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EDITED BY

Prakash Kumar Jha,
Mississippi State University, United States

REVIEWED BY

Bipin Bastakoti,
Mississippi State University, United States
Sunil Madan,
World Bank Group and International
Monetary Fund Library Network, United States

*CORRESPONDENCE

Caiwang Ning
✉ ncw0103@jxau.edu.cn
Shubin Zhu
✉ shubinzhuzhu@jxau.edu.cn

[†]These authors have contributed equally to this work

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The impact of digital infrastructure construction on grain production resilience: evidence from the “Broadband China” pilot policy

Lei Zhang^{1†}, Chengxun You^{1†}, Ziyi Guo², Suyu Liu¹,
Caiwang Ning^{1,3*} and Shubin Zhu^{1,3*}

¹College of Economics and Management, Jiangxi Agricultural University, Nanchang, China, ²Bureau of Agriculture and Rural Affairs of Guangchang County, Fuzhou, Jiangxi Province, China, ³Rural Development Research Center of Jiangxi Province, Jiangxi Agricultural University, Nanchang, China

Introduction: The role of digital infrastructure construction in bolstering grain production resilience is widely recognized.

Methods: This paper investigated the impact of digital infrastructure construction on grain production resilience by exploiting the “Broadband China” pilot policy as a quasi-natural experiment, using a two-way fixed effects model on panel data from 80 prefecture-level cities in China’s six major grain-producing central provinces from 2012 to 2022.

Results: The results show that the “Broadband China” pilot policy has significantly improved grain production resilience, a conclusion that holds after a series of robustness tests. Mechanism analysis reveals that the policy enhances grain production resilience by advancing the level of digital inclusive finance and boosting agricultural technological progress. Heterogeneity analysis indicates that the policy’s positive effects are more pronounced in economically less-developed regions and in southern regions.

Discussion: This paper offers targeted recommendations for strengthening digital infrastructure construction to improve grain production resilience, thereby contributing to national food security.

KEYWORDS

“Broadband China” pilot policy, China, digital infrastructure development, grain production resilience, six central provinces

1 Introduction

Food security is a vital component of national security and a cornerstone of social stability and public well-being (Huang and Yang, 2017). For over a decade, China’s total grain output has consistently exceeded 650 million tons, successfully meeting its basic food security objectives. However, the stability of China’s grain supply faces severe challenges from factors such as the increasing frequency of extreme weather events, volatility in international grain trade, and sharp rises in production costs. Consequently, the focus of China’s food security is shifting from ensuring quantity to securing sustainable supply capacity (Liang et al., 2025). The 2025 Central Document No.1 emphasizes the need to continuously enhance the supply and guarantee capabilities of grain and other major agricultural products, with a key pathway being to enhance the resilience of China’s grain production system. Therefore, developing a scientific and rational framework for measuring grain production resilience, and subsequently exploring effective paths to enhance it, holds significant practical importance for ensuring

China's long-term food security and achieving its goal of becoming a leading agricultural nation.

The concept of “resilience” was first proposed by the ecologist Holling, who defined it as the capacity of a system to absorb disturbances and reorganize while undergoing change (Cinner and Barnes, 2019). Folke (2006) was the first to introduce resilience into the field of agricultural economics. Since then, scholars have conducted research on various aspects, including agricultural economic resilience (Yao et al., 2024), agricultural development resilience (Xue et al., 2025), ecological resilience of agricultural water resources (Haddad et al., 2023), household economic resilience of farmers (Xie et al., 2024), and farmer livelihood resilience (Niu and Zhou, 2025). Research specifically on grain production resilience can be summarized into three main areas. First, regarding its conceptualization, Tendall et al. (2015) defined the resilience of a food security system as the ability of a grain production economy to recover after sustaining shocks, whether natural, political, social, or economic. Béné et al. (2016) noted that the resilience of a food system is not only reflected in a household's ability to withstand and absorb the negative impacts of unpredictable shocks but should also include its capacity to adapt and promote transformative change in the face of such shocks. Second, concerning the measurement of grain production resilience, most scholars have constructed “Pressure-State-Response” (PSR) models or “resistance, adaptability, and transformability” frameworks using provincial-level panel data (Xu et al., 2023; Wang A. et al., 2025; Wang J. L. et al., 2025). Third, in terms of influencing factors, existing studies have primarily explored the effects of rural labor migration (Blanco and Raurich, 2022), water resource carrying capacity (Wang A. et al., 2025; Wang J. L. et al., 2025), land consolidation and farmland property rights reform (Liu et al., 2025; Wei et al., 2025), climate change (Gao et al., 2025; Zhou et al., 2025), agricultural science and technology innovation and training (Jamil et al., 2021; Pandey et al., 2025), policy-based agricultural insurance and agricultural digitalization (Luo et al., 2025; Zheng and Zhao, 2025), and the digital economy (Xie et al., 2025).

It is evident that scholars have widely focused on the impact of agricultural digitalization on grain production resilience. Previous research and practical experience have shown that upgrading traditional agricultural infrastructure, such as water conservancy and land consolidation, helps mitigate the damage from droughts and floods, reduces the risk of yield loss, and effectively promotes stable and increased grain production (Yi and McCarl, 2018). In recent years, with the in-depth implementation of the “Digital Village” strategy, China has made significant progress in the construction of rural digital infrastructure. This new infrastructure has the function of digitally transforming traditional agriculture (Chen et al., 2025). A critical question then arises: Can the development of rural digital infrastructure effectively improve agricultural production capacity and thus enhance grain production resilience? Although existing literature provides a solid foundation for answering this question, there are still two areas for further exploration. First, most studies have examined grain production resilience from the perspective of the broader digital economy, with few focusing specifically on the impact of digital infrastructure construction as measured by the “Broadband China” pilot policy. Second, existing research often relies on provincial or county-level panel data. However, provincial-level data can be too broad, potentially leading to data distortion, while county-level data is often too granular, leading to issues with missing data. Constructing a

panel dataset at the prefecture-level can mitigate the distortion problems of provincial data while avoiding the data availability issues common at the county level.

In summary, this paper adopts the perspective of the “Broadband China” pilot policy and constructs a panel dataset for 80 prefecture-level cities in the six central provinces from 2012 to 2022. Using a progressive difference-in-differences (DID) method, we investigate the impact of digital infrastructure construction on grain production resilience and its underlying mechanisms. The objective is to provide a theoretical basis and policy insights for enhancing grain production resilience.

The marginal contributions of this paper are twofold: First, it explores the effect of the “Broadband China” pilot policy on grain production resilience and tests the mediating roles of digital inclusive finance and agricultural technological innovation, offering theoretical and empirical evidence for improving China's grain production resilience. Second, it delineates the boundary effects of the policy's impact from the perspectives of economic development levels and regional differences, providing targeted recommendations for refining policies aimed at enhancing grain production resilience.

2 Theoretical mechanism and hypothesis proposal

2.1 Direct impact of digital infrastructure on grain production resilience

Digital infrastructure is the cornerstone of the “Digital Village” construction, establishing the foundational logic for rural digital development through technological empowerment, industrial upgrading, and governance optimization. In the process of digitalization, information asymmetry can exacerbate efficiency losses and resource waste in production and trade. With the popularization of information infrastructure, the development and application of information technology, and the enhancement of information acquisition and processing capabilities, farmers with lower digital literacy face an income gap caused by “information poverty” (Helen and Reza, 2021). However, stable digital infrastructure, such as communication networks and power supply, ensures the real-time transmission of information related to the agricultural production environment and markets. This not only helps farmers to assess production and market risks and make precise decisions (Attour and Barbaroux, 2016), but also enables the dissemination of relevant risk-mitigation measures through new media channels.

In practical agricultural production, the integration of intelligent agricultural equipment and digital technology is driving a shift from traditional, extensive farming to precise and intelligent agriculture. This enhanced scientific and intelligent approach helps to reduce operating costs and significantly improve management efficiency. Furthermore, by optimizing the use of chemical inputs like pesticides and fertilizers, it not only reduces soil damage and the incidence of pests and diseases but also substantially increases land input efficiency (George et al., 2016; Sridhar et al., 2022). This also lays a foundation for rural land transfer and promotes large-scale land management (Zanello, 2012; Zhang X. et al., 2023; Zhang D. J. et al., 2023), thereby effectively strengthening the risk-resistance capacity of grain production. Concurrently, in the aftermath of natural disasters or unexpected events, the development of digital infrastructure enhances

regional logistics and distribution capabilities, making it possible to rapidly deploy production materials and resume agricultural activities in a timely manner. Moreover, improved digital infrastructure can lower market transaction costs, enhancing the recovery capacity of grain production in response to market risks. It also solidifies the foundation for the popularization of sustainable planting models like ecological and pollution-free agriculture, thereby strengthening the self-repairing ability of the food system (Liang et al., 2022). Additionally, the advancement of digital infrastructure drives the development of digital technologies, which helps to innovate traditional agricultural production and business models and promotes the integrated upgrading of the grain industry, thus increasing the added value and market competitiveness of agricultural products and enhancing the overall transformative capacity of grain production. Therefore, the following hypothesis is proposed:

H1: Digital infrastructure significantly enhances grain production resilience.

2.2 Mechanism of digital infrastructure on grain production resilience

2.2.1 Digital inclusive finance

Agriculture is characterized by long production cycles and high market uncertainty, which poses challenges for traditional rural financial products to serve agricultural production. The long-standing mismatch between supply and demand in rural finance has led to insufficient funding for agricultural production, severely constraining the development of large-scale and modern agriculture and creating a vicious cycle of mutual restraint. According to the endogenous financial growth theory, as the level of financial development improves, reductions in information asymmetry and transaction costs can effectively weaken the constraints on accessing rural financial services, thereby fostering a mutually beneficial relationship between rural finance and agriculture.

With the continuous improvement of rural digital infrastructure, digital technologies such as artificial intelligence and big data are enabling financial institutions to innovate and launch agricultural credit, insurance services, and other financial products. This enriches the rural financial service system and effectively enhances farmers' investment capacity in agricultural production factors (Morshadul et al., 2020). Among these, rural credit and agricultural insurance have become effective institutional arrangements for alleviating financial constraints and balancing agricultural risks (Ai et al., 2023). At the same time, enhanced digital infrastructure helps financial institutions to accurately obtain real-time information on agricultural production and operations, which aids in evaluating and predicting risks associated with agricultural practitioners, thereby increasing the likelihood and efficiency of farmers accessing financial products. Digital inclusive finance is a new digital financial model that utilizes technology to lower the threshold for financial services and expand their scope (Hathroubi, 2019). As rural digital infrastructure improves, digital inclusive finance can achieve broader coverage of rural areas and agricultural market entities. Through digital financial platforms, farmers and agricultural enterprises can conveniently obtain loan services, which increases the availability of productive capital (Ozili, 2017). This provides strong financial support for expanding operational scales and for post-disaster recovery of grain production

(Balogun et al., 2020), thus strengthening the recovery capacity of grain production when faced with external shocks. Accordingly, the following hypothesis is proposed:

H2: Digital infrastructure enhances grain production resilience by promoting the development of digital inclusive finance.

2.2.2 Agricultural technological progress

Technological progress is a fundamental force driving sustained increases in grain yield and improvements in agricultural quality and efficiency (Gouvea et al., 2022). Innovation theory suggests that technological transformation and upgrading of existing production systems can promote the free flow of resource elements such as labor, capital, and information. This, in turn, leads to optimized resource allocation, industrial upgrading, and an overall increase in production efficiency (Das et al., 2020), which is conducive to nurturing new industries, new models, new driving forces, and enhancing the risk resistance of product markets.

As rural digital infrastructure is upgraded, the application scenarios for digital and intelligent technologies in rural areas are continually enriched. The application of rapidly iterating digital and mechanized products alleviates rural labor shortages, improving agricultural production efficiency while reducing dependence on traditional production factors, thereby effectively enhancing agricultural production resilience. Smart agriculture and Internet of Things (IoT) projects reduce the information-matching costs for land transfers, accelerate the orderly digital transfer of farmland, and increase farmers' motivation to cultivate grain. The establishment of digital platforms such as "Yinong" information service stations and e-commerce service points effectively integrates smallholder farmers and connects them to larger markets. This not only facilitates the rapid sharing of production information among smallholders but also expands their sources of information for grain sales channels, thereby strengthening their grain production resilience. On this basis, the following hypothesis is proposed:

H3: Digital infrastructure enhances grain production resilience by fostering agricultural technological innovation.

2.3 Boundary effects of digital infrastructure on grain production resilience

2.3.1 Level of economic development

Digital infrastructure across China's provinces is not synchronized and is often closely linked to regional economic development levels. Generally, cities with higher levels of economic development are capable of investing more financial, technical, and human resources into digital infrastructure. Their construction timelines are often ahead of less developed cities, and they can provide more comprehensive digital services to farmers, helping them to conduct agricultural production more effectively. In contrast, economically underdeveloped cities have relatively lagging digital infrastructure and fewer application scenarios for digitally empowering agricultural production. Based on the theory of latecomer advantage, this paper posits that the implementation of the "Broadband China" pilot policy will have a more significant effect on improving digital applications in less economically developed regions, and consequently, a stronger enhancement effect on

grain production resilience. Therefore, the following hypothesis is proposed:

H4: Digital infrastructure exerts a stronger positive impact on grain production resilience in economically underdeveloped cities compared to their developed counterparts.

2.3.2 Regional differences

Compared to the plain areas in the north, the cultivated land in southern regions is characterized by steep slopes and fragmentation, which is unfavorable for both mechanized operations and large-scale farming. This results in a relatively weaker risk-resistance capacity for agricultural production in the south. The construction of digital infrastructure can enhance the disaster resistance and production efficiency of grain cultivation through precision meteorological monitoring, early warning systems, and smart agricultural technologies. It can also provide farmers with more accurate market information, comprehensively improving agricultural production resilience. Based on the latecomer advantage theory, this paper argues that because the effectiveness of digital infrastructure construction in southern regions is initially lower due to complex topography, the “Broadband China” pilot policy will have a more pronounced effect on improving its digital service level and, consequently, on enhancing grain production capacity. Based on this reasoning, the following hypothesis is proposed:

H5: Digital infrastructure exerts a stronger positive impact on grain production resilience in southern regions compared to their northern counterparts.

In summary, the following theoretical analysis framework is constructed (Figure 1).

3 Data and methodology

3.1 Data

The six central provinces (Shanxi, Henan, Anhui, Hubei, Hunan, and Jiangxi) are crucial grain production bases in China.

With one-tenth of the national population and one-quarter of the country’s arable land, this region supplies nearly one-third of the nation’s grain, making an outstanding contribution to China’s food security. Concurrently, over the past 11 years, despite certain disparities in the speed and level of economic development among these provinces, the overall trend of digital construction in the central region has been one of growth. Therefore, selecting a sample of 80 prefecture-level cities from the six central provinces for the period 2012–2022 is considered representative for this study.

The data for this paper were sourced from the *China Urban Statistical Yearbook*, the *Peking University Digital Financial Inclusion Index of China*, as well as the provincial statistical yearbooks, prefecture-level city statistical yearbooks, and statistical bulletins for the six central provinces: Shanxi, Henan, Anhui, Hubei, Hunan, and Jiangxi. Due to inconsistencies in statistical calibers across different regions and to ensure the adequacy and scientific validity of the sample, linear interpolation was used to fill in a small number of missing data points.

3.2 Variable

3.2.1 Dependent variable: grain production resilience

Following the existing research (Hao and Tan, 2022), this study constructs a comprehensive index system for grain production resilience based on three dimensions: Resistance, Recovery, and Transformability. This system comprises 6 subsystems and 16 elemental indicators (as shown in Table 1).

Resistance refers to the ability of the grain production system to mitigate and absorb internal and external risks and shocks. It includes two sub-dimensions: internal stability and supply-production robustness. Recovery denotes the speed of internal restoration and the degree of adaptation after the grain production system has been subjected to a shock. It includes two sub-dimensions: sustainability and recoverability. Transformability represents the capacity for self-adjustment and reorganization of the grain production system following a shock. It includes two

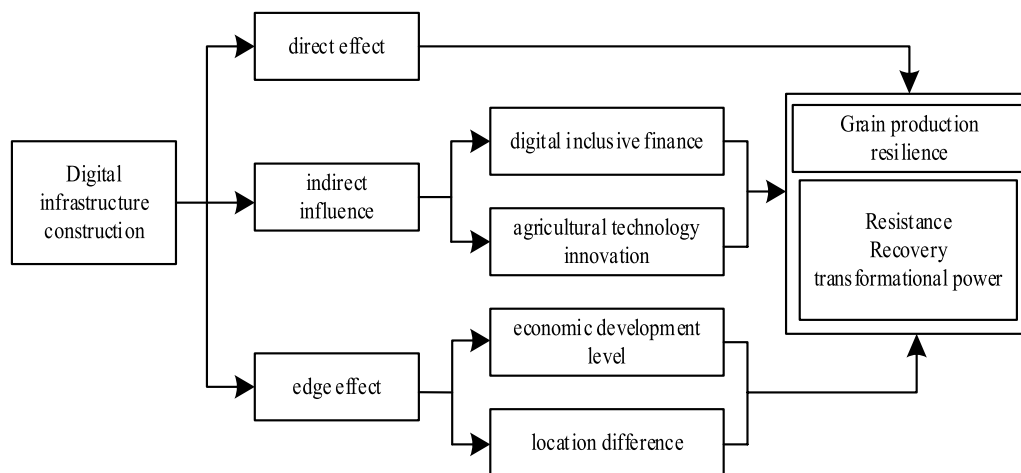


FIGURE 1
Theoretical analysis framework.

TABLE 1 Grain production resilience indicator system.

Primary indicator	Secondary indicators	Tertiary indicator	Indicator definition	Unit	Expected direction
Resistance	Internal stability	Arable land resources	Arable land area	Thousand hectares	Positive
		Irrigated farmland area	Effectively irrigated area	Thousand hectares	Positive
		Agricultural labor force size	Primary industry employment	Ten thousand people	Positive
		Grain sowing status	Grain sown area	Thousand hectares	Positive
	Production-supply robustness	Grain price stability index	Grain consumer price index	%	Positive
		Total grain production	Total grain output	Tons	Positive
		Grain yield per unit sown area	Grain yield/grain sown area	Kilograms per hectare	Positive
Recovery	Sustainability	Fertilizer consumption	Fertilizer application volume	Tons	Negative
		Agricultural economic output value	Primary industry value added	Ten thousand yuan	Positive
		Rural residents' economic income level	Rural <i>per capita</i> disposable income	Yuan	Positive
	Recoverability	Environmental policy intensity	Environmental regulations	%	Positive
		Rural electricity usage	Rural electricity consumption	Ten thousand kilowatt-hours	Positive
Transfer-mative Power	Diverse collaboration	Agricultural product logistics volume	Freight volume	Ten thousand tons	Positive
		Agricultural mechanization capacity	Total agricultural machinery power	Ten thousand kilowatts	Positive
	Diverse coordination	Agricultural technical talent reserve	R&D personnel*total output value of agriculture, forestry, animal husbandry, and fisheries/regional GDP	People	Positive
		Agricultural R&D investment	R&D Expenditure*agricultural, forestry, animal husbandry, and fishery output value/regional GDP	Ten thousand yuan	Positive

sub-dimensions: diversity and collaboration and diversity and coordination.

To minimize bias in the measurement of the grain production resilience index, this paper refers to the study by Gao et al. (2024), and employs the entropy weight method for objective weighting. The specific calculation steps are as follows:

Step 1: Data Standardization. The range method is used to perform dimensionless and directional standardization on the positive and negative indicators within the evaluation system. The formula for positive indicators is equation (1), and the formula for negative indicators is equation (2):

$$\text{For positive indication: } x'_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (1)$$

$$\text{For negative indication: } x'_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad (2)$$

Step 2: Calculate the proportion matrix. In equation (3), it involves calculating the proportion of the *j* indicator in the *i* year, where *m* is the number of years included in the evaluation.

$$p'_{ij} = \frac{x'_{ij}}{\sum_{i=1}^m x'_{ij}} \quad (3)$$

Step 3: Calculate the information entropy and information entropy redundancy of the indicator. The formula for information entropy is equation (4):

$$e_j = -k \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (i = 1, 2, \dots, m) \quad (4)$$

Among them, $k = \frac{1}{\ln m}$. The formula for information entropy redundancy of the indicator is equation (5):

$$d_j = 1 - e_j \quad (j = 1, 2, \dots, m) \quad (5)$$

Step 4: Calculate the indicator weights. The formula is equation (6):

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (j = 1, 2, \dots, n) \quad (6)$$

Step 5: Calculate the comprehensive score. The comprehensive score for grain production resilience is calculated using the following formula:

$$S_{ij} = \sum_{j=1}^n W_j \times x'_{ij} \tag{7}$$

In equation (7), S_{ij} is the standardized value of the j indicator for city i , x'_{ij} is the original value of the j indicator for city i , W_j is the weight of the j indicator, and S_{ij} represents the score of the j indicator for city i . A higher score indicates a greater contribution of that indicator to the comprehensive grain production resilience score, while a lower score signifies a smaller contribution.

3.2.2 Core explanatory variable: Broadband China

This paper uses the implementation of the “Broadband China” strategic pilot policy as a proxy variable for digital infrastructure construction. The variable did takes a value of 1 if city i has been selected as a “Broadband China” pilot city in year t , and 0 otherwise.

3.2.3 Mechanism variables

Agricultural Technological Innovation (inno). Following the study by Liu et al. (2021), this paper measures agricultural technological innovation by the sum of patents granted in four categories: agriculture, forestry, animal husbandry, and fishery.

Digital Inclusive Finance (fin). Drawing on the research of Du Yanan et al. (2023), this paper uses the Peking University Digital Financial Inclusion Index as the proxy variable for digital inclusive finance.

3.2.4 Control variables

Previous studies have laid a foundation for our investigation into the impact of digital infrastructure on grain production resilience. Referencing relative researches (Hu et al., 2024; Zhang et al., 2024), this

paper selects the following covariates that may influence grain production resilience: economic development level, industrial structure, education level, and openness to foreign investment. Specifically: Economic Development Level means the logarithm of per capita regional GDP. Industrial Structure means the proportion of the sum of the added value of the secondary and tertiary industries to the regional GDP. Education Level means the ratio of the number of students enrolled in regular institutions of higher education to the total year-end resident population. Openness to Foreign Investment means the ratio of foreign direct investment (FDI) to the city’s GDP. Government Intervention means the ratio of local general public budget expenditure to the regional GDP. The descriptive statistics for all variables are presented in Table 2.

3.3 Model specification

3.3.1 Baseline regression model

This study uses the “Broadband China” pilot policy shows the digital infrastructure construction. Given that the “Broadband China” pilot policy was implemented in three batches in 2014, 2015, and 2016, the implementation times of the “Broadband China” pilot policy vary across different regions. Since the implementation timing of this policy varies across different regions, this study adopts the method from existing research (Tian and Zhang, 2022) to construct a staggered difference-in-differences (DID) model with two-way fixed effects. The model is specified as follows:

$$F_{it} = \alpha_0 + \alpha_1 DiD_{it} + \alpha_2 X_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{8}$$

In Equation (8), F_{it} represents the grain production resilience index for city i in year t . DiD_{it} denotes the policy implementation

TABLE 2 Descriptive statistics of variables.

Type	Variable name	Year of 2012				Year of 2022			
		Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Dependent Variable	Grain production resilience	0.174	0.102	0.045	0.535	0.197	0.112	0.043	0.621
Core explanatory variable	Broadband China	0	0	0	0	0.425	0.497	0	1
Mechanism variable	Agricultural technological innovation	59.187	77.797	0	411	218.623	341.786	0	1889
	Digital inclusive finance	69.103	17.298	48.76	107.01	181.564	44.062	119.42	272.29
Instrumental variable	Internet Broadband users	391.313	356.797	112	2,670	1631.55	1038.967	458	5,770
	Number of post offices in 1984	49.151	22.821	23.364	170.184	49.151	22.821	23.364	170.184
Control variable	Level of economic development	10.280	0.504	9.133	11.486	11.038	0.449	10.267	12.205
	Degree of opening up	0.084	0.093	0.004	0.567	0.099	0.103	0.004	0.591
	Level of education	0.016	0.022	0.001	0.115	0.022	0.030	0.001	0.146
	Industrial structure	0.868	0.072	0.728	0.985	0.892	0.094	0.176	0.991
	Level of government intervention	0.177	0.050	0.976	0.296	0.172	0.048	0.091	0.318

status for city i in year t . Control X_{it} is a vector of other control variables that affect grain production resilience. μ_i represents city-level fixed effects, and ω_t represents year fixed effects. α_0 , α_1 and α_2 are the coefficients to be estimated, and ε_{it} is the random error term.

3.3.2 Parallel trends test model

The validity of the staggered DID model relies on the satisfaction of the parallel trends assumption. This assumption requires that, prior to the implementation of the “Broadband China” policy, the treatment and control groups exhibited a consistent trend in the evolution of their grain production resilience. Drawing on the work of Jacobson et al. (1992), this study employs an event study approach to conduct the parallel trends test. The model is specified as follows:

$$y_{it} = \alpha + \sum_{k=-4}^{k=6} \alpha_k D_{i,t_0+k} + \beta X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{9}$$

In Equation (9), D_{i,t_0+k} is a dummy variable that corresponds to the timing of the policy implementation. As the base year is 2016 and the sample period is 2012–2022, the value of k ranges from -4 to 6 . X_{it} represents the control variables. The coefficient α_k captures the difference in grain production resilience between the treatment and control groups in the k year relative to the policy’s implementation.

3.3.3 Mediation analysis model

The theoretical analysis suggests that digital infrastructure construction may enhance grain production resilience by promoting

agricultural technological innovation and developing digital inclusive finance. To test these mediating mechanisms, we refer to the research (Jiang, 2022), and specify the mediation model as follows:

$$M_{it} = \beta_0 + \beta_1 DiD_{it} + \beta_2 X_{it} + \mu_i + \omega_t + \varepsilon_{it} \tag{10}$$

In Equation (10), M_{it} represents the mediating variables, which include digital inclusive finance and agricultural technological innovation. DiD_{it} denotes the policy implementation status for city i in year t . Control X_{it} is the vector of control variables, μ_i represents city-level fixed effects, and ω_t represents year fixed effects. β_0 , β_1 and β_2 are the coefficients to be estimated, and ε_{it} is the random error term. Based on our theoretical analysis and the general consensus in the academic literature that digital inclusive finance and agricultural technological innovation significantly enhance grain production resilience, we can infer that a mediation effect exists if the coefficient β_1 is statistically significant.

4 Results and discussions

4.1 Baseline regression analysis

To examine the impact of digital infrastructure construction on grain production resilience, this study employs a two-way fixed-effects model for empirical testing. Furthermore, to address potential concerns that “the observed positive effects may be attributable to unobserved urban-specific trends rather than fixed effects,” this paper mitigates endogeneity from three perspectives. Columns (1) to (3) in

TABLE 3 Baseline regression results.

Variables	(1)	(2)	(3)
Broadband China	0.011*** (0.002)	0.004** (0.002)	0.005*** (0.002)
Level of economic development			-0.009 (0.005)
Degree of openness to the outside world			-0.023 (0.019)
Level of education			-0.385*** (0.074)
Industrial structure			0.005*** (0.016)
Degree of government intervention			-0.058* (0.030)
Control variables	No	No	Yes
Region	No	Yes	Yes
Time	No	Yes	Yes
Constant term	0.179*** (0.012)	0.174*** (0.001)	0.282*** (0.058)
Sample size	880	880	880
R ²	0.053	0.282	0.316

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

Table 3 report the estimation results under three different model specifications: column (1) presents results with no control variables or fixed effects; column (2) includes only city and year fixed effects; and column (3) incorporates both control variables and city and year fixed effects. Under the joint constraints of the above two types of fixed effects and control variables, the possibility of estimation bias caused by omitted variables has been greatly reduced, and the results from all specifications consistently show that the “Broadband China” pilot policy has a significant positive effect on grain production resilience, thus verifying H1.

These findings, combined with insights from field research, suggest that the implementation of the “Broadband China” policy has improved digital infrastructure, which in turn has fostered the development of numerous application scenarios for digitally empowering agriculture. For instance, agricultural service centers, operating on an underlying architecture of the Internet of Things (IoT) and big data, provide services for the entire process of grain production, including pest and disease monitoring and management, market risk prevention, and natural disaster prediction. These services mitigate the risk of yield reduction and directly enhance the resistance dimension of grain production resilience. Furthermore, in the context of post-disaster recovery, the “Broadband China” policy increases the likelihood of farmers obtaining production materials and market information through internet channels, thereby improving the recovery capacity of grain production resilience. Additionally, the policy has accelerated the development of rural e-commerce, transforming traditional production and business models and strengthening the transformative capacity of grain production resilience.

4.2 Robustness test

4.2.1 Parallel trends test

To ensure the robustness of the baseline regression results, this paper conducts a parallel trends test, with the year prior to policy

implementation ($k = -4$) set as the reference period. As shown in Figure 2, for all periods before the implementation of the “Broadband China” policy ($k < 0$), the estimated coefficients fluctuate around zero and their 95% confidence intervals include zero, indicating no statistically significant difference in grain production resilience between pilot and non-pilot cities prior to the policy rollout. In contrast, the regression coefficients become statistically significant in all periods following policy implementation, suggesting that digital infrastructure construction significantly enhanced grain production resilience in pilot cities after the policy took effect. Moreover, the positive effect exhibits a strengthening trend over time. These results confirm that the parallel trends assumption holds for the sample used in this study.

4.2.2 Placebo test

To address potential biases from unobservable factors in the baseline estimates, this study performs a placebo test following the approach of Chetty et al. (2009). The sample was randomly reshuffled without stratification, with treatment status and policy timing assigned randomly across observations to construct a pseudo-policy shock variable. This variable was then incorporated into Model (1) for 1,000 repeated regressions. The distribution of the p -values of the estimated coefficients from these regressions is shown in Figure 3. The results indicate that the estimated coefficients of the randomly generated pseudo-policy variable are concentrated around 0 and follow an approximately normal distribution. This allows us to largely rule out the possibility that the positive effect of the “Broadband China” pilot policy on grain production resilience is driven by unobservable factors, thereby confirming the reliability of our research conclusions.

4.2.3 Propensity score matching-difference-in-differences (PSM-DID)

To mitigate the potential influence of systematic differences between pilot and non-pilot cities, this study re-estimates the model

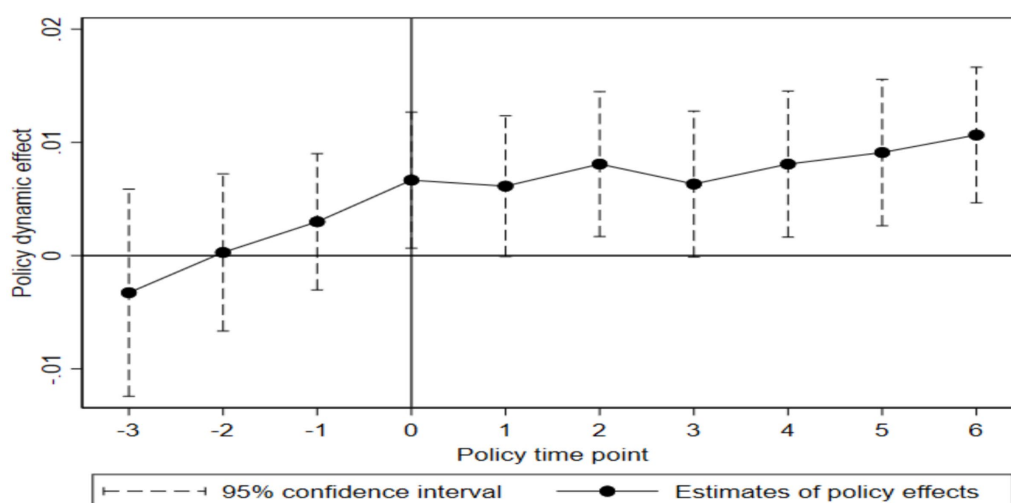


FIGURE 2
Parallel trend test.

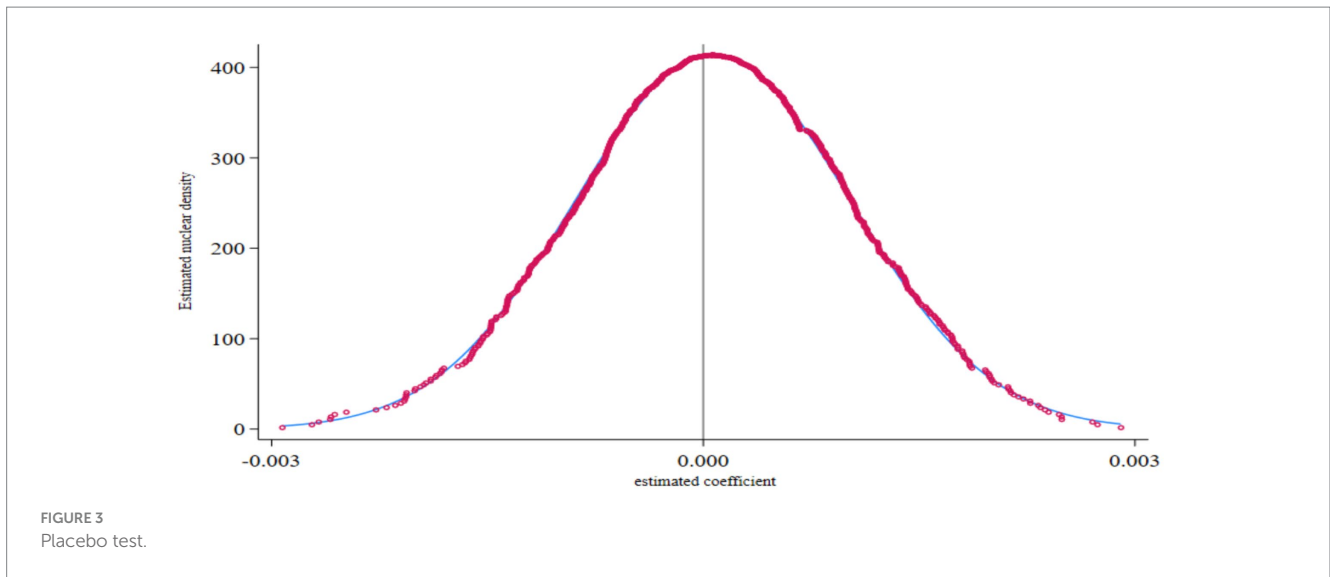


TABLE 4 Balance test.

Indicator	Matching status	Treatment	Group mean	Control group mean deviation (%)	Standardized mean difference	p-value
Level of economic development	Before matching	11.028	10.487	111.5	1.115	0.001***
	After matching	10.928	10.903	5.1	-0.063	0.542
Degree of openness to the outside world	Before matching	0.124	0.067	60.3	0.603	0.001***
	After matching	0.107	0.114	-7.2	-0.072	0.476
Level of education	Before matching	0.036	0.124	79.9	0.799	0.001***
	After matching	0.026	0.030	-12.8	0.008	0.187
Industrial structure	Before matching	0.916	0.876	71.4	0.717	0.001***
	After matching	0.909	0.910	-1.4	-0.023	0.878
Degree of government intervention	Before matching	0.167	0.200	-61.2	-0.612	0.001***
	After matching	0.171	0.170	-3.5	0.032	0.692

*p < 0.1, **p < 0.05, ***p < 0.01.

using the Propensity Score Matching-Difference-in-Differences (PSM-DID) method. To ensure consistency with the original full sample (including control variables), we use the control variables from the baseline regression as covariates and employ the nearest-neighbor caliper matching method to match treatment and control group samples on a year-by-year basis. As shown in Table 4, after matching, the absolute standardized mean differences (SMD) of all covariates fall below 0.1, and t-tests for between-group differences become statistically insignificant, indicating that the balancing assumption is satisfied. The subsequent regression results, presented in column (1) of Table 5, show that even after controlling for sample-selection bias, the “Broadband China” pilot policy continues to exert a significant positive effect on grain production resilience. This finding further supports H1.

4.2.4 Excluding provincial capital cities

Considering that the six provincial capitals (Taiyuan, Nanchang, Zhengzhou, Hefei, Changsha, and Wuhan) have relatively advanced

digital infrastructure, their inclusion in the regression sample could potentially inflate the overall estimated coefficients. Therefore, we exclude these six cities and re-run the empirical test. The results in Table 5, column (2), show that the implementation of the “Broadband China” pilot policy still significantly enhances grain production resilience.

4.2.5 Excluding interference from other policies

The implementation of “Smart City” policies has driven urban digital transformation and intelligent development, which has also spurred the upgrading of agricultural productive services (Jia, 2023), playing a positive role in ensuring China’s food security. To exclude the potential impact of the “Smart City” policy and the “National Big Data Comprehensive Pilot Zone” on grain production resilience, we include dummy variables for these two policies as additional controls in a robustness test. The results, shown in Table 5, column (3), indicate that the “Broadband China” pilot policy continues to significantly promote grain production resilience, once again verifying H1.

TABLE 5 Robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)
	PSM-DID	Exclude provincial capitals	Eliminate smart city policy interference	Phase 1 (2SLS)	Phase 2 (2SLS)
Did_psm1	0.005*** (0.002)				
Broadband China		0.004*** (0.001)	0.007*** (0.002)		0.019** (0.007)
Instrumental variables				0.118*** (0.023)	
Constant term	0.229*** (0.609)	0.282*** (0.058)	0.281*** (0.058)		
Control variables	Control	Control	Control	Control	Control
Time fixed	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
Sample size	789	814	880	880	880
R ²	0.329	0.411	0.316		
Kleibergen-Paaprk LM					19.956 [0.001]
Kleibergen-Paaprk Wald					25.451 [16.38]

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

4.2.6 Addressing endogeneity

The selection of “Broadband China” pilot cities could be influenced by pre-existing factors such as the city’s original infrastructure level. Therefore, using this policy as a proxy for digital infrastructure to study its impact on grain production resilience may be subject to endogeneity from omitted variables or reverse causality. To address this issue, this study follows the approach of Huang et al. (2019) and Nunn and Qian (2014) by using an instrumental variable (IV). The IV is constructed as the interaction between the lagged number of national internet users and the number of post offices per million people in each city in 1984. A two-stage least squares (2SLS) approach is employed to capture the net effect. The distribution of post offices in 1984 was primarily determined by administrative planning during the planned-economy era and is not directly linked to contemporary grain production resilience. As early communication infrastructure, however, the historical distribution of post offices may have influenced subsequent internet penetration, thereby relating indirectly to the intensity of “Broadband China” policy implementation. The lagged number of internet users at the prefecture-level city level reflects regional trends in technology diffusion, which can affect local Broadband deployment but is unlikely to be reversely influenced by grain production resilience in any single city, thus satisfying the exclusion restriction of the IV. The first-stage results are reported in column (4) of Table 5, where the estimated coefficient of the IV on the “Broadband China” policy is statistically significant at the 1% level, confirming the relevance of the instrument. Column (5) presents the second-stage results, which indicate that the “Broadband China” policy continues to have a significant positive effect on grain production resilience. These findings suggest that endogeneity does not substantially undermine the main conclusions of the study.

TABLE 6 Mechanism testing.

Variables	(1)	(2)
	Agricultural technology innovation	Digital inclusive finance
Broadband China	0.323*** (0.073)	0.145*** (0.045)
Constant terms	-11.694 (2.321)	-7.343*** (1.436)
Control variables	Control	Control
Time fixed	Yes	Yes
City fixed	Yes	Yes
Sample size	880	880
R ²	0.325	0.865

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

4.3 Mechanism analysis

The preceding theoretical analysis indicated that digital infrastructure construction might enhance grain production resilience by fostering agricultural technological innovation and promoting digital inclusive finance. Therefore, this paper conducts an empirical test using the mechanism analysis method proposed (Jiang, 2022). As shown in Table 6, the results in column (1) reveal that the “Broadband China” pilot policy significantly promotes agricultural technological innovation. This indicates that digital infrastructure construction can effectively improve the level of agricultural technology, thereby

enhancing grain production resilience. The results in column (2) show that the “Broadband China” pilot policy significantly increases the level of digital inclusive finance, indicating that digital infrastructure construction effectively promotes its development, which in turn boosts grain production resilience. Thus, H2 and H3 are verified.

4.4 Heterogeneity analysis

4.4.1 Level of economic development

A city’s level of economic development is a core support for digital infrastructure construction and an enabler for ensuring grain production resilience. In this study, the sample is divided into “economically developed” and “economically less developed” groups based on per capita GDP. The results of the grouped regression (columns 1–2 in Table 7) show that while the “Broadband China” pilot policy enhances grain production resilience in both, the effect is only statistically significant in the group of economically less developed cities.

As shown in Table 8, before the policy implementation, cities selected as “Broadband China” pilot sites exhibited significantly lower levels of economic development (mean = 0.285) than non-pilot cities (mean = 0.689), indicating that the policy has covered more areas with initially weaker economic conditions. In these “low-starting-point” regions with limited existing digital infrastructure, the pilot policy has generated a notable “catch-up effect.” By rapidly narrowing the digital divide, it has substantially unlocked the potential for empowering agricultural production systems, thereby significantly strengthening grain production resilience. In contrast, economically developed cities already possessed relatively complete digital infrastructure and mature

smart-agriculture applications prior to the policy. For these cities, the “Broadband China” policy offered limited scope for further digital infrastructure improvements, resulting in a weaker effect on enhancing grain production resilience. These findings support H4.

4.4.2 Regional differences

This study categorizes sample cities into northern and southern regions based on agro-geographical conditions and dominant grain crop types for subgroup analysis. The regression results, reported in columns 3–4 of Table 7, indicate that the “Broadband China” pilot policy significantly enhances grain production resilience in southern cities, whereas its effect in northern regions is not statistically significant. This heterogeneous impact stems primarily from differences in resource endowments and production risks between the two regions. Compared with the plains-dominated north, southern China is characterized by steep, fragmented arable land with extensive mountainous and hilly terrain. This topography limits the application of traditional large-scale mechanization and inherently weakens the risk-resistance capacity of agricultural production. Prior studies have shown that land fragmentation is more severe in mountainous and hilly areas than in plains, raising costs for labor, fertilizer, and seeds while constraining the use of machinery and other productive inputs (Wang et al., 2019; Zhang X. et al., 2023; Zhang D. J. et al., 2023).

Digital infrastructure—particularly the technologies it enables, such as precision meteorological monitoring, early-warning systems, remote sensing, and smart agricultural IoT—can effectively mitigate these topographic constraints. As argued by Zhao (2021), digital-enabled smart agriculture represents a crucial pathway for addressing land fragmentation and advancing large-scale agricultural management. For example, high-precision spatial

TABLE 7 Heterogeneity analysis results.

Variables	(1)	(2)	(3)	(4)
	Economically developed	Economically underdeveloped	Northern regions	Southern regions
Broadband China	−0.001 (0.004)	0.008*** (0.003)	0.003 (0.002)	0.007** (0.003)
Constant terms	0.243*** (0.087)	0.506*** (0.091)	0.400*** (0.065)	−0.046 (0.135)
Control variables	Control	Control	Control	Control
Time fixed	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes
Sample size	360	520	484	396
R ²	0.347	0.281	0.293	0.439

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

TABLE 8 Comparison of baseline characteristics of pilot and non-pilot cities before policy.

Variables	Broadband China		Comparison of means between groups (<i>T</i> -test)
	Pilot city	Non-pilot cities	
Economically developed	0.285	0.689	−0.404***
location difference	0.410	0.541	−0.131***
Sample Size	270	610	

p* < 0.1, *p* < 0.05, ****p* < 0.01.

information supports optimized soil-water management and enables precise input allocation across scattered plots, reducing resource waste while enhancing disaster resilience and productivity of small-scale farmland. Consequently, the marginal benefits of digital technologies are more pronounced where traditional farming models face greater constraints. At the same time, the complex terrain in the south raises the cost of deploying digital infrastructure. The “Broadband China” policy, through concentrated investment, effectively improves digital service levels in these regions, making its role in strengthening grain production resilience more evident. In contrast, the northern plains are more suited to large-scale mechanized operations, where existing production systems already possess relatively strong stability and risk resistance. Although digital technologies—such as smart machinery scheduling and big-data market analysis—can bring further optimization, their marginal contribution to overall resilience is comparatively limited. These findings support H5.

5 Discussion

5.1 Limitations

First, although both pesticide and fertilizer usage are widely recognized as critical indicators for assessing the recovery dimension of agricultural production resilience, only fertilizer application was incorporated into the analytical framework. This omission is due to inconsistent reporting of pesticide data in municipal statistical yearbooks. In the panel dataset of 80 prefecture-level cities over the period 2012–2022 (880 city-year observations), pesticide usage exhibits large-scale systematic missing values. For instance, data are severely absent for most prefecture-level cities in Hunan Province (except Changsha, Xiangtan, and Chenzhou) as well as for Datong, Jincheng, Yuncheng, and Shuozhou in Shanxi Province throughout the entire sample period. Consequently, the number of valid observations for this variable is insufficient for meaningful analysis. To maintain data consistency and comparability, pesticide use was excluded from the set of control variables.

Second, linear interpolation was applied to address a small share of missing observations. Among the variables used to construct the composite index of grain production resilience, eight indicators (such as cultivated land area and grain consumption index) contained intermittent missing values, accounting for less than 7% of the total 880 observations. Given the low missing rate and its concentration mainly in 2012, 2022, and a few intervening years, linear interpolation helps minimize distortion of the underlying data distribution while preserving time-series continuity, and is unlikely to introduce substantial bias into the regression results.

Third, the generalizability of the findings may be constrained by the spatiotemporal scope of the sample. This study focuses on specific provinces during a defined period, and its conclusions are derived from the relatively particular hydrothermal conditions and cropping structures of this region. Therefore, the results may not be directly applicable to areas with distinct agro-climatic conditions, economic structures, or policy environments. For example, in arid northwestern China—where agriculture relies heavily on irrigation—or in highly commercialized southeastern coastal regions—where grain cultivation

occupies a low proportion—ecological vulnerabilities and factor input structures differ significantly from those in the central region examined here. The mechanisms through which digital infrastructure enhances grain production resilience in such areas may vary, calling for future comparative research with expanded geographical coverage.

5.2 Future research directions

Building upon the limitations identified in this study, several promising avenues for future research emerge. Addressing these gaps would not only validate our findings but also significantly deepen the understanding of agricultural production resilience.

First, future studies should prioritize the construction of more comprehensive and standardized datasets. Efforts could be directed toward collecting finer-grained data on critical inputs like pesticide usage through field surveys or by integrating non-official data sources. Furthermore, applying advanced missing data handling techniques, such as multiple imputation or machine learning-based interpolation methods, would better preserve the inherent variability of the data and provide more robust parameter estimates.

Second, the scope of analysis should be expanded to enhance the external validity of the findings. Replicating this study in regions with different agro-climatic conditions, economic development levels, and policy regimes is essential to test the generalizability of the relationships uncovered here. Comparative studies across regional contexts could reveal the context-specific versus universal drivers of resilience.

Finally, moving beyond the current analytical framework is crucial. Subsequent research could develop and incorporate more direct, multi-dimensional metrics of agricultural resilience that capture its buffer, adaptive, and transformative capacities. Moreover, investigating the complex interplay between ecological, economic, and social factors—such as the role of farmer cooperatives, digital agriculture adoption, or specific climate adaptation policies—as mediating or moderating variables would offer a more nuanced mechanistic understanding of how resilience is built and sustained.

6 Conclusion and policy implications

6.1 Conclusion

Based on panel data from 80 prefecture-level cities in China’s six central provinces from 2012 to 2022, this paper employed a two-way fixed-effects model to explore the impact and mechanisms of digital infrastructure construction on grain production resilience from the perspective of the “Broadband China” pilot policy. The main conclusions are as follows: The “Broadband China” pilot policy significantly promotes grain production resilience. This conclusion remains robust after a series of tests, including PSM-DID, excluding provincial capitals, and addressing endogeneity. Mechanism analysis reveals that the “Broadband China” policy can enhance grain production resilience by developing digital inclusive finance and promoting agricultural technological innovation. Further analysis finds that the policy’s promoting effect is particularly significant in economically less developed and southern regions.

6.2 Policy implications

Based on the above conclusions, the following policy recommendations are proposed:

First, accelerate the implementation of digital enhancement policies, represented by the “Broadband China” policy, with a strategic focus on economically less developed and geographically complex southern regions. On one hand, the government should intensify policies that use digital intelligence to benefit agriculture, introducing incentives to guide farmers and agricultural enterprises to actively participate in the construction of smart agriculture, thereby enhancing grain production resilience through digital development. On the other hand, the government should increase financial support for digital infrastructure construction in underdeveloped and southern regions, solidifying the foundation of rural digital infrastructure and solving the “last mile” problem of empowering agricultural production with digital intelligence.

Second, improve digital financial services to adapt to the digital and intelligent development of agriculture. On one hand, the government should encourage financial institutions to develop digital financial products tailored to local conditions, such as credit products based on agricultural production cycles and agricultural product price index insurance. This would increase farmers’ access to digital financial products and enhance their ability to withstand agricultural production risks. On the other hand, the government must take responsibility for digital financial supervision, improving the legal framework for digital finance to suit the new era and ensuring the effective deployment of digital financial products.

Third, enhance agricultural technological innovation capabilities from multiple perspectives. On one hand, the government should increase investment in basic agricultural research and development, establishing special funds to support the R&D of digital technologies in the agricultural sector, such as the agricultural Internet of Things (IoT), agricultural artificial intelligence, and big data analytics. On the other hand, the government must strengthen the grassroots agricultural technology extension system. By establishing agricultural technology demonstration bases and conducting technical training, advanced agricultural technologies and digital tools can be transferred to farmers, increasing the technological content and risk-resistance capacity of agricultural production, and ultimately enhancing grain production resilience.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

This study complies with the Measures for Ethical Review of Science and Technology established by the Ethics Committee for Science and Technology of China. And the authors confirm that the study has been conducted ethically and responsibly, in full compliance with the relevant experimentation codes and legislation.

Author contributions

LZ: Validation, Investigation, Writing – review & editing, Writing – original draft, Formal analysis, Methodology, Data curation. CY: Writing – original draft, Software, Investigation, Formal analysis, Data curation. ZG: Formal analysis, Validation, Data curation, Writing – review & editing, Investigation. SL: Writing – review & editing, Investigation, Formal analysis. CN: Conceptualization, Writing – original draft, Writing – review & editing, Project administration, Validation, Formal analysis, Visualization, Supervision, Data curation. SZ: Conceptualization, Supervision, Funding acquisition, Project administration, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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