Malmquist–Luenberger (GML) index.

$$GML^{t,t+1}(y^{t+1}, x^{t+1}, b^{t+1}; y^t, x^t, b^t) = \frac{S_c^{t,t+1}(y^{t+1}, x^{t+1}, b^{t+1})}{S_c^{t,t+1}(y^t, x^t, b^t)} \quad (6)$$

$$AGTFP^{t+1} = \prod_{t=1}^t AGTFP^t \quad (7)$$

where: S_c – the production possibility set; y – the desirable output; x – the input; b – the undesirable output.

The input indicators utilised in this study include the number of employees in the primary industry, total sown area of crops, agricultural chemical fertiliser application, total agricultural machinery power, agricultural pesticide application, agricultural plastic film usage, and effective irrigated area. The desirable outputs comprise the gross output value of agriculture, forestry, animal husbandry, and fishery, and the total agricultural carbon sink. The undesirable output is measured by total agricultural carbon emissions.

The calculation of total agricultural carbon emissions adopts the methodology referenced from Yang and Tong (2023), which quantifies carbon emissions (ACE) as the product of agricultural carbon emission sources and their corresponding carbon emission coefficients.

$$ACE = \sum_{i=1}^k T_i \quad (8)$$

where: T_i – the i^{th} carbon emission source; δ_i – the emission coefficient of the i^{th} carbon emission source.

As the GML index is a dynamic chain index, it needs to be converted into a static fixed-base index to reflect the level of green ecological efficiency. Therefore, this study sets 2007 as the base period ($AGTFP = 1$ for all provinces) and uses the cumulative product of the GML index to calculate the $AGTFP$ level value for each period.

Independent variable. The core independent variable in this study is the level of agricultural digitalisation ($Rdig$). At present, there is no academic consensus on a standard evaluation system for agricultural digitalisation. Drawing on the evaluation framework of the County Digital Rural Index, which was jointly developed by Ali-Research and

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the Institute of New Rural Development at Peking University (Digital Village Project of Institute of New Rural Development, 2022), and informed by existing research, this study develops an innovative set of indicators. These indicators capture agricultural digitalisation across three dimensions: the digital hardware foundation, the digital soft environment, and the integration of the digital and real economies. The design adheres to the principles of comprehensiveness, scientific rigour, and data availability. The specific indicators are presented in Table 1.

Mediating variable. The mediating variable is farmland scale management (*Lscale*), measured by the land scale operation indicator. The proxy variable is defined as the ratio

of the number of land transfer management rights certificates issued *per capita* to the cultivated land area in each region. The data are drawn from the China Rural Operation and Management Statistical Yearbook (2007–2022).

Moderating variable. The moderating variable is agricultural organisation (*DegreeOa*). The small-scale and fragmented nature of farm operations in China significantly constrains agricultural modernisation. Integrating smallholders into modern agricultural organisation systems is therefore essential. In this article, agricultural organisation refers to the process of establishing stable economic and social linkages between smallholders (measured at the household level) and other actors

Table 1. Quantitative indicator system for the agricultural digitalisation level

Primary indicator	Secondary indicator	Explanation	Direction
Agricultural digital hardware foundation	rural telephone penetration rate	number of mobile phones per 100 rural households	+
	rural computer penetration rate	number of computers per 100 rural households	+
	rural internet penetration rate	average number of internet broadband access subscriptions per 10 000 rural residents	+
	IoT & IT investment	fixed asset investment in information transmission, software, and IT services	+
	total agricultural machinery power	total power of various machinery in agriculture, forestry, animal husbandry, and fishery	+
Agricultural digital soft environment	scale of agricultural technicians	number of agricultural professionals/number of rural employed persons	+
	educational level of agricultural workers	number of rural labourers with an education level above primary school per 100 persons	+
	intensity of agricultural S&T fiscal expenditure	R&D expenditure × (agricultural output value/regional GDP)	+
Degree of digital-real economy integration	scale of smart agricultural production	greenhouse production area/total cultivated area	+
	scale of new agricultural formats	number of new agricultural business entities	+
	scale of rural online payments	Peking University digital financial inclusion index	+
	scale of rural e-commerce platforms	number of Taobao villages/number of villages	+
	volume of rural express delivery	average weekly delivery frequency in rural areas	+

+ – a positive indicator

Source: Authors' own elaboration

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Table 2. Quantitative indicator system for the agricultural organisation level

Primary indicator	Secondary indicator	Explanation	Direction
Agricultural contractualisation	land transfer disputes	total land transfer disputes accepted/number of rural employed persons	–
Agricultural cooperation	village collective economy scale	number of village collective economic organisations/number of villages	+
	village cooperative economy scale	number of farmer cooperatives/number of villages	+
Agricultural specialisation	agricultural production trusteeship services	total area of agricultural production trusteeship services/total cultivated area	+

– and + – a negative and positive indicator, respectively

Source: Author's own elaboration

through interest-alliance mechanisms, thereby consolidating dispersed operations and enabling economies of scale. This approach, which facilitates the inclusive integration of smallholders via cooperatives and digital service platforms, has been validated in European contexts (Wang and Shi 2019). On the basis of prior research and following the principles of systematicity, representativeness, and data availability, this study develops a comprehensive indicator system for agricultural organisations, with specific indicators detailed in Table 2.

Control variables. To minimise estimation bias arising from omitted variables, this study includes five control variables. Fiscal support for agriculture (*Gov*) is measured as the ratio of expenditures on agriculture, forestry, and water affairs to the gross output value of agriculture, forestry, animal husbandry, and fishery. Financial support for agriculture (*Fin*) is measured as the ratio of regional agricultural loan balances to the gross output value of agriculture, forestry, animal husbandry, and fishery. Agricultural electricity input (*Elec*) is captured by *per capita* actual electricity consumption in agriculture within each region. The agricultural industrial structure (*Astru*) is measured as the ratio of planting income to total agricultural income. The agricultural natural environment (*Rne*) is measured as the ratio of the disaster-affected area of the crop to the total cultivated area.

Data source description

Data sources. This study employs data from 31 provincial-level administrative regions in mainland China, excluding Hong Kong, Macao, and Taiwan, covering the period from 2007 to 2022. The raw data are sourced from the China Statistical Yearbook, China Population and Employment Statistical Yearbook, China Rural Statistical Yearbook, China Rural Operation and Management

Statistical Yearbook, China Urban–Rural Construction Statistical Yearbook, the National Greenhouse Data System, and the Peking University Digital Finance Research Center. Missing values for basic indicators in individual years were supplemented using interpolation.

Kernel density estimation of agricultural digitalisation. MATLAB R2024b was employed to conduct kernel density estimation to examine the evolution of agricultural digitalisation in China. The visualisation of trends from 2007 to 2022 reveals distinct temporal evolution characteristics, as shown in Figure 1. Overall, the peak of the kernel density curve gradually declines, whereas the right tail consistently shifts leftwards, indicating a significant increase in the level of agricultural digitalisation across provinces, accompanied by widening interprovincial disparities. After 2015, the curve exhibited multipeak characteristics, reflecting a transition from a unimodal to a multimodal distribution and suggesting a growing trend of regional concentration in China's agricultural digitalisation.

Spatial distribution characteristics of agroecological efficiency. To analyse the spatial distribution of agroecological efficiency across Chinese provinces, data from 2007 to 2022 were visualised using ArcGis 10.7 (Figure 2). Temporally, provincial agroecological efficiency improved overall. Notably, since the central government formally introduced the concept of green development in 2016, regions have actively implemented related policies, leading to reduced carbon emission intensity and enhanced agricultural total factor productivity (TFP). Spatially, significant heterogeneity was observed. High- and relatively high-efficiency areas were concentrated mainly in central and eastern China and exhibited distinct clustering. Among the northeastern provinces, Henan exhibited rapid growth, whereas Liaoning performed notably well. In contrast,

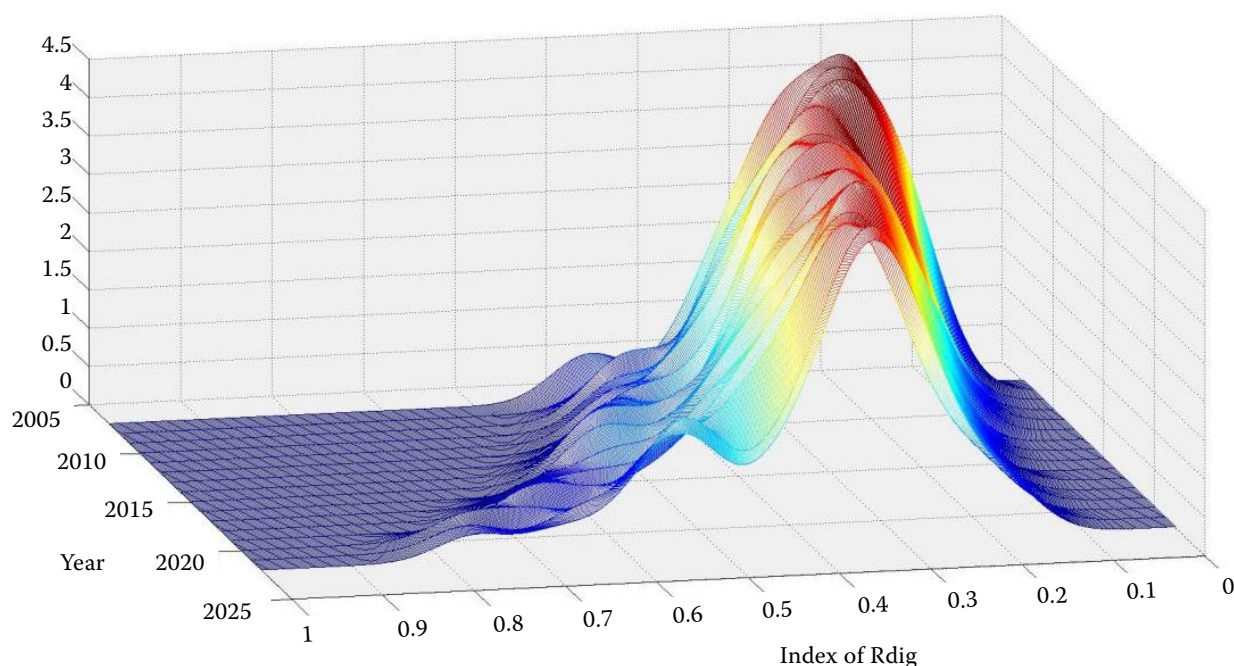


Figure 1. Three-dimensional kernel density estimation graph of interprovincial agricultural digitalisation levels in China, 2007–2022

Rdig – the level of agricultural digitalisation

Source: Authors' own elaboration

the western region generally displayed lower efficiency, corresponding to higher carbon emission intensity per unit of agricultural output. Qinghai and Tibet consistently recorded low agroecological efficiency with slow growth, whereas Inner Mongolia and Guizhou achieved faster improvements. These spatial patterns can be attributed to regional disparities in resource endowments and varying interactive effects between low-carbon development policies and land resources.

RESULTS AND DISCUSSION

Baseline regression. To verify the direct impact of agricultural digitalisation on China's agroecological efficiency, pooled ordinary least squares and individual fixed-effects panel models were employed to conduct baseline regressions of Equation (1). The results are presented in Table 3.

On the basis of the LR and Hausman test results for Table 3, the two-way fixed effects model was identified as the appropriate specification for the baseline regression. The regression results show that column 1 reports the estimates without control variables, where the coefficient for *Rdig* is 0.051 but not statistically significant.

Column 2, which includes control variables, reports a coefficient of 0.049 for *Rdig*, which is significant at the 10% level. Columns 3 and 4 report the panel random and fixed effects estimates, respectively. In column 4, which represents the two-way fixed effects model, the coefficients of *Rdig* and its squared term ($Rdig^2$) are both significant at the 5% level. The coefficient of *Rdig* is negative, whereas that of $Rdig^2$ is positive, indicating that agricultural digitalisation improves *AGTFP*, although the relationship is nonlinear and exhibits a U-shaped pattern of initial suppression followed by promotion. These findings support research hypothesis H_1 . Moreover, with the inclusion of control variables, the promoting effect of $Rdig^2$ on *AGTFP* slightly decreased (from 0.041 4 to 0.039 2), yet its statistical significance increased; these findings demonstrate the long-term impact of agricultural digitalisation on *AGTFP*. These results are consistent with the findings of Chen (2017), Foster and Rosenzweig (2022), and Jia et al. (2025), which indicate that the diffusion of digital agricultural technologies does not necessarily improve agroecological efficiency; the effective application and scaling of any advanced agricultural technology require corresponding infrastructural support

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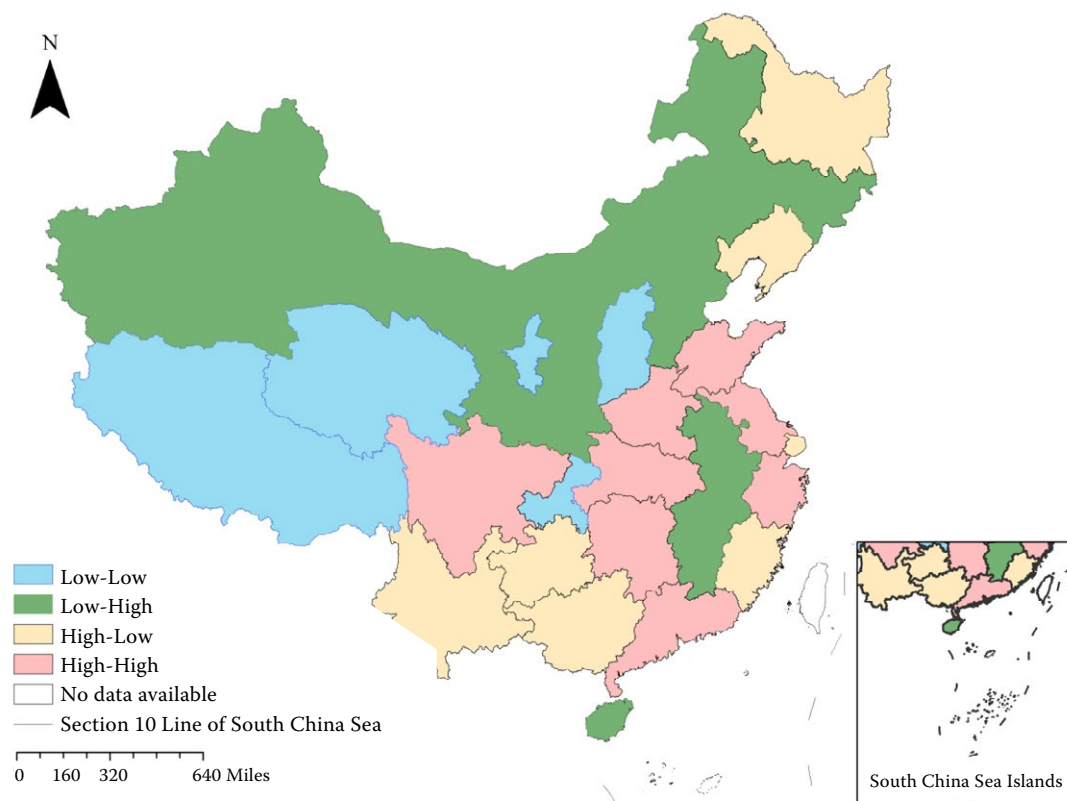


Figure 2. Spatial distribution pattern of agricultural eco-efficiency in China's interprovincial areas

Source: Authors' own elaboration

(Toop et al. 2017; Novaković et al. 2026). This implies that technology compatibility is constrained by resource endowments, geographical conditions, and the availability of ancillary agricultural facilities. A mismatch between technology supply and local agricultural needs may lead to a negative dynamic in the early stages of adoption – characterised by high investment, weak compatibility, and low efficiency – potentially entrapping the system in the productivity paradox.

Spatial correlation test. Given the nonexcludability of agricultural green innovation technologies within digital environments, the baseline regression model may fail to capture the spatial interdependencies inherent in agricultural green development. It is therefore essential to examine potential spatial spillovers – specifically, whether spatial correlation exists between agricultural digitalisation and provincial agroecological efficiency. Research indicates that the strong externalities of the digital economy significantly promote the cross-regional flow and diffusion of technology and knowledge, thereby attenuating the role of geographical distance in technology dissemination (Li and Tan 2021; Fan et al. 2025).

As a preliminary step in spatial econometric analysis, this study employs Moran's I index to test for spatial autocorrelation. The results are presented in Figure 3.

In this study, the global Moran's I index for provincial agroecological efficiency in China between 2007 and 2022 fluctuated between 0.128 and 0.163. The local Moran's I index exhibited an overall upwards trend during the study period and passed the significance tests. These results indicate a significant spatial correlation and geographical agglomeration in China's provincial agroecological efficiency, confirming the presence of spatial spillover effects.

Spatial Durbin model regression. The spatial correlation test results reveal that China's provincial agroecological efficiency is significantly positively spatially correlated. To mitigate estimation bias arising from model selection, spatial econometric models were employed to estimate the spatial spillover effects of agricultural digitalisation on *AGTFP*. The LM, LR, and Wald test results in columns 1 and 2 of Table 4 indicate that spatial effects cannot be ignored. In conjunction with the Hausman test (χ^2) results for the pooled model in Table 3, the two-way fixed effects SDM was ultimately chosen.

Table 3. Estimation results of agricultural digitalisation's impact on China's agroecological efficiency ($n = 310$)

Variable	(1) Pooled OLS	(2) Pooled OLS	(3) Random effects	(4) Fixed effects
<i>Rdig</i>	0.051 0 (0.96)	0.049 4* (1.60)	−0.038 1* (−1.58)	−0.022 8** (−2.29)
<i>Rdig</i> ²	–	0.029 9 (1.44)	0.041 4** (1.95)	0.039 2*** (2.14)
<i>Fin</i>	–	0.055 3 (1.78)	0.127 4*** (4.27)	−0.008 2 (−0.44)
<i>Elec</i>	–	0.064 5** (2.96)	0.284 7*** (9.59)	0.129 1*** (4.62)
<i>Astru</i>	–	0.253 7*** (7.46)	0.403 4*** (8.47)	0.136 0** (2.98)
<i>Rne</i>	–	−0.097 3*** (−5.91)	−0.092 6*** (−7.72)	−0.016 7* (−2.21)
_cons	−0.046 6 (−1.09)	0.443 3* (2.15)	1.313 2*** (5.33)	0.777** (−5.42)
Year FE	no	no	yes	yes
Province FE	no	no	no	yes
Hausman			530.69 (0.000)	
R^2	0.413 6	0.632 0	0.353 9	0.631 2

***, **, and *significance at the 1%, 5%, and 10% levels, respectively; *t*-values are in parentheses; *Astru* – agricultural industrial structure; *Elec* – agricultural electricity input; *Fin* – financial support of agriculture; OLS – ordinary least squares; *Rdig* – the level of agricultural digitalisation; *Rne* – agricultural natural environment; FE – fixed effect

Source: Authors' own elaboration

The regression results in columns 3, 4, and 5 of Table 4 show that the direct effect coefficient of *Rdig* is significantly negative. The coefficient for the spatial lag term $W \times Rdig$ is also negative, indicating that the mutual imitation of digital technologies among peer groups under spatial autoregression exerts a direct inhibitory effect on local *AGTFP*. The direct effect coefficient of *Rdig*² is significantly positive, and the coefficient of the spatial lag term $W \times Rdig^2$ is likewise positive. This suggests that the benefits of agricultural digitalisation technologies exhibit lagged and cumulative effects; in the long term, the spatial diffusion of digital technologies in neighbouring provinces has a direct promoting effect on local *AGTFP*. These findings further validate H_1 .

Additionally, the significance levels of the regression coefficients under the economic–geographical weight matrix in columns 3 and 4 of Table 4 are notably higher than those under the adjacency weight matrix. This finding indicates that imitation behaviour

exists between Chinese provinces, where agricultural digitalisation in leading regions generates strong demonstration effects; however, these effects do not diminish with increasing spatial distance. On the one hand, this implies that leading provinces do not exhibit digital hegemony, as digital technologies transcend spatial barriers, accelerating regional economic connections and promoting the spatial spillover of digital agricultural technologies. On the other hand, it demonstrates that the effectiveness of spatial spillovers is closely linked to local economic development levels and the foundations of digital infrastructure.

The staged nature of technology diffusion spillover effects provides circumstantial evidence for the productivity paradox and further suggests that risks such as the overuse of fertilisers and pesticides, as well as labour displacement, may emerge during the initial diffusion phase. These results are consistent with the conclusions drawn by Chari et al. (2021), who used

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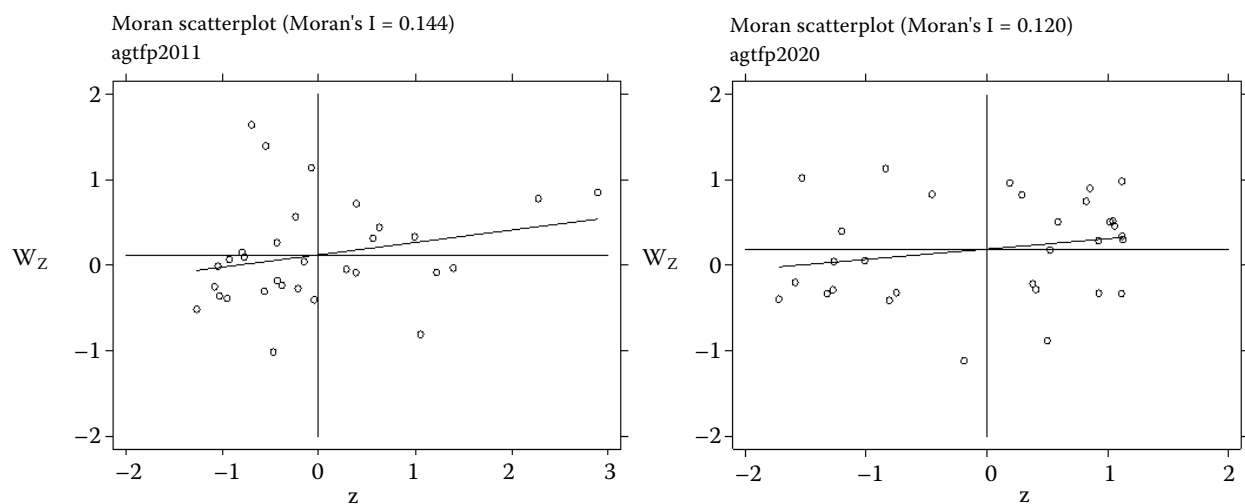


Figure 3. Scatter plot of the local spatial correlations of interprovincial agroecological efficiency in China

Source: Authors' own elaboration

rural data in China and suggested that the relationship between the diffusion of agricultural digitalisation and agroecological efficiency is not simply linear. The indiscriminate introduction of advanced technologies without due consideration of local digital infrastructure can lead to mismatches between the technology supply and local demand, along with incompatibility arising from insufficient supporting infrastructure and institutional frameworks. This results in outcomes of high input, weak adaptability, low output outcomes. As argued by Ye (2025), in the short term, the spatial diffusion of technologies may fail to deliver the expected spillover benefits and may instead provoke negative chain reactions across economic, social, and ecological domains because of external siphoning effects. This reflects the long-term dynamics of technology dividend realisation and highlights that technological progress in enhancing ecological efficiency may be constrained by technological adaptability and institutional coordination. Therefore, improvements in the land transfer system are essential for facilitating farmland scale management and providing practical scenarios for the effective implementation of digital technologies.

Endogeneity and robustness tests. To address potential endogeneity, this study adopts an instrumental variable (IV) approach. Following Huang et al. (2019), the number of telephones per 100 rural households in each province in 2000 is selected as the IV. This historical measure is relevant to contemporary agricultural digitalisation but exogenous to current agricultural green development trends. It interacts with annual rural internet broadband subscribers to form a panel IV.

The results (Table 5, column 1) show an LM statistic of 87.59 and a first-stage F statistic of 173.02, rejecting underidentification and weak identification, thus confirming the instrument's validity. The estimated coefficients for digitalisation ($Rdig$) and its square ($Rdig^2$) remain significant and retain their expected signs, supporting the productivity paradox (H_1). The magnitude of the coefficient is smaller than that in the baseline model, indicating that endogeneity had previously led to an overestimation.

Mediation effect test. As indicated in the study by Qiu et al. (2022), farmland-scale management provides crucial application scenarios for technology implementation. Therefore, on the basis of H_2 , this study employs land-scale management ($Lscale$) as the mediating variable to examine the mechanism through which agricultural digitalisation affects agroecological efficiency. To ensure the robustness of the results, IV methods were applied, along with LM and Wald F -statistic tests, within the stepwise regression models. The results of the mediation effect test are reported in Table 6.

The results of the land-scale management mechanism analysis reveal that the effect of agricultural digitalisation on land-scale management is significantly positive at the 1% level. After $Lscale$ was added to the original regression, the coefficient of $Rdig$ decreased to 0.003 4. These findings indicate that agricultural digitalisation can significantly increase the level of farmland scale. Furthermore, the results in Table 5 show that the Sobel–Goodman and Karlson–Holm–Breen (KHB) tests confirm that land-scale management plays a partial mediating role. Therefore, the mediation effect holds,

Table 4. Spatial Durbin model tests and regression results ($n = 310$)

Variable/Test	Test		Regression results		
	(1) SEM	(2) SLM	(3) SDM (contiguity)	(4) SDM (econ dist)	(5) dynamic SDM
<i>L.Rdig</i>	–	–	–	–	1.117 5*** (31.61)
<i>Rdig</i>	–0.109 6** (–2.35)	–0.106 9** (–1.98)	–0.043 3** (–2.26)	–0.087 7*** (–2.74)	–0.056 2** (–2.51)
<i>Rdig</i> ²	0.087** (2.15)	0.049** (1.98)	0.037* (1.87)	0.066*** (17.05)	0.053*** (3.84)
<i>Controls</i>	yes	yes	yes	yes	yes
<i>Fixed effects</i>	yes	yes	yes	yes	yes
<i>W × Rdig</i>	–	–	–0.065 9** (–2.07)	–0.079 2*** (–4.64)	–0.018 2*** (–11.94)
<i>W × Rdig</i> ²	–	–	0.050 6*** (3.55)	0.068 5*** (2.67)	0.092 5** (1.96)
<i>Spatial rho</i>	0.288 3*** (4.13)	0.152 1*** (7.46)	0.131 8*** (4.66)	0.390 2*** (6.26)	0.032 6* (0.38)
<i>Sigma2_e</i>	0.004 8*** (12.40)	0.004 5*** (12.35)	0.004 2*** (12.42)	0.004 6*** (12.28)	0.001 3*** (13.13)
<i>Moran's I</i>	7.235***				
<i>LM-error</i>	50.087***				
<i>Robust LM-error</i>	32.080***				
<i>LM-lag</i>		19.084***			
<i>Robust LM-lag</i>		1.077			
<i>LR test</i>		29.51***			
	42.01***				
<i>Wald test</i>		30.18***			
	42.68***				
<i>R</i> ²	0.559 5	0.513 3	0.279 0	0.301 3	0.425 9

***, **, and *significance at the 1%, 5%, and 10% levels, respectively; *t*-values are in parentheses; LM – Lagrange multiplier, LR – likelihood ratio; *Rdig* – the level of agricultural digitalisation; SEM – spatial error model; SLM – spatial lag model; SDM – spatial Durbin model; *W* – spatial weight matrix

Source: Authors' own elaboration

and H_2 is validated. These results are consistent with the conclusions drawn by Wang et al. (2022), who used rural data in China and suggested that farmland-scale management leads to an expansion of farmers' production scale, thereby effectively promoting the adoption of advanced agricultural technologies.

However, the test results also reveal that the contribution rate of the mediating effect of land-scale management is relatively weak. Geng and Luo (2022) argued

that whether farmland-scale management adopts new digital technologies, land improvement, and other long-term investments depends on expectations regarding the stability of land operation rights, which suggests that clear land ownership can promote land transactions between farmers, expand the scale of arable land, eliminate improper land allocation, and thereby improve *AGTFP*. Otherwise, the opportunistic motives and short-term profit maximisation tendencies of large

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Table 5. Endogeneity and robustness estimation results

Variable/Method	(1) IV approach	(2) Replace dependent variable	(3) Reduce sample	(4) Winsorisation
<i>Rdig</i>	−0.003 7* (−1.60)	−0.051 5** (−2.10)	0.079 0* (1.73)	−0.006 6*** (−2.54)
<i>Rdig</i> ²	0.010 2** (1.98)	0.002 8** (2.42)	0.115 9 (1.11)	0.036 8** (2.35)
<i>Controls</i>	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes
<i>Province FE</i>	yes	yes	yes	yes
LM statistic	87.59***	–	–	–
<i>F</i> statistic	173.02	–	–	–
<i>n</i>	279	279	243	279
<i>R</i> ²	0.565 7	0.677 3	0.455 6	0.677

***, **, and *significance at the 1%, 5%, and 10% levels, respectively; *t*-values are in parentheses; LM – Lagrange multiplier; *Rdig* – the level of agricultural digitalisation

Source: Authors' own elaboration

operators perpetuate traditional production methods, failing to alleviate the abuse of fertilisers and pesticides and thus hindering *AGTFP* improvement.

Moderation mechanism test. Farmland-scale management is critical for reducing costs and enhancing efficiency in the application of advanced agricultural

Table 6. Mediating mechanism test results (*n* = 310)

Variable	lnAGTFP	lnLscale	lnAGTFP
ln <i>Rdig</i>	−0.028 86* (−1.82)	0.019 2*** (3.21)	−0.010 04*** (−17.81)
ln <i>Lscale</i>	–	–	0.003 4*** (2.75)
Controls	yes	yes	yes
_cons	−0.121 2** (−1.97)	0.123 5** (3.06)	−0.146 4 (−0.99)
<i>Year FE</i>	yes	yes	yes
<i>Province FE</i>	yes	yes	yes
LM statistic	–	82.692	87.511
Wald <i>F</i> statistic	–	204.177	236.154
<i>R</i> ²	0.531 5	0.483 1	0.635 2
<i>Sobel</i>		0.007 983 67**	
<i>Goodman–1</i>		0.007 983 67**	
<i>Goodman–2</i>		0.007 983 67**	
<i>Total effect</i>		0.028 86	
<i>Indirect effect</i>		0.007 9	
<i>Proportion</i>		0.027 6	

***, **, and *significance at the 1%, 5%, and 10% levels, respectively; *t*-values are in parentheses; *AGTFP* – agricultural green total factor productivity; LM – Lagrange multiplier; *Lscale* – farmland-scale management; *Rdig* – the level of agricultural digitalisation

Source: Authors' own elaboration

Table 7. Moderating mechanism test results

Variable	Model (3)	Model (4)	Model (5)
<i>lnRdig</i>	0.018 1*** (4.72)	–0.029 6** (–2.13)	–0.008 2** (2.41)
<i>lnLscale</i>		0.008 6** (2.02)	0.045 1** (1.97)
<i>DegreeOa</i>			0.060*** (2.68)
<i>lnLscale × DegreeOa</i>			0.073*** (11.98)
<i>Controls</i>	yes	yes	yes
<i>_cons</i>	3.228 (0.209)	0.929 (1.47)	0.264** (2.42)
<i>Year FE</i>	yes	yes	yes
<i>Province FE</i>	yes	yes	yes
Log likelihood	37.255	5.390	29.086
Adjusted R^2	0.720 0	0.490 9	0.620 1

***, **, and *significance at the 1%, 5%, and 10% levels, respectively; *t*-values are in parentheses; *DegreeOa* – agricultural organisation; *Lscale* – farmland-scale management; *Rdig* – the level of agricultural digitalisation

Source: Authors' own elaboration

technologies (Liang et al. 2024). This signifies that technological advancement in agriculture is a critical catalyst for the transformation of traditional farming into green agriculture. Agricultural digitalisation equips digital agricultural technologies and production practices with strong capabilities for information integration, dissemination, feedback, and knowledge sharing through internet, big data, and resource-sharing platforms. This breaks spatial constraints and fosters a dandelion effect pattern of spatial spillover. However, both the construction of digital infrastructure and the application and promotion of digital agricultural technologies require an appropriate carrier. Given China's fundamental agricultural conditions, land transfer remains the primary means of achieving farmland scale management (Feng et al. 2023; Yang et al. 2024). To fully mobilise land transfer in promoting scale operations, ensuring stable profit expectations for large operators and addressing the fragmented nature of rural land are necessary. As the microfoundation of land transfer, agricultural organisation plays a crucial role in the mechanism through which farmland-scale management influences agroecological efficiency.

The test results for the moderating effect of agricultural organisation on farmland scale management are

presented in Table 7. The results indicate that the interaction term *lnLscale × DegreeOa* is significantly positive (0.073*** in Model 5, column 3). The coefficient for *lnLscale* alone increases in magnitude and significance from 0.008 6 in Model 4 to 0.045 1 when it interacts with *DegreeOa* in Model 5. Simultaneously, the negative effect of *lnRdig* on *AGTFP* weakens, shifting from –0.029 6** in Model 4 to –0.008 2* in Model 5. These findings confirm that higher levels of agricultural organisation positively moderate the relationship between farmland-scale management and agroecological efficiency. As land policies improve and organisational capacity strengthens, farmers' willingness to transfer land increases, positioning scale economies as a key mechanism to overcome the Solow paradox. These findings support H_2 .

The concept of China as 'a large country with small-scale farming', as analysed by Huang (1991), regarding the land-fragmentation farming model of smallholders in rural China, offers a penetrating and realistic assessment. Diverging from the top-level design of the government's Rural Revitalisation strategy, the grassroots logic prevalent in rural China – centred on how households sustain low-cost livelihoods – serves as a major impediment to land circulation. As rural society evolves

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and urbanisation progresses, the opportunity cost for farmers increases, and the benefits of fragmented landholding decrease significantly. Nonetheless, this does not necessarily lead to the widespread adoption of large-scale farmland across all parts of China. Therefore, Chen (2019) argues that reversing the trend of rural deorganisation is essential to link smallholders with modern agriculture. While strengthening policy guarantees for land rights is critical, efforts to promote land transfer and reduce fragmentation must acknowledge the vital role of village collective economic organisations. The capacity of these organisations to establish effective interest linkage mechanisms directly influences smallholders' land transfer decisions and profit motivations, thereby affecting the degree of farmland scale, the adoption of advanced technologies, and ultimately the enhancement of agroecological efficiency. Guided by the principle of extensive consultation, joint contribution, and shared benefits, China has achieved significant milestones in establishing overseas agricultural industrial parks (Li et al. 2024). These accomplishments present a distinct Chinese approach to agricultural organisation for global agricultural governance.

CONCLUSION

Research conclusions. Agricultural digital technology is a pivotal driver for safeguarding the ecological environment and achieving high-quality agricultural development in China, with farmland-scale management serving as a critical carrier for its application and diffusion. By utilising provincial panel data from 2007 to 2022, this study employs SDMs and mediation effect models to empirically analyse the impact of agricultural digitalisation on agroecological efficiency, in addition to its underlying mechanisms and effect magnitudes. The investigation further explores the mediating role of farmland scale management and the moderating factors affecting this relationship. The principal findings are as follows:

Baseline regression results indicate that the influence of agricultural digitalisation on agroecological efficiency is consistent with the productivity paradox, a finding that remains robust after a battery of rigorous tests.

The results from the SDM reveal significant positive spatial spillover effects of agricultural digitalisation on agroecological efficiency. The coefficients under the economic–geographical weight matrix are more pronounced than those under the adjacency matrix, implying that the efficacy of digital technology spillovers is contingent upon the quality of local digital

infrastructure. Spillover effects may fail to yield anticipated outcomes when they are misaligned with local agricultural needs.

The results of the mediation analysis confirm that farmland-scale management plays a significant mediating role in the relationship between digital technology and agroecological efficiency. Enhancing agricultural organisational capacity helps stabilise profit expectations for large-scale operators, mitigate land tenure disputes, and facilitate land transfers, thereby positively moderating the pathway through which digitalisation enhances efficiency via scale management.

Policy recommendations. Farmland-scale management provides the foundation for digital technology diffusion, with agricultural organisations serving as a key pathway to achieve it. Integrating smallholders through cooperatives and digital platforms – as seen in European practices – offers a viable model. Internationally, the prevalent company + farmer arrangement connects smallholders to markets. However, evidence from China suggests that this model alone is insufficient: it often fails to formalise land transfer, strengthen profit expectations for large-scale operators, or lower digital technology adoption costs. This paper argues that while corporatised cooperatives are important, the kinship- and locality-based structure of rural Chinese society necessitates the recognition of the pivotal role of village-level collective economies. These community-based institutions critically influence smallholders' land disposition decisions and profit-driven behaviour, thereby shaping the extent of farmland consolidation and advanced technology uptake.

Therefore, this paper proposes the following policy improvements:

First, digital agriculture should be integrated with ecological governance globally. Digital technology offers a strategic opportunity to align economic and ecological goals (Sanyaolu and Sadowski 2024; Gherțescu et al. 2025). To realise this potential, it is critical to draw on advanced international models (e.g. Dutch Smart Agriculture and U.S. Precision Agriculture) and the scaling experiences of emerging economies; policies should balance scale management with the strengths of precision-oriented smallholder farming.

Second, context-specific digitalisation pathways should be promoted. Given the inherent spatial spillovers of digital technologies (Ju et al. 2023; Yin et al. 2024), strategies must align with local agricultural foundations and foster interregional collaboration. Encouraging models such as agricultural digital service providers and machinery-sharing cooperatives

can integrate smallholders into modern agriculture while reducing data acquisition costs and enhancing inclusivity.

Third, the institutional foundations for land and organisational innovation should be strengthened. Governments should act as institutional architects by advancing rural land transfer marketisation, establishing transparent information platforms, and securing land tenure. Improving village-level governance to promote diversified transfer models (e.g. land trusteeship and share-based cooperation) reinforces the coordinating role of village collectives, reduces disputes, stabilises investment expectations, and fosters an enabling environment for scaling sustainable practices.

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