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Financial Synergy, Spatial Spillover, and Agricultural Eco-efficiency: Evidence from Provincial Panel Data in China

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Abstract. To identify pathways for improving agricultural ecological efficiency, this study starts from a financial perspective and studies the comprehensive effects of the collaborative interaction between digital finance and green finance, using China as a case study. Based on the Double Machine Learning (DML) approach and panel data from 31 Chinese provinces during 2012-2023, this paper investigates how digital and green finance work in synergy, affecting agricultural eco-efficiency. Further spatial econometric analysis is conducted to investigate the spatial variation in agricultural eco-efficiency and synergistic effects. Empirical results show that green finance prominently improves agricultural eco-efficiency. This effect is amplified when digital finance acts synergistically with green finance. Agricultural ecological efficiency has a negative spatial spillover effect, with the financial synergistic effect being more pronounced in this stage. Both the spatial spillovers and the synergistic impact of green and digital finance exhibit remarkable regional heterogeneity. To achieve sustainable agricultural development, it is necessary to develop region-specific strategies to fully leverage the synergistic effects of digital and green finance.

Keywords: Agricultural eco-efficiency, green finance, digital finance, synergistic effect, agricultural development

1. Introduction

Over the past decade, the importance of China's issues according to rural areas, agriculture and farmers has gradually increased, emerging as fundamental concerns for economic stability and social welfare. China's agriculture is facing multiple challenges, including stringent resource constraints, severe environmental pollution, and ecosystem degradation. These challenges manifest in land scarcity, soil degradation, intensifying non-point source pollution, and inadequate ecological conservation systems [1]. Such practical problems show the urgent need for agriculture to transition toward resource-efficient and environmentally sustainable practices. Internationally, the advancement of agricultural ecological efficiency has emerged as a central pillar of the global sustainable development agenda. The European Union's Common Agricultural Policy has established greenhouse gas emission reduction as a core target for 2030 [2]. Developing countries undergoing rapid industrialization face even more acute resource and environmental pressures [3]. As one of the world's largest agricultural producers and carbon emitters, China's experience in agricultural green transformation holds worldwide significant reference value [4].

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Existing research shows that green finance enhances agricultural eco-efficiency, partly operating through economic scale expansion, indirect capital guidance and incentives for technological innovation [5, 6]. It also exhibits positive direct and spatial spillover effects, which directly reduce agricultural carbon emissions [7]. Studies on digital finance often treat it in parallel with green finance, with their synergistic mechanisms receiving less scrutiny. Evidence suggests their synergy drives industrial upgrading, where digital technology lowers the transaction costs for green finance, while green finance provides direction for digital applications [8]. Spatially, the agricultural eco-efficiency exhibits significant spatial autocorrelation and spillover effects [9]. Furthermore, technological and industrial structural factors demonstrate regional variation in their effects [10]. Financial development also shows a spatial distribution on eco-efficiency. Positive spillovers are found in the eastern areas for digital finance, whereas competitive inhibition occurs in the central and western parts [11, 12]. The differences in financial inclusion lead to different effects [13]. The regional economic conditions and factor mobility are responsible for the above-mentioned spatial heterogeneity and promote the spillover of technology [14, 15]. Furthermore, digital finance enhances the energy efficiency and environmental results through the advancement of green technology, playing a middle role [16], and has an important threshold effect on the green economic growth [17].

Previously, many studies have shown that green finance can improve agricultural eco-efficiency. However, a comprehensive knowledge about the synergy between this two factors is still inadequate. The interaction between these two types of finance, as well as the spatial spillovers and regional differences in agricultural eco-efficiency, has not been sufficiently investigated. Hence, this research aims to answer two main questions: Is the synergy more efficient in increasing agricultural eco-efficiency than each one separately? Do both the synergy and agricultural eco-efficiency show spatial spillovers and regional variations?

This study makes three main contributions. It overcomes the shortcomings of single-factor analysis by investigating the synergistic improvement of agricultural eco-efficiency through digital and green finance, thus enriching the theory of rural finance [18]. In addition, it considers the spatial heterogeneity to show the regional differences and spillover effects, which provides guidance for differentiated financial strategies and the optimal distribution of resources across regions [5]. Furthermore, taking China as an instance and extending to the entire world, this work connects financial ecology, environmental economics and regional economics, expanding the scope of finance in agricultural sustainability and introduces a financial ecology viewpoint into the study of agricultural eco-efficiency.

2. Theoretical hypothesis

2.1. Green finance and agricultural ecological efficiency

Green finance is directed towards economic activities and projects that deliver positive environmental impacts, encompassing climate change mitigation, environmental conservation, and resource efficiency. Theory suggests that green finance mainly affects agricultural ecological efficiency through three main ways. Preferential credit policies channel social capital toward green agricultural projects, expanding sustainable industry scale [5], while environmental disclosure mechanisms and constraints on high-pollution financing drive the transformation of agricultural production mode [6]. Risk-sharing arrangements further encourage clean technology adoption and innovation [6]. These pathways collectively suggest that green finance enhances agricultural eco-efficiency, leading to the following hypothesis:

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H1: Green finance alone can significantly improve agricultural ecological efficiency.

2.2. Digital finance and synergy mechanisms

Digital finance refers to the provision of financial services in which traditional financial institutions and internet enterprises use digital technology to provide payment, investment, financing and other financial services [16]. However, digital finance alone has limitations in improving agricultural ecological efficiency. It lacks a clear green orientation, so funds may flow to high-pollution areas [13]. Agricultural green projects also have the characteristics of a long cycle and high risk, which make it difficult to meet financing needs through itself alone [4]. The synergy of green finance and digital finance can bring each other advantages. Technologies facilitate cost reductions in information search and risk assessment for green finance through digital finance, which enhances its accessibility and comprehensiveness [7]. Green finance offers definite environmental standards and sets a guideline for digital finance, guaranteeing that the funds for agricultural projects comply with the sustainable development objectives [8]. Hence, this research puts forward the following hypotheses:

H2: Digital finance needs to act synergistically with green finance to significantly improve agricultural ecological efficiency.

2.3. Impacts on spatial dimensions

From a spatial perspective, financial impacts on agricultural eco-efficiency display marked geographic variation. Differences in economic development, financial infrastructure, and institutional quality across regions create distinct spatial patterns. Eastern China combines advanced economies with well-developed financial systems, while central and western regions lag in technology and infrastructure, generating divergent impacts [11, 12]. Factor mobility and technology diffusion further shape these spatial spillovers.

Investigating digital and green finance separately, digital finance breaks through the traditional geographical limitations which promote resource distribution between regions [14]. Green finance regulations might transfer pollution-intensive industries to adjacent areas, resulting in negative externalities [17]. The eco-efficiency of agriculture is influenced by the utilization of resources, environmental conditions and production quantities, which may show spatial autocorrelation and affect the relationships among nearby regions. With the progress of time, various spatial externalities and regional differences appear [9]. Consequently, the following hypotheses are proposed:

H3a: Agricultural eco-efficiency demonstrates persistent negative spatial spillovers with regional heterogeneity.

H3b: The effect of digital-green finance synergy on agricultural eco-efficiency demonstrates regional variation, with certain regions impacting agricultural eco-efficiency via spatial spillover mechanisms.

3. Variable setting

3.1. Variables

In this study, the dependent variable is agricultural ecological efficiency, which serves as a crucial indicator for assessing sustainable agricultural development, focusing on achieving greater agricultural output with less resource consumption and environmental pollution [19]. Following Lin

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et al., this study constructs a super-efficiency SBM model with undesirable outputs to quantify the agricultural ecological efficiency of the main grain-producing areas [20]. This study uses the practice of Yin et al. to construct the coupling coordination index GDFO to capture the synergistic effect generated by digital and green finance [21]. The variables' definitions are presented in Table 1.

Table 1. Variable introduction

type of variable	symbol	construction
explained variable	Agricultural ecological efficiency (agri_evo)	Measured by the super-efficiency SBM model incorporating undesirable outputs
	Digital finance (dig)	The Digital Inclusive Finance Index, published by Peking University
explanatory variable	Green finance (green)	Composite indicator derived from the entropy method, covering 7 dimensions, including green credit, green bonds, green insurance, green investment, green securities, carbon finance, and green development support
	Coupling coordination index (GDFO)	Coupling coordination index between dig and green
	Agricultural mechanization level (agri_mach)	The ratio of the total power of agricultural machinery to the total sowing area of agriculture
	Urbanization rate (urban)	The ratio of the urban population to the total population at the end of the year
	Government intervention (gov)	The ratio of general government fiscal expenditure to regional gross domestic product
	Economic development (gdp)	Captured by the common logarithm of nominal provincial gross domestic product
control variable	Agricultural agglomeration (agri_con)	Calculate the quotient obtained by dividing the ratio of provincial agricultural output value to national agricultural output value by the ratio of provincial GDP to national GDP using location entropy.

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Table 1. (continued)

Environmental regulation (env)	The ratio of environmental expenditure to government fiscal expenditure
Human capital investment (edu)	The ratio of education expenditure to government fiscal expenditure
Technological innovation (tech_innovation)	Take the logarithm of the number of patent authorizations
Agricultural scale (agri_dev)	Take the logarithm of the total agricultural output value

3.2. Data sources

This study uses provincial-level panel data spanning 31 Chinese provinces over the 2012-2023 period, sourced from China Statistical Yearbook, National Bureau of Statistics, provincial statistical yearbooks, China Rural Statistical Yearbook, China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, and China Financial Yearbook. For missing data, this study uses linear interpolation technology to complete it. The descriptive statistical characteristics are shown in Table 2.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
(agri_evo)	372	0.531	0.249	0.192	1.071
(dig)	372	2.401	0.184	1.789	2.676
(green)	372	0.432	0.244	0.0703	0.928
(GDFO)	372	0.617	0.208	0	0.984
(agri_mach)	372	3.325	0.496	1.973	4.126
urban)	372	0.603	0.126	0.229	0.896
(gov)	372	0.284	0.199	0.105	1.326
(gdp)	372	4.075	0.445	2.679	4.924
(agri_con)	372	1.223	0.666	0.0454	3.543
(env)	372	0.0286	0.00949	0.0100	0.0680
(edu)	372	0.162	0.0280	0.0989	0.222
(tech_innovation)	372	0.137	0.130	0.0217	0.766
(agri_dev)	372	0.177	0.0866	0.0789	0.687

3.3. Research methodology

This work is based on the partial linear regression model, estimated via Double Machine Learning to address the limitations of rigid functional form assumptions of conventional methods and captures nonlinear patterns in the data. Given the two-stage estimation framework, the implicit errors are

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corrected to eliminate confounding effects among multiple control variables, analyzing the effect of core variables on agricultural ecological efficiency. The formal specification is as follows. An econometric model was constructed to estimate the net effect α0 of the core variable Lit.

Baseline regression model:

$$G_{i,t+1}=\alpha_0 L_{it}+g(X_{it})+U_{it} \tag{1}$$

$$E(U_{it}|L_{it},X_{it})=0 \tag{2}$$

Auxiliary regression model:

$$L_{it}=m(x_{it})+V_{it} \tag{3}$$

$$E(V_{it}|X_{it})=0 \tag{4}$$

Gi,t+1 is used as the dependent variable with controls Xit. The residual term Vit is incorporated into the main equation. Flexible machine learning functions g(·) and m(·) are estimated via gradient boosting trees. The model addresses endogeneity and nonlinearity, and obtains robust estimates based on Neyman orthogonal scores.

4. Empirical analysis

4.1. Baseline regressions

Table 3 presents the empirical findings derived from the double machine learning estimation. Digital finance fails to achieve statistical significance, indicating an absence of direct impact on agricultural ecological efficiency. By contrast, green finance independently produces a positive effect, evidenced by a coefficient of 0.142(significant at the 10% level), which suggests that green finance contributes positively to enhancing agricultural ecological efficiency. The coefficient of the coupling coordination index (GDFO) is 0.191 with linear controls, and 0.161 with the addition of quadratic controls. (Significant at 1% and 5% levels). The interactive effect is greater than that of green finance working alone. This indicates that the joint action of digital and green finance has a statistically significant and positive impact on agricultural ecological efficiency. When there is an increase of one unit in this interaction term, it results in an improvement of 0.191 units in agricultural eco-efficiency. This result suggests that digital finance mainly enhances efficiency through its combination with green finance, leading to a "1+1>2" effect.

Table 3. Baseline regression results

Variable	(1) agri_evo	(2) agri_evo	(3) agri_evo	(4) agri_evo
dig	-0.044(0.142)			
green		0.142*(0.076)		
GDFO			0.191***(0.065)	0.161**(0.063)
First-order terms of control variables	Yes	Yes	Yes	Yes
Second-order terms of control variables	No	No	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	372	372	372	372

DOI: 10.54254/2754-1169/2026.BL34054

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

The above results fully demonstrate H1 and H2, indicating that green finance alone can improve agricultural eco-efficiency notably. The synergy between digital finance and green finance could further enhance agricultural eco-efficiency

4.2. Robustness checks

4.2.1. Alternative construction of the interaction term

In the baseline regression, this research evaluated the synergy by means of the coupling coordination index. In order to confirm the stability of the results, this model was estimated again by substituting GDFO with the multiplication of the two financial indices. The results shown in Columns (1)-(2) of Table 4 indicate that the synergy of the product term is still statistically significant and positive, with or without the quadratic control variables. This implies that the promoting influence of the synergy is valid under different methods of measuring the synergy.

4.2.2. Specification with control variables

To further confirm the reliability of the results, this study incorporates agricultural innovation as an important control factor which may affect both financial synergy and agricultural eco-efficiency in the model formulation. The estimation results are shown in columns (3) and (4) of Table 4. After taking into account agricultural innovation, the estimated value of the main explanatory variable still has a positive sign and is statistically significant at the 1% level, with its magnitude being close to that of the initial results. This supports the validity of the model.

Table 4. Robustness checks — alternative interaction terms and extended controls

Variable	Interaction Term:green*dig		Adding New Control: Agricultural Innovation	
Synergy Index (GDFO)	0.069**	0.08***	0.22***	0.179***
	(0.027)	(0.03)	(0.063)	(0.06)
Linear Control Variables	Yes	Yes	Yes	Yes
Quadratic Control Variables	No	Yes	No	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	372	372	372	372

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

4.2.3. Placebo tests

To exclude the possibility of unobserved factors or randomness that may drive the research conclusion, a placebo test is carried out in this study.The core explanatory variables were randomly assigned 200 times for regression analysis. As shown in Table 5, the average of the false coefficient obtained from the placebo test is approximately 0.002. The 95% confidence interval is [-0.038, 0.044]. The estimated coefficients are significantly different from the random distribution interval, indicating that the significant effect found in the initial regression is unlikely to be caused by

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accidental factors or other confounding factors except for the model settings. This result confirms the stability of the findings.

Table 5. Placebo tests

Variable	True Coefficient	Placebo Mean	Placebo SD	95% Quantile Range	Outside Range
GDFO	0.191***	0.002	0.021	(-0.038,0.044)	Yes

Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

4.2.4. Endogeneity checks

The model might remain susceptible to endogeneity concerns from potential reverse causality. To address this concern, this study re-estimates the specification using two-stage least squares (2SLS) with instrumental variables. As reported in Table 6, the instrument is constructed as the product of the provincial number of mobile phone owners per 100 people in 2001 with the lagged synergy index. The first-stage results indicate that the instrument is positively and significantly correlated with the endogenous variable (GDFO). The F-statistic is 18.73, which exceeds the critical value of 16.38, showing that the instrument is not weak. The second-stage estimates show the coefficient on the digital-green finance synergy (GDFO) is 0.634 (significant at the 1% level) after addressing endogeneity. This positive effect corroborates the baseline results, further confirming the robustness.

Table 6. Endogeneity checks

Variable	First Stage	Second Stage
IV	0.0307*** (0.0071)	—
GDFO	—	0.6340* (0.3383)
Control Variables	Included	Included
Observations	372	372
F-statistic	18.73***	96.50***
Weak Instrument Test	F(1,320)=18.73 (p=0.0000)	—

Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

4.3. Spatial dependence analysis

4.3.1. Moran's I estimation

To further examine spatial effects, first, the spatial dependence is judged by calculating the Moran index of the synergy term (GDFO) and agricultural eco-efficiency. As shown in Table 7, both variables exhibit strong spatial autocorrelation.

Table 7. Moran's I statistics

year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
GDFO	0.5212***	0.5474***	0.5515***	0.4138***	0.4645***	0.5259***	0.4904***	0.4798***	0.4954***	0.5239***	0.4976***	0.4932***
agri-evo	0.0594	0.0654	0.053	0.0753	0.0281	0.1543*	0.1926**	0.2099**	0.2863***	0.263**	0.3346***	0.3744***

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

Figure 1 presents the scatter diagram of the local Moran index for GDFO and agricultural ecological efficiency in 2012, 2015, 2019 and 2023. The majority of provincial observations are located in the first and third quadrants, indicating strong spatial clustering both in high and low values. The spatial autocorrelation test indicates significant spatial association, which supports the application of spatial econometric models (Figure 1).

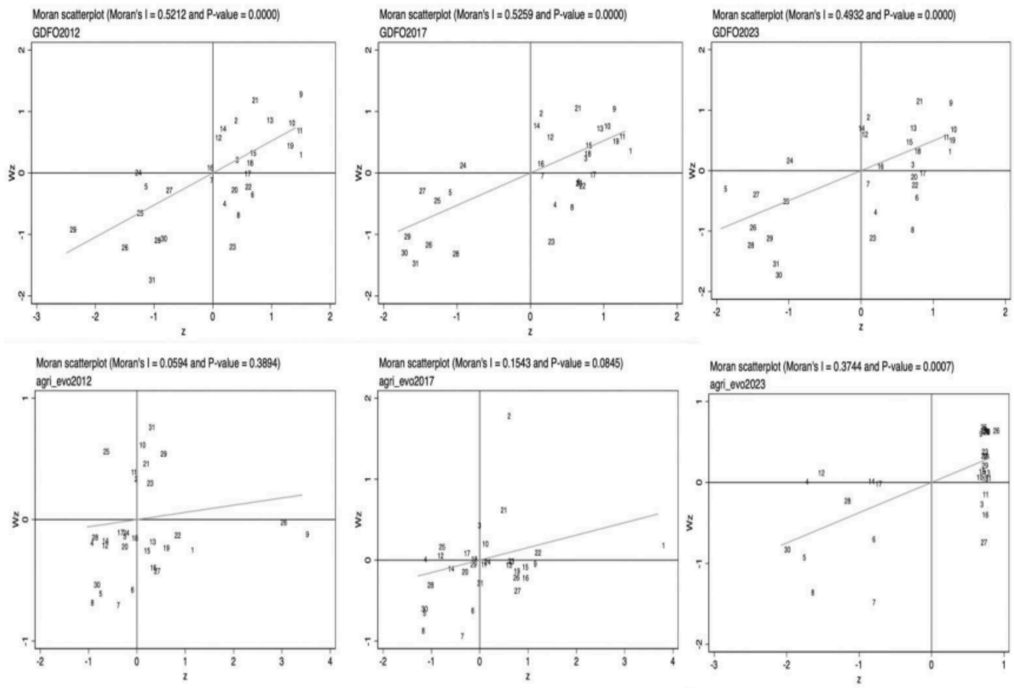

Figure 1. Moran scatter plot (picture credit: original)

4.3.2. LM, LR and Wald tests

LM test showed that LM lag statistic (100.869) and robust LM lag statistic (40.029) were significant at 1% level. Robust LM error was not significant, which demonstrate spatial lag model (SAR) should be selected. Through LR test (χ^2=13.54, P=0.195) and Wald test, it is concluded that the regression can degenerate into SAR model, and SAR model will be used for regression analysis

4.4. Spatial lag model baseline regression

Construct a gdfo*period dummy variable to fit the effect after the year 2017. From Table 8, the spatial autoregressive coefficient (ρ) is significantly negative, confirming the negative spatial spillover effect of agricultural eco-efficiency in H3a. In the spatial lag model, GDFO is significant at the 5% level. Its influence is more obvious in the later period, suggesting that the value of digital-green finance synergy is fully utilized when agricultural green development reaches the "regional competition" stage. A stronger negative spatial spillover indicates a greater external pressure on local agricultural eco-efficiency, which needs more effective use of financial resources to keep and enhance the efficiency; therefore, the synergy effect becomes more evident.

DOI: 10.54254/2754-1169/2026.BL34054

Table 8. Spatial lag model baseline regression

	agri_evo	agri_evo
GDFO	0.114 (0.122)	0.219* (0.113)
GDFO_period	0.137** (0.064)	
Control variables	Included	Included
rho	-0.363*** (0.086)	-0.370*** (0.086)
N	372.000	372.000

Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

4.5. Spatial heterogeneity analysis

Following economic development criteria, the 31 provinces are categorized into four regional groups: eastern, central, western, and northeastern China. The measurement results using the spatial Durbin model are shown in Table 9.

Table 9. Spatial heterogeneity

	(1)East	(2)central	(3)West	(4)Northeast
	agri_evo	agri_evo	agri_evo	agri_evo
GDFO	-0.321	0.011	0.196*	-0.542***
	(0.310)	(0.340)	(0.112)	(0.186)
GDFO*w	-1.044	-1.220	0.079	-1.044***
	(0.826)	(0.979)	(0.345)	(0.383)
rho	-0.389***	-0.312***	-0.636***	-0.295**
	(0.151)	(0.145)	(0.121)	(0.131)
N	120.000	72.000	144.000	36.000

The spatial autoregressive coefficient (rho) is significantly negative (at the 1% level) across all regions, supporting Hypothesis H3a, agricultural eco-efficiency exhibits a long-term negative spatial spillover effect, and the intensity of the effect shows significant regional differences . Besides,the effect of GDFO in the northeastern region exhibits a significant spatial spillover effect on agricultural eco-efficiency. Not only the direct, but also the spatial spillover effects of digital-green finance synergy (GDFO) display marked regional heterogeneity, supporting Hypothesis H3b.

5. Conclusion

5.1. Main findings and limitations

Through theoretical analysis and empirical analysis tests, this study comes to the following core conclusions:

Green finance significantly improves agricultural eco-efficiency. The synergy of digital and green finance is a more significant factor in improving agricultural eco-efficiency. Agricultural eco-

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efficiency additionally displays negative spatial externalities. In the later period, as agricultural green development progresses, this negative spatial spillover becomes more pronounced with the synergy effect of digital and green finance strengthening at the same time. The synergistic effects exhibit regional heterogeneity directly and indirectly (through spillover impacts) on agricultural eco-efficiency. Specifically, the northeastern region exerts adverse effects on adjacent regions' agricultural eco-efficiency via spatial spillover mechanisms.

The research is subject to limitations: variables are measured at a relatively macro level. The interaction mechanisms of specific dimensions, such as digital payment and green credit, are not examined in depth. In the spatial effect analysis, post-2017 estimates may be confounded by policy interventions such as the "Rural Revitalization" strategy. The provincial panel data have limited observations in some regions, so county-level data can be used to improve accuracy in the future.

5.2. Policy implications and future research

The study confirmed notable synergy between digital and green finance. Policymakers should promote agricultural credit products that integrate both dimensions, meanwhile, provide preferential rates for ecological farming and water-saving technologies in order to strengthen the coordination of the two to improve the precision of agricultural ecological efficiency.

Strong negative spatial spillovers in eco-efficiency gives out a conclusion that coordinated cross-regional governance and optimized geographic allocation of financial resources should be introduced. The competitive pressure from these spillovers can accelerate digital-green finance adoption, further helping stabilize and enhance local agricultural outcomes.

Spatial heterogeneity demands differentiated regional strategies. Regions with slow industrial transformation, such as Northeast China, require industrial restructuring and integrated service platforms to mitigate negative spillovers. In western China and comparable underdeveloped regions, sustained collaborative financial support is needed alongside digital infrastructure investment. In contrast, Eastern, Central China and the same advanced regions around the world should focus on optimizing marginal utility, matching financial resources to agricultural green transition needs precisely to maximize effectiveness.

Future research might analyze the synergistic mechanism between digital credit, insurance and green finance, particularly how industrial structure and digital infrastructure moderate these effects. Such inquiry would support the construction of differentiated digital-green financial systems and shift towards smart, low-carbon agriculture.

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