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Agricultural sustainability in the digital era: the role of ICT adoption in advancing grain production in China

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In the digital era, the adoption of digital technologies has become one of the most significant technological revolutions, affecting various economic sectors, including agriculture. Currently, digital innovation greatly benefits the agricultural industry by providing weather updates, facilitating financial services, modernizing farming practices, delivering input prices, and enhancing knowledge transfer. Hence, this study examines the long-run impact of digital technologies adoption, including Internet connectivity and Mobile phone use, on grain production in major Chinese grain-producing areas from 2001 to 2022. This study estimates the long-run effects using the Driscoll-Kraay specification. Then it verifies robustness using alternative estimators, including Feasible Generalized Least Squares (FGLS) and the Mean Group (MG) approach. This research results reveal that Internet access directly impacts grain production by 0.066% and Mobile phone technology has a similar long-term impact of 0.053%. This research supports the theory that distributing tools across the system will increase agricultural yields. Furthermore, the findings show that production factors, including cultivated land area, fertilizer application, and government investment, also significantly enhance grain production by 1.026%, 0.089%, and 0.013%, respectively, in the long run. This study provides recommendations for policymakers on strengthening rural infrastructure and sustaining ICT funding to realize the full potential of food production.

KEYWORDS
agricultural sustainability, DKSE method, grain production, internet connectivity, mobile phone technology

1 Introduction

Ensuring a food supply for the world's population sits at the very core of both economic stability and social harmony. As the global headcount swells and climate change's effects become ever more severe, the strain on land and water resources keeps tightening [Intergovernmental Panel On Climate Change (IPCC), 2023; Rockström et al., 2017]. The United Nations Sustainable Development Goal 2 spells it out: eliminate hunger and guarantee food security for everyone by 2030 (Lee et al., 2016). Projections suggest that the global population will approach 10 billion by 2050, implying that agricultural output must rise by more than 60% relative to 2010 levels (Calicioglu et al., 2019). In that context, China, as a populous country, confronts food security challenges that not only affect the everyday lives of its citizens but also reverberate through global markets. Nevertheless, the agricultural sector in China finds itself entangled in a web of difficulties: a per-capita allotment of farmable soil, an erratic spread of water resources, a labor pool that is progressively graying, and an intensifying environmental strain stemming from the excessive application of synthetic fertilizers and pesticides (Huang and Yang, 2017). A sizable swath of research now points to the fact that information and communication technologies (ICT) can sharpen the deployment of production factors, which, through precision agriculture, intelligent decision-support tools, and tighter market-information networks, make ICT a pivotal catalyst for output growth (Lio and Liu, 2006; Oyelami et al., 2022; Sethi et al., 2024). Therefore, as resource constraints tighten further, it's essential to explore how ICT actually works and the routes it takes to see how it relieves pressure on resources and lifts productivity. From a sustainability perspective, evidence from Vietnam suggests that agricultural output and forest land are closely linked with CO_2 emissions, highlighting the need to consider production gains alongside environmental constraints (Raihan et al., 2024).

A growing body of evidence from developing nations continues to underscore that ICT can boost agricultural output. Research carried out in Niger (Aker and Mbiti, 2010), Kenya (Ogutu et al., 2014), India (Cole and Fernando, 2012) and Pakistan (Khan et al., 2022), and Vietnam (Kaila and Tarp, 2019) all converge on the story: digital tools sharpen producers' decision-making, slash information costs, speed up the spread of knowledge, and consequently expand production capacity. While China's ICT infrastructure ranks among the world's broadband and mobile phone adoption is virtually universal (Center, 2023) the actual influence of ICT on crop yields, across its principal grain belts still suffers from a dearth of systematic consistent empirical proof. Many investigations zero in on crops (e.g., potatoes, rice) or on particular locales (Chandio et al., 2023; Lun et al., 2024; Min et al., 2020; Zhou and Deng, 2023), leaving the broader intertwined influence of multiple digital tools across the major grain-producing regions largely concealed. Many of these studies fail to control for production variables (government investment, fertilizer usage, cultivated land area, and labor dynamics). Recent macro-level evidence from provincial panel data shows that the digital economy significantly promotes food security and exhibits spatial spillover effects across regions (Lee et al., 2023). The digital economy can enhance China's food production capacity, with non-linear and heterogeneous effects across contexts (Wang et al., 2024).

Despite the growing attention to digital agriculture, macro-level evidence on whether ICT expansion translates into higher aggregate grain output across provinces remains limited. Existing studies are often crop-specific or micro-level, and many treat digitalization as a single umbrella concept, making it difficult to disentangle the roles of different ICT channels. In addition, some studies do not sufficiently account for conventional production inputs such as cultivated land, fertilizer use, government investment, and agricultural labor. Consequently, a clear, province-level, long-horizon assessment of how ICT development relates to grain production remains lacking.

The objective of this study is to examine the long-run relationship between ICT adoption and grain production in China's central grain-producing provinces over the period 2001–2022, with a particular focus on two distinct ICT channels: Internet connectivity and mobile-phone penetration. Using provincial panel data and an econometric framework consistent with this study design, the analysis evaluates whether these ICT measures are associated with grain output after controlling for key production factors, and it further investigates the direction of causality among ICT variables, production inputs, and grain production.

This study focuses on 18 leading grain-producing provinces (Henan, Shandong, Hebei, and their peers), which constitute the backbone of China's grain supply. Over 2001–2022, both grain output and ICT adoption expanded rapidly but unevenly across provinces, providing substantial variation for panel-data analysis. Meanwhile, food security has faced tightening constraints from limited arable land, environmental pressures, and structural changes in the rural labor force. Figures 1–4 summarize these cross-provincial trends and heterogeneity and motivate the subsequent empirical analysis.

Against this background, China's grain-yield growth has stagnated, constrained by limited arable land and diminishing returns from intensive practices such as irrigation and fertilizer use. Furthermore, environmental issues like soil degradation and water pollution have become increasingly significant. In this context, understanding how the adoption of digital technologies impacts grain production and the mechanisms involved is a critical research question. Clarifying this relationship is essential for both theoretical insights into the benefits of adopting digital technologies and practical applications for improving food production, supporting rural revitalization, and promoting agricultural modernization. Thus, this study contributes to understanding how mobile phone technology and internet connectivity positively impacts grain production, underscoring their critical role in advancing grain production in major grain-producing regions of China (Anhui, Guangdong, Guangxi, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Shaanxi, Shandong, Shanxi, Sichuan, Xinjiang, and Yunnan). The present research underscores the significance of digital tools in grain farming. It identifies the expanding adoption of mobile and internet technologies as an opportunity to catalyze agricultural innovation, enhance sustainable farming practices, and address food security concerns. This research significantly improves understanding of the influence of digital technologies on agriculture, specifically examining the implications of internet access and mobile phone use for grain production. The work demonstrates methodological rigor through the application of advanced econometric approaches, including the Pesaran CD statistic as a diagnostic of cross-sectional correlation, the Cross-sectionally Augmented Dickey-Fuller (CADF) procedure to evaluate whether the series are stationary, and the Westerlund ECM cointegration test to validate long-term relationships between variables. This study estimates the long-run effect of digital technology adoption on grain production using the DKSE method. For robustness check and ensuring the consistency and reliability of the DKSE estimates, this study uses the FGLS, MG, and FMOLS methods. Finally, this study employs the Dumitrescu and Hurlin (2012) panel causality test to assess directional linkages across the variables. Together, these steps address essential gaps in prior

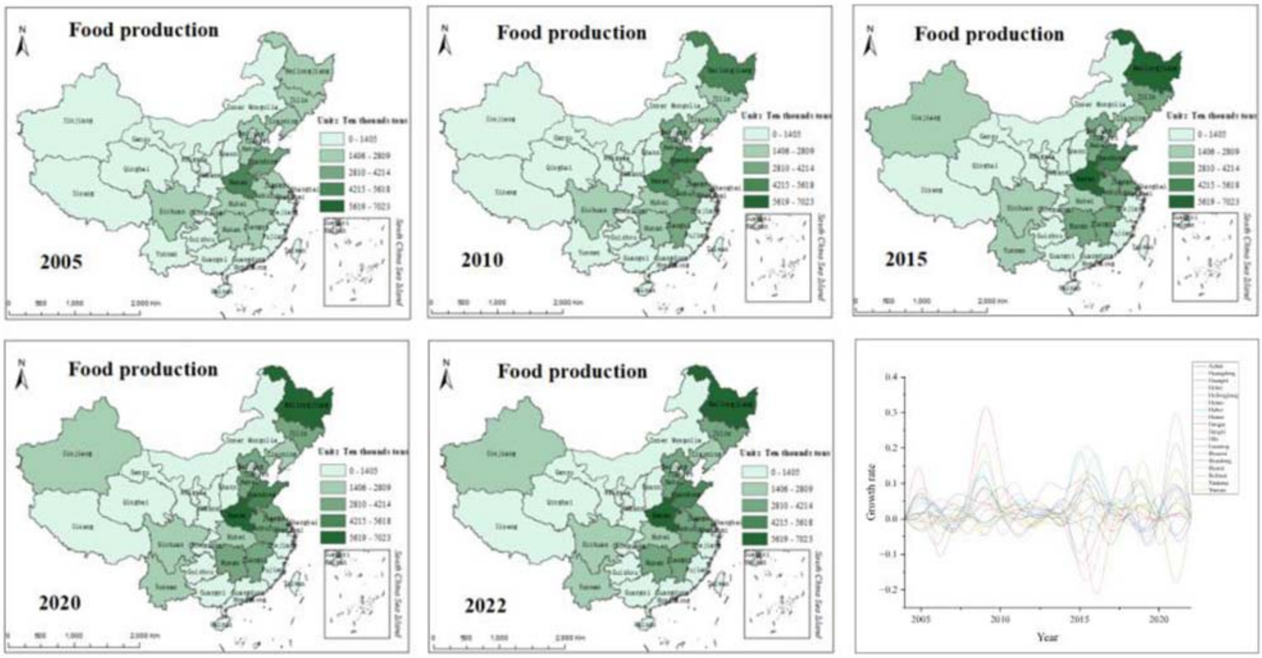

FIGURE 1
Trends in food production output in selected provinces (2005–2022).

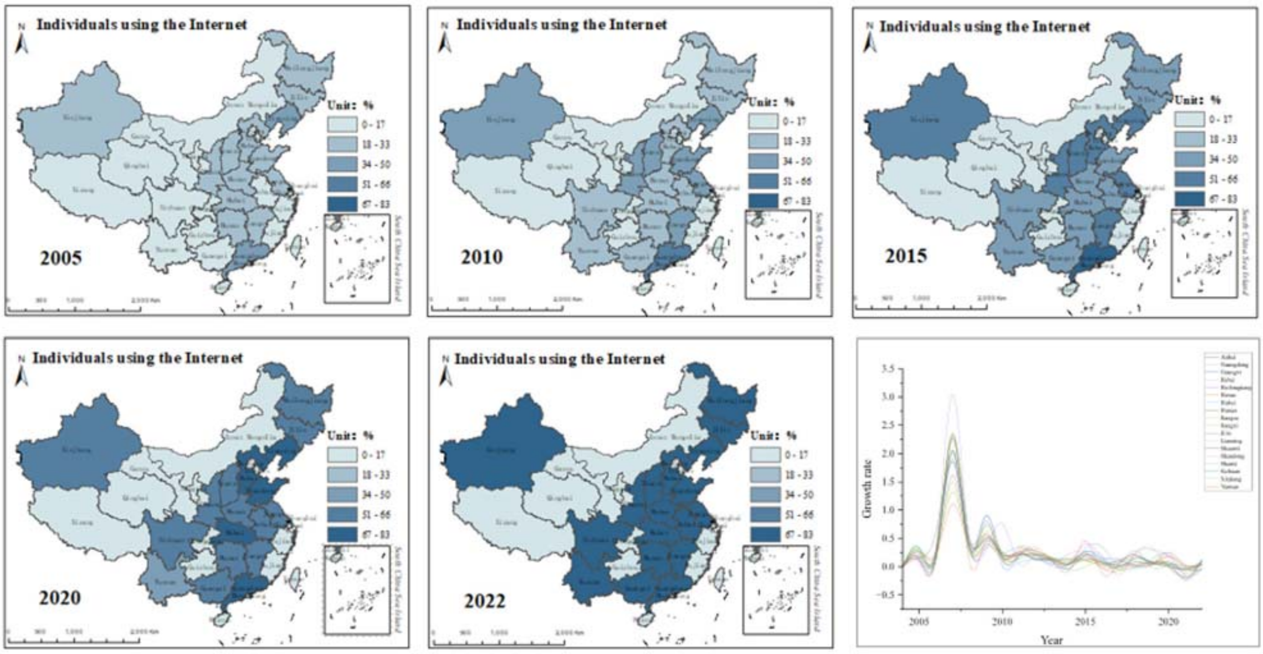

FIGURE 2
Internet users' (% of population) change in selected provinces (2005–2022).

work and offer policymakers empirically grounded guidance on expanding digital access and improving the targeting of public investment to support national food security.

This study proceeds in a logical sequence, moving from motivation and background to empirical evidence and implications. This study first synthesizes the related literature and develops the hypotheses. This study then describes the data, variable construction, and econometric strategy. Next, this study reports the empirical results, along with robustness checks and a discussion. Finally, this study closes with a summary of the key results, a discussion of their policy relevance, and suggestions for subsequent research.

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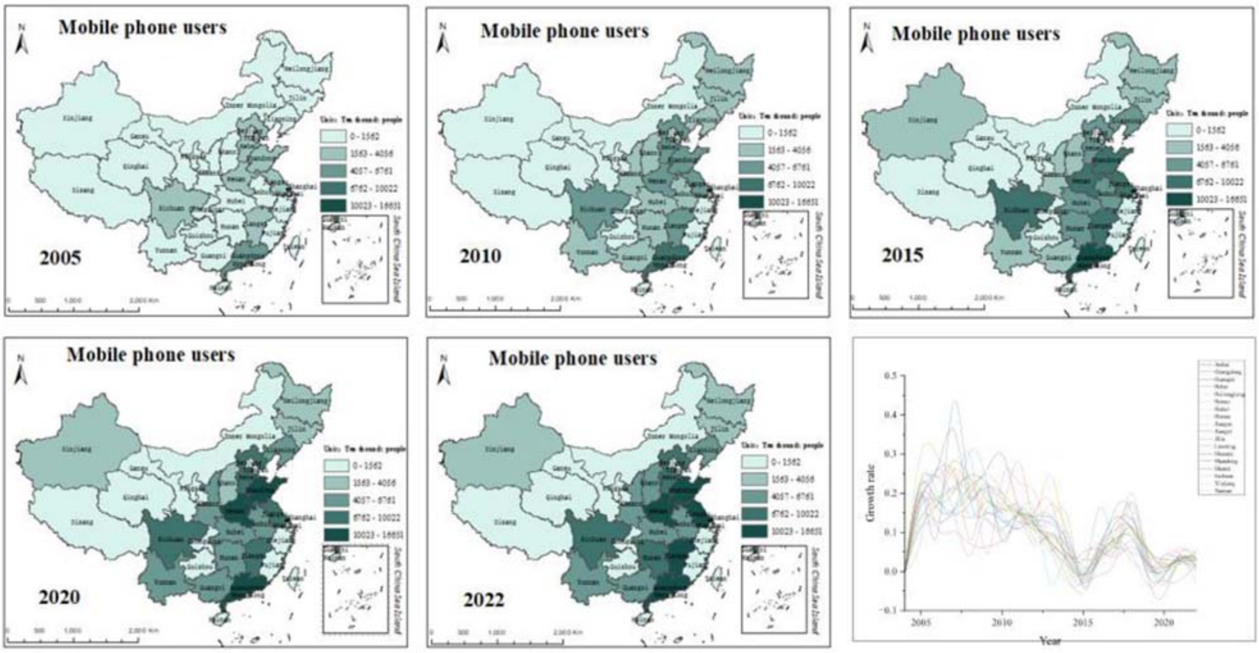

FIGURE 3
Mobile phone users' change in selected provinces (2005–2022).

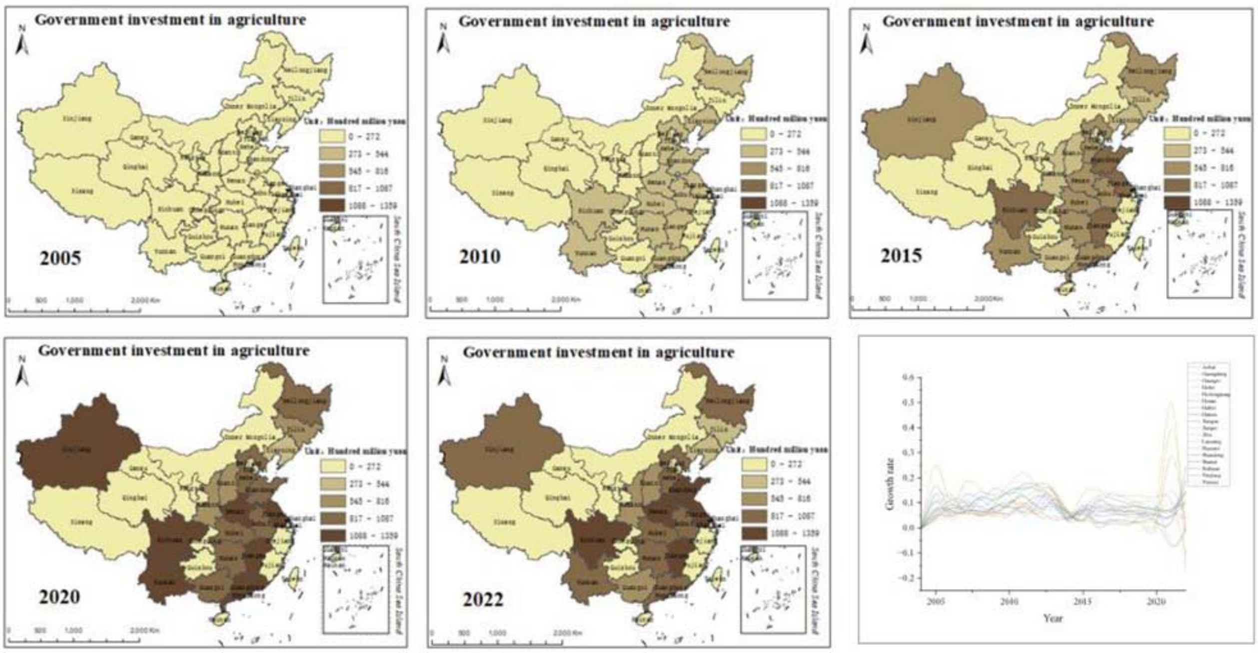

FIGURE 4
Government investment change in agriculture in selected provinces (2005–2022).

2 Literature review and hypothesis development

A growing literature examines how ICT development affects agricultural production at the global, regional, and national levels. Most studies report positive associations between ICT and agricultural performance, although the underlying mechanisms and the magnitude of the effects remain context-dependent and are still debated. This section reviews the key evidence and motivates the conceptual framework used to develop the hypotheses.

2.1 ICT and agricultural production: global and regional evidence

This research by Lio and Liu (2006) analyzed 81 countries worldwide and demonstrated that ICT enhances agricultural productivity, with the effect stronger in high-income countries. This research established initial evidence that supported ICT's positive effects at the macroeconomic level. Research conducted in developing economies has established that ICT has a positive effect on agricultural productivity. This research by Sethi et al. (2024) analyzed 27 developing nations and found that their ICT index, which combined internet and mobile phone subscriptions, was associated with higher agricultural productivity. Oyelami et al. (2022) conducted a panel ARDL model analysis to demonstrate that ICT creates positive long-term effects on agricultural output in Sub-Saharan Africa. This research by Rehman et al. (2024) on South Asian countries established a positive link between ICT and food security, and found that ICT directly affects food security through their causal analysis. Research indicates that ICT functions as a vital driver of agricultural growth worldwide because it enhances information access and reduces costs, and enables knowledge sharing in developing countries. Overall, the studies reviewed above describe multiple ways in which ICT development can be associated with agricultural performance. This motivates the province-level analysis, which distinguishes between internet connectivity and mobile phone penetration when linking ICT diffusion to grain production.

2.2 Research at the national level: focus on China

Research conducted in China focuses on provincial and farm household levels to understand how ICT affects agricultural production. This research by Chen et al. (2022) demonstrated that Yangtze River Basin rice farmers who used the internet achieved better technical performance in rice farming. This research by Fu and Zhu (2023) demonstrated that internet usage enhances technical efficiency in grain production. This research by Ma et al. (2020b, 2023) demonstrated that ICT adoption leads to growth in rural household income through improved credit access. Multiple studies have shown that ICT adoption creates an indirect path to boosting rural household income by enhancing credit access. This research by Yu et al. (2022) demonstrated an inverted U-shaped relationship between internet usage and agricultural green production efficiency which indicates a maximum benefit point exists. The existing research investigates technical efficiency and income and particular crops but lacks studies that use provincial panel data to evaluate total grain output while analyzing internet and mobile phone effects. In summary, while the preceding discussion of China provides essential context for understanding ICT diffusion in agriculture, it also highlights a gap in understanding long-run, province-level trends in total grain production. This study addresses this gap by employing provincial panel data spanning an extended period and by formulating hypotheses that directly link specific ICT measures to key production inputs within the empirical model.

2.3 The role of other production factors

Classical production theory views agricultural output as relying on land, labor, capital, and intermediate inputs. The agricultural sector can benefit from government investment (GIN), which can support agricultural growth by improving infrastructure, fostering technological progress, and easing financing constraints (Salim and Islam, 2010; Zhang et al., 2022). This research by Pickson et al. (2022) demonstrates that proper fertilizer application increases crop yields in contemporary agricultural systems. The fundamental land component of cultivated area (CUA) remains a primary predictor of agricultural output while maintaining stability in its effects. The marginal value of agricultural labor (AGL) has become a complex factor due to technological advancements in farming practices. The essential nature of labor as a production factor persists, but modern mechanization and digitalization technologies reduce its marginal contribution to the point that it becomes insignificant or even negative (Baig et al., 2024). These considerations motivate the hypotheses on the expected signs of government investment, fertilizer use, cultivated area, and agricultural labor in the grain production function.

2.4 Research hypotheses

This study focuses on two observable ICT channels: internet connectivity (INT) and mobile phone penetration (MOBT). This research examines their association with grain output across China's key grain-producing provinces. Grounded in the conceptual framework outlined in previous sections, this research first summarizes the principal mechanisms through which INT and MOBT may influence agricultural performance. As discussed, ICT access can affect grain production through multiple practical pathways. These include improving access to timely market information and agricultural knowledge, supporting production and management decisions, and facilitating communication and service delivery in agricultural activities. Based on these mechanisms, this research then formulates distinct testable hypotheses for the effects of both internet connectivity and mobile phone penetration. The empirical model also accounts for the role of conventional production factors. This research hypotheses include the following statements:

- ***H1:*** *The implementation of Internet access (INT) leads to significant positive effects on grain production (FDP). This hypothesis follows from the channels summarized above, in which improved internet access supports the acquisition of information and knowledge relevant to agricultural decisions.*
- ***H2:*** *The expansion of Mobile phone penetration (MOBT) leads to significant positive effects on grain production (FDP). This hypothesis follows from the channels summarized above, where mobile technologies provide accessible communication and information pathways that can support agricultural activities.*
- ***H3:*** *Other traditional production factors, including government investment (H3a), fertilizer use (H3b), and cultivated area (H3c), affect grain production positively, but agricultural labor*

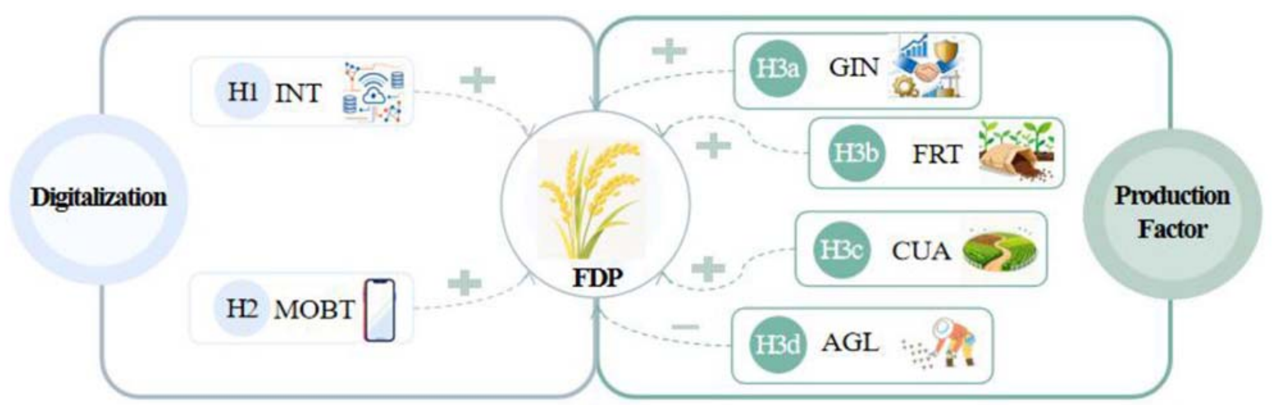

FIGURE 5
Theoretical framework: hypothesized relationships between ICT, Production Factors, and Food Production.

(H3d) produces negative effects on grain production. This hypothesis follows the production-factor discussion in Section 2.3 and is consistent with the set of control variables included in the empirical specification.

This study presents its framework in Figure 5, which demonstrates the proposed connections between grain production and ICT technologies and control variables.

3 Methodology and data

3.1 Data

Ensuring food production is fundamental to national governance and serves as a cornerstone of national security. ICT adoption has become a key component of China's agricultural transformation and is increasingly important for improving production structure and efficiency. Accordingly, the analysis examines how ICT adoption relates to sustainability outcomes in the grain sector, using a province-year panel covering 18 of China's key grain provinces over 2001–2022, which covers the country's principal grain-producing areas, but differs from the conventional set of 13 central grain-producing provinces, this study found that one or more key series required were not consistent, so this study excluded some options. This study focuses on the 2001–2022 period because it is the time window for which this research compiled a province-level panel with consistent coverage of all variables used in the empirical specification across the selected provinces. At the same time, to ensure sufficient and comparable research samples, this study also included some provinces in this study. The dataset is compiled based on series reported in the China Statistical Yearbook and the China Rural Statistical Yearbook. Variables were selected in line with the 2030 Sustainable Development Goals (SDGs). Additional information on variable definitions and measurement is reported in Table 1. In line with the focus on farmers, INT and MOBT are compiled for the population employed in agriculture rather than the total provincial population.

TABLE 1 Variables description.

Variable type	Variable name	Symbol	Definition
Dependent variable	Grain food production	FDP	The total output of rice, wheat, and corn (10,000 tons)
Independent key variables	Digitalization	INT	Individuals using the internet (%)
		MOBT	Mobile phone users (10,000 people)
Control variables	Government investment	GIN	Government investment in agriculture (100 million yuan)
	Fertilizer	FRT	Amount of fertilizer applied (10,000 tons)
	Cultivation area	CUA	Cultivation area (thousand hectares)
	Agricultural labor force	AGL	Employment in agriculture (10,000 people)

INT and MOBT both indicators are measured within the population employed in agriculture; Source: China Statistical Yearbook; China Rural Statistical Yearbook.

3.2 Model specification

Following Lio and Liu (2006), Oyelami et al. (2022), Rahaman et al. (2024), this research specifies the empirical model below to assess how digital-technology adoption affects food grain productivity, while controlling for agricultural investment, fertilizer use, cultivated land, and labor. The econometric connection among the studied variables is developed as:

$$FDP_{it} = f\left(INT_{it}, MOBT_{it}, GIN_{it}, FRT_{it}, CUA_{it}, AGL_{it}\right) \quad (1)$$

where, FDP denotes the food grain production, INT refers to internet technology use, MOBT indicates mobile phone technology use, GIN is government investment, FRT is fertilizer use, CUA is cultivation land, and AGL is agricultural labor. Following Sethi et al. (2024), this research applies a natural-log transformation to the panel variables. This transformation helps mitigate heteroscedasticity and yields estimates that are more consistent and statistically efficient, thereby improving the reliability of the results relative to a simple linear specification. Accordingly, this study specifies a log-linear model as shown in Equations (2), (3).

Model 1:

$$\ln(FDP)_{it} = \beta_0 + \beta_1 \ln(INT_{it}) + \beta_2 \ln(GIN_{it}) + \beta_3 \ln(FRT_{it}) + \beta_4 \ln(CUA_{it}) + \beta_5 \ln(AGL_{it}) + \varepsilon_{it} \quad (2)$$

Model 2:

$$\ln(FDP)_{it} = \beta_0 + \beta_1 \ln(MOBT_{it}) + \beta_2 \ln(GIN_{it}) + \beta_3 \ln(FRT_{it}) + \beta_4 \ln(CUA_{it}) + \beta_5 \ln(AGL_{it}) + \varepsilon_{it} \quad (3)$$

The term β_0 is the constant, while $\beta_1 - \beta_5$ captures the long-run elasticities. This study uses i to label the 18 provinces and t to denote the annual observations over 2001–2022.

3.3 Estimation strategy

In this section, this research follows a stepwise econometric workflow: this study first tests for cross-sectional dependence (CSD), then apply second-generation panel unit-root procedures, conduct cointegration analysis using Westerlund (2007) and Kao (1999), estimate long-run elasticities, and finally perform the Dumitrescu and Hurlin (2012) panel Granger-causality test.

3.3.1 Cross-sectional dependence (CSD) tests

A key challenge in panel-data analysis is CSD, which can undermine the efficiency and consistency of estimates. To address this issue, this study explicitly accounts for CSD across the variables. Before testing the panel unit root, this study first employs the various CSD tests: the Breusch-Pagan Lagrange multiplier (LM), including the Pesaran CSD and Pesaran scaled LM statistics, to diagnose cross-sectional dependence across the variables. The Pesaran CSD test is formalized in Equation (4):

$$\text{Pesaran CD} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \to N(0,1) \quad (4)$$

3.3.2 Unit root analysis

Given the presence of CSD in the panel, this study relies on Pesaran's (2007) cross-sectionally augmented unit-root framework. Specifically, this study implements the CADF together with the corresponding cross-sectionally augmented IPS statistic. These procedures explicitly accommodate CSD, thereby reducing the risk of spurious inference. By comparison, conventional first-generation panel unit-root tests (e.g., ADF, LLC, and IPS) do not properly account for such dependence in this setting. The CADF regression underlying the analysis is reported in Equation (5):

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \gamma_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (5)$$

3.3.3 Westerlund bootstrap co-integration test

Panel cointegration testing helps assess whether the variables move together in a stable long-run equilibrium. This study applies Kao's (1999) first-generation cointegration test and the Westerlund (2007) approach to examine long-term linkages between food grain productivity and the explanatory variables. Relative to the first-generation procedure, the Westerlund method allows for heterogeneous slopes and CSD. This study specifies an ECM-based cointegration framework, which is summarized in Equations (6)–(9):

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\eta_i}{S.E(\hat{\eta}_i)} \quad (6)$$

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\eta_i}{\hat{\eta}_i(1)} \quad (7)$$

$$P_\tau = \frac{\hat{\eta}_i}{SE\hat{\eta}_i} \quad (8)$$

$$P_\alpha = T\hat{\eta} \quad (9)$$

3.3.4 Long-run estimates

After establishing that the variables are linked in the long run, this study estimates long-run effects using the Driscoll-Kraay (D-K) approach. Specifically, this study assesses how ICT adoption, measured by Internet connectivity and mobile phone penetration, relates to food grain productivity in China's major grain-producing regions, while controlling for government investment, fertilizer use, cultivated land, and agricultural labor. The D-K estimator is well suited to panels with CSD, providing robust inference under such dependence. As an additional robustness check, this study also uses the FGLS, MG, and FMOLS estimates. The FGLS and MG estimators provide an alternative approach to obtaining stable coefficient estimates. They can help mitigate common econometric concerns in panel settings, including autocorrelation, heteroscedasticity, slope heterogeneity, and endogeneity. The model hyperlinks connecting parameters can be specified in the following manner:

$$y_{it} = \alpha_0 + \sum_{i=1}^{p} \Upsilon_k X_{it} + \varepsilon_{it} \quad (10)$$

where, y_{it} denotes for food grain production and X_{it} is the set of explanatory variables. α_0 is the constant term, and Υ_k is the parameter vector to be estimated. The subscript i indexes the 18 key grain-belt provinces, while t denotes the annual observations over

2001–2022. Building on Bai et al. (2021) and Abdi et al. (2025), this study expresses the FGLS procedure using the following equations:

$$\hat{\beta}_{FGLS} = [X'\widehat{\Omega}^{-1}X]^{-1}\, X'\widehat{\Omega}^{-1}Y \tag{11}$$

3.3.5 Panel causality

The direction of causality among the tested variables cannot be determined using the D-K, FGLS, MG or FMOLS estimators, which only yield long-run parameter estimates (Kibria et al., 2023). Accordingly, this study applies the Dumitrescu and Hurlin (2012) panel causality test to examine directional linkages between the variables. This test addresses CSD and heterogeneity in the panel data. The Equation is formulated as follows:

$$y_{it} = \delta_i + \sum_{k=1}^{p} \Upsilon_{1ik} y_{i,t-k} + \sum_{k=1}^{p} \Upsilon_{2ik} X_{i,t-k} + \varepsilon_{it} \tag{12}$$

Based on the equation, Υ_{2ik} and Υ_{1ik} denotes the regression variables and autoregressive coefficients for the panel coefficients i at time t, respectively. Assuming a panel of observations for y_{it} and X_{it}, this research tests the no-causality null and allow for heterogeneous causal effects under the alternative.

4 Results and discussion

4.1 Preliminary examination of the data

This section provides an overview of the panel data used in the analysis, which examines how ICT adoption relates to grain output in China's key grain-producing provinces over 2001–2022. Table 2 summarizes the descriptive statistics for the variables, and Figures 6–8 display their pairwise correlation patterns. Overall, grain production is positively associated with both ICT indicators and the main input variables, suggesting that digital adoption and conventional inputs are relevant correlates of higher grain output.

4.2 Cross-sectional dependence tests

The present study relies on the 18 major grain-producing regions of China for the empirical analysis. Before estimating the empirical model, this research conducts CSD tests to assess the panel data (Table 3). The test statistics indicate that, at the 1% significance threshold, this study can reject the null of no CSD for every variable in the panel, implying the presence of CSD across the series. Given this evidence, this study then proceeds with second-generation panel unit-root testing.

4.3 Unit root test

Because the panel exhibits CSD, conventional first-generation unit-root procedures may yield unreliable inferences. This research, therefore, applies the second-generation CADF panel test. The corresponding statistics are reported in Table 4. At levels, the series are generally non-stationary, with CUA as the exception. After taking first differences, FDP, INT, MOBT, GIN, FRT, and AGL become stationary.

4.4 Co-integration tests

To examine whether the variables in the specification move together in the long run, this study applies panel cointegration tests based on Westerlund (2007) and Kao (1999). It is worth noting that the Westerlund ECM co-integration method is robust to cross-sectional dependence in the dataset. Tables 5, 6 report the outcomes of the cointegration tests. The cointegration results indicate that, at the 1% significance threshold, this research rejects the null of no long-run cointegration for the variables considered. This provides evidence of a stable long-run linkage across the series included in the analysis.

4.5 Long-run results for Model 1

After establishing long-run cointegration among the variables, this study estimates long-run effects using the D-K estimator technique (see Table 7). Under the D-K estimates, Internet connectivity is associated with a statistically significant 0.066% increase in long-run grain production in China's major grain-producing regions. Related empirical work reports comparable evidence in China (Chandio et al., 2023; Chen et al., 2022; Fu and Zhu, 2023). Currently, internet connectivity has improved agricultural production systems by integrating digital technologies, transforming traditional practices into digitized agriculture (Fu and Zhu, 2023). Internet access can be obtained through various devices, including smartphones, computers, tablets, digital televisions, and similar technologies (Kaila and Tarp, 2019). Adopting digital technologies, such as GPS-guided systems, drones, soil moisture sensors, and farm management software, significantly enhances efficiency and farm productivity (Hasan et al., 2023). Moreover, internet access allows farmers to revolutionize their farming methods by enabling real-time field monitoring and precise resource management (Zou and Mishra, 2022). Since 2023, China has made significant progress in digitalization, particularly with 5G technology, which is now widely accessible. A large portion of the population is connected to 5G networks, which have extensive coverage across all regions. This advanced and widespread use of 5G technology has a significant impact on the food production process (Ma et al., 2023).

Table 7 shows that government investment enters the long-run specification with a positive and statistically significant coefficient. The implied elasticity is 0.0130, meaning that a 1% increase in government investment corresponds to a 0.0130% increase in grain output. This pattern highlights the importance of public spending for agricultural performance: well-designed policies at both central and provincial levels, together with sustained resource allocation, can strengthen production capacity and ultimately support food security. This aligns with prior evidence reported for Australia

TABLE 2 Descriptive statistics.

Item	FDP	INT	MOBT	GIN	FRT	CUA	AGL
Mean	7.6853	3.5469	7.9420	5.3010	5.4211	8.2477	6.9802
Median	7.7219	3.6000	8.0900	5.9644	5.4493	8.2453	7.0175
Maximum	8.8663	4.5000	9.7300	7.2147	6.5738	9.3369	8.1542
Minimum	6.2908	1.8000	5.2000	0.8085	4.4224	7.0872	5.9614
Std. Dev.	0.5562	0.5667	0.9157	1.5947	0.4568	0.4891	0.5127
Skewness	0.0830	−0.5190	−0.4692	−0.9024	0.1649	0.1872	−0.0256
Kurtosis	2.2526	2.5130	2.6789	2.5962	2.8642	2.4292	2.0350
Jarque-Bera	9.6712	21.6949	16.2327	56.4376	2.0999	7.6889	15.4069
Probability	0.0079	0.0000	0.0002	0.0000	0.3499	0.0213	0.0004
Sum	3,043.409	1,404.600	3,145.070	2,099.200	2,146.769	3,266.091	2,764.169
Sum Sq. Dev.	122.2349	126.8664	331.2270	1,004.516	82.4579	94.5147	103.8459
Observations	396	396	396	396	396	396	396

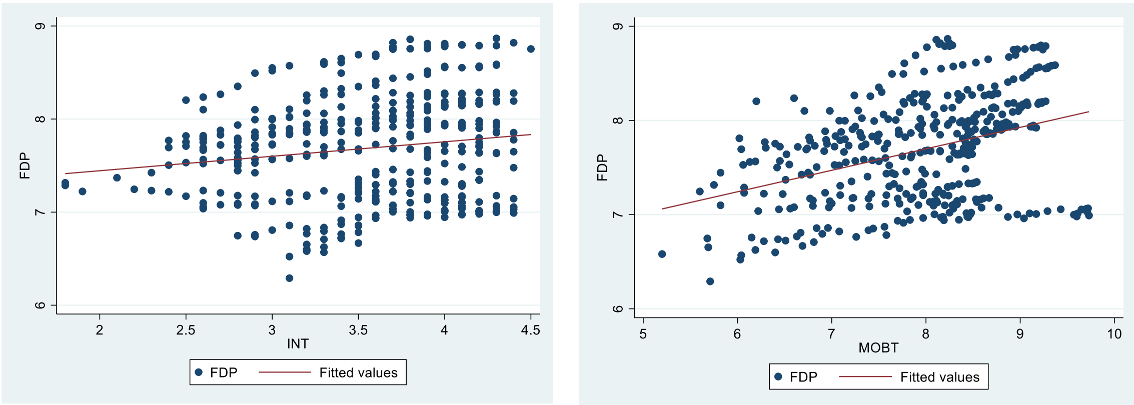

FIGURE 6
Relationship between FDP and INT **(left)**, FDP and MOBT **(right)**.

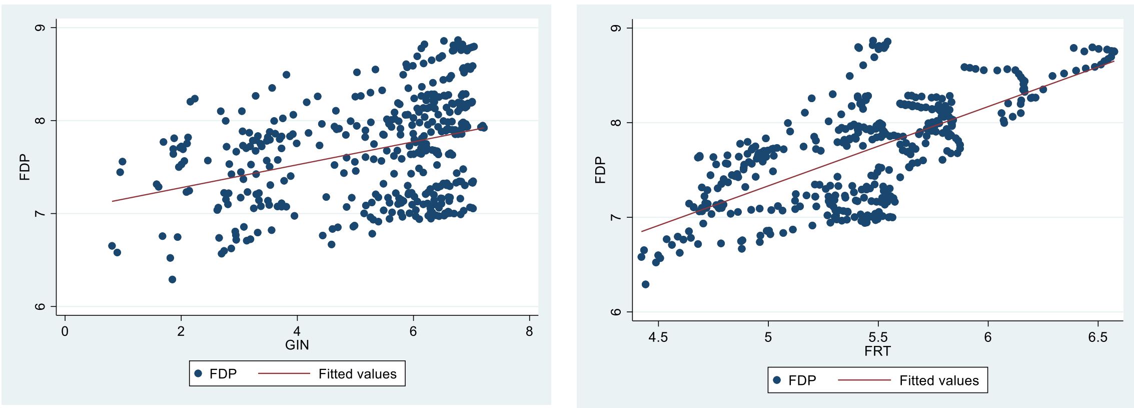

FIGURE 7
Relationship between FDP and GIN **(left)**, FDP and FRT **(right)**.

(Salim and Islam, 2010), Nepal (Pickson et al., 2025a,b), and China (Zhang et al., 2022).

Production factors, such as cultivated land and fertilizer application, contribute significantly to increasing grain food production, while the negative impact of labor is observed. In the long-run estimates, a 1% expansion in cultivated land corresponds to a 1.0263% rise in grain output, while a 1% increase in fertilizer use is associated with a 0.0895% gain. Both inputs,

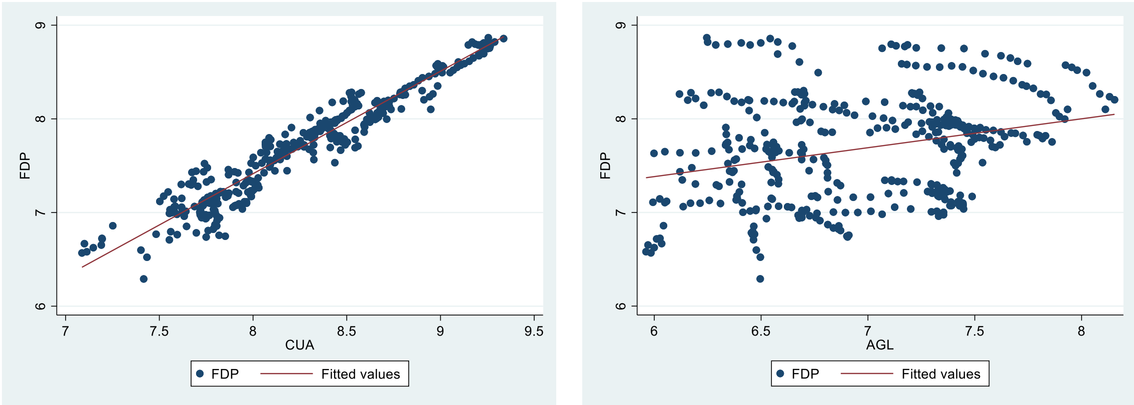

FIGURE 8
Relationship between FDP and CUA **(left)**, FDP and AGL **(right)**.

TABLE 3 Result of cross-sectional dependence tests.

Item	FDP	INT	MOBT	GIN	FRT	CUA	AGL
Breusch-Pagan LM	2,469.105 (0.0000)	3,277.920(0.0000)	3,326.508 (0.0000)	3,327.930(0.0000)	1,927.753 (0.0000)	2,455.910(0.0000)	2,397.544 (0.0000)
Pesaran scaled LM	132.4029 (0.0000)	178.6398(0.0000)	181.4174 (0.0000)	181.4986(0.0000)	101.4559 (0.0000)	131.6486(0.0000)	128.3120 (0.0000)
Bias-corrected scaled LM	131.9743 (0.0000)	178.2112(0.0000)	180.9888 (0.0000)	181.0701(0.0000)	101.0273 (0.0000)	131.2200(0.0000)	127.8835 (0.0000)
Pesaran CD	36.23717 (0.0000)	57.25037(0.0000)	57.67554 (0.0000)	57.68748(0.0000)	36.96730 (0.0000)	17.89290(0.0000)	43.35909 (0.0000)

TABLE 4 Results of CADF unit root test.

Item	Level		First Δ	
	t-value	*P-value*	*t-value*	*P-value*
FDP	−1.805	0.404	−2.481	0.001
INT	−1.370	0.952	−2.276	0.011
MOBT	−2.059	0.088	−2.361	0.004
GIN	−1.975	0.163	−2.132	0.047
FRT	−1.682	0.617	−2.429	0.001
CUA	−2.446	0.001	−2.519	0.000
AGL	−1.006	0.999	−3.219	0.000
Critical values	10%	5%	1%	
	−2.110	−2.200	−2.380	

TABLE 5 Westerlund ECM co-integration test.

Statistic	Value	*Z-value*	*P-value*	Robust *P-value*
Model 1:				
G_τ	−3.416	−5.078	0.000	0.000
G_α	−9.006	1.502	0.933	0.000
P_τ	−11.548	−2.917	0.002	0.023
P_α	−8.862	−0.443	0.329	0.020
Model 2:				
G_τ	−3.441	−5.179	0.000	0.000
G_α	−9.632	1.156	0.876	0.000
P_τ	−12.358	−3.580	0.000	0.008
P_α	−11.579	−1.892	0.029	0.003

fertilizer and land, significantly influence crop yields and total agricultural output. Fertilizers supply vital nutrients that stimulate plant growth, enhance soil fertility, and improve crop quality. The quantity and variety of fertilizer utilized can profoundly influence the efficacy of cereal production. Similar patterns have been documented in prior work, including evidence for China (Pickson et al., 2022), broader developing-country samples (Sethi et al., 2024), and Pakistan (Farooq et al., 2023), all of which emphasize that cultivated land and fertilizer application make meaningful contributions to agricultural productivity.

4.6 Robustness check for Model 1

This study explores how fast Internet connectivity and Mobile phone access influence grain output across China's central grain-producing provinces. As a robustness exercise for the D-K long-run estimates, this study also employs the FGLS, MG, and FMOLS methods. These estimation techniques provide a similar sign for all estimated coefficients. The findings from Table 8 show that Internet access, government investment, fertilizer application, and cultivated land positively contribute to grain food production.

4.7 Long-run results for Model 2

This study used food grain production as the dependent variable, focusing on food production, enabling a clear assessment of how technological innovations contribute to the agricultural industry. Moreover, this industry is highly sensitive to innovations in farming practices, such as adopting precision agriculture facilitated by digital tools. The D-K estimates are reported in Table 9. The long-run coefficient on mobile phone use is positive and statistically significant. The estimated elasticity is 0.0530, so a 1% increase in mobile-phone use corresponds to about a 0.0530% increase in food production. Ma et al. (2020a) emphasized that smartphones are powerful tools for progressing agricultural practices. Aker and Mbiti (2010) and Khan et al. (2022) stated that increased smartphone penetration indicates farmers' potential access to digital tools. The results are consistent with existing evidence reported in the literature (LoPiccalo, 2022; Rehman et al., 2024; Sethi et al., 2024; Zheng et al., 2021). The main input variables enter with positive and statistically significant long-run effects on food output. A 1% increase in government investment, fertilizer use, and cultivated land corresponds to 0.003%, 0.089%, and 1.041% higher grain production, respectively. This indicates that in grain-producing regions, adequate investment in the agricultural industry, improved agricultural land, and appropriate fertilizer use can boost the food industry and promote food security. Behera et al. (2024) reported that the quantity and variety of fertilizer utilized can profoundly enhance the efficiency of food production. Land use

TABLE 6 Kao co-integration test.

Item	t-statistic	Prob.
Model 1:		
ADF	−7.1504	0.0000
Model 2:		
ADF	−7.1730	0.0000

TABLE 7 Driscoll-Kraay standard errors regression.

Model 1: FGP = f(INT, GIN, FRT, CUA, AGL)				
Variables	Coef.	St.Err.	*t-value*	*p-value*
INT	0.0660***	0.0132	4.970	0.000
GIN	0.0130*	0.0072	1.840	0.080
FRT	0.0895**	0.0418	2.140	0.044
CUA	1.0263***	0.0247	41.410	0.000
AGL	−0.0478**	0.0208	−2.290	0.032
Constant	−1.2360***	0.2421	−5.100	0.000
Wald chi2(5)		5,853.02		
Prob > chi2		0.0000		
Overall R-squared		0.9459		
Number of obs		396		

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

TABLE 9 Driscoll-Kraay standard errors regression.

Model 2: FGP = f(MOBT, GIN, FRT, CUA, AGL)				
Variables	Coef.	St.Err.	*t-value*	*p-value*
MOBT	0.0530***	0.0132	4.020	0.001
GIN	0.0030	0.0081	0.390	0.702
FRT	0.0890*	0.0470	1.890	0.072
CUA	1.0410***	0.0308	33.800	0.000
AGL	−0.0860***	0.0262	−3.280	0.004
Constant	−1.2237***	0.2765	−4.380	0.000
Wald chi2(5)	12,487.08			
Prob > chi2	0.0000			
Overall R-squared	0.9446			
Number of obs	396			

***$p < 0.01$, *$p < 0.1$.

TABLE 8 Robustness check for Model 1.

Model: 1	FGP = f(INT, GIN, FRT, CUA, AGL)											
	FGLS method				Mean Group (MG) Estimator				FMOLS method			
Variables	Coef.	St.Err.	*t-value*	*p-value*	Coef.	St.Err.	*z*	P>|z|	Coef.	St.Err.	t-statistic	Prob.
INT	0.0703	0.0026	26.86	0.000	0.0540	0.0312	1.73	0.083	0.0731	0.0195	3.7470	0.000
GIN	0.0011	0.000	1.22	0.221	0.0104	0.0180	0.58	0.564	0.0105	0.0068	1.5440	0.123
FRT	0.1031	0.002	37.41	0.000	0.1429	0.1219	1.17	0.241	0.0817	0.0384	2.1240	0.034
CUA	1.0811	0.003	311.23	0.000	0.7281	0.1169	6.23	0.000	1.0250	0.0314	32.6419	0.000
AGL	−0.13545	0.002	−46.76	0.000	−0.1034	0.0307	−3.36	0.001	−0.0493	0.0299	−1.6466	0.100
Constant	−1.1016	0.025	−44.73	0.000	1.4844	1.0046	1.48	0.140	R-squared		0.9931	
SD dependent var		0.556			Wald chi2(5)		158.16		Adjusted R^2		0.9927	
Chi-square		347,027.525			Prob > chi2		0.0000		S.E. of regression		0.0474	

for crop cultivation is considered a vital input factor in agricultural production systems (Shi et al., 2021). Research shows that adequate fertilizer supply and the availability of agricultural land can raise cereal output and strengthen food security. This interpretation is consistent with prior evidence (Ahsan et al., 2020; Behera et al., 2024; Huynh, 2024; Shi et al., 2021).

4.8 Robustness check for Model 2

This research uses the FGLS, MG, and FMOLS estimators to assess the robustness of long-run estimates of the D-K model. Table 10 displays the estimated outcomes. The FGLS, MG, and FMOLS methods validate that MOBT significantly enhanced food production. Therefore, this research concludes that Mobile phone technology use, government investment, and fertilizer application are also positively associated with food production across China's major grain-producing regions. Additionally, the FGLS results validated the food production-enhancing effects of MOBT, GIN, FRT, and CUA at the 1% level of significance for all variables except AGL. The robustness of the D-K results is verified.

4.9 D-H causality test results

To investigate directional causal linkages among grain food production, Internet access, Mobile phone use, government investment, fertilizer application, cultivated land, and agricultural labor, this study employs the Dumitrescu and Hurlin (2012) panel causality test. Table 11 reports the panel causality results, indicating a one-way causal link running from Internet access to grain food production, government investment to grain food production, Mobile phone use to Internet access, Internet access to fertilizer application, Mobile phone use to fertilizer application, Mobile phone use to agricultural labor, government investment to fertilizer application, cultivated land to agricultural labor, and a bidirectional causality connection between Mobile phone use to grain food production, fertilizer application to grain food production, cultivated land to grain food production, agricultural labor to grain food production, government investment to Internet access, agricultural labor to Internet access, government investment to Mobile phone use, cultivated land to Mobile phone use, cultivated land to government investment, agricultural labor to government investment, cultivated land to fertilizer application, agricultural labor to fertilizer application, respectively. Table 11 also indicates a two-way causal relationship between mobile-phone technology (MOBT) and food production (FDP), implying that broader mobile use in agricultural practices is associated with higher grain output. Therefore, policy initiatives aimed at boosting food production should enhance funding for sustainable agricultural development and improve ICT infrastructure in rural areas. This will help farmers adopt better farming methods and promote the food production industry. In addition, the unidirectional causality from INT to FDP indicates that changes in Internet access precede changes in grain food production in the panel. This result aligns with the long-run estimates reported earlier.

4.10 Hypothesis evaluation and evidence

The baseline Driscoll-Kraay estimates, together with the robustness checks based on alternative long-run estimators, provide a coherent picture of how ICT adoption and conventional production factors relate to long-run grain output in China's major grain-producing regions. Figure 9 summarizes the findings.

H1 proposes that Internet connectivity (INT) has a positive long-run effect on grain production (FDP). The results support H1: INT is positive and statistically significant in the baseline long-run estimates (Table 7), and the robustness checks confirm the same sign (Table 8). Moreover, the Dumitrescu and Hurlin causality test indicates a unidirectional causal link running from INT to FDP (Table 11), which reinforces the interpretation that changes in Internet access precede changes in grain output in the panel. This evidence is consistent with macro-level findings reported in

TABLE 10 Robustness check for Model 2.

Model: 2	FGP = f(MOBT, GIN, FRT, CUA, AGL)											
	FGLS Method				Mean Group (MG) Estimator				FMOLS Method			
Variables	Coef.	St.Err.	*t-value*	*p-value*	Coef.	St.Err.	*z*	P>|@ z|@	Coef.	St.Err.	t-statistic	Prob.
MOBT	0.0225	0.0022	9.94	0.000	0.0934	0.0477	1.73	0.083	0.0731	0.0195	3.7470	0.000
GIN	0.0076	0.0011	6.62	0.000	0.0248	0.0166	0.58	0.564	0.0105	0.0068	1.5440	0.123
FRT	0.1189	0.0029	40.62	0.000	0.1133	0.1036	1.17	0.241	0.0817	0.0384	2.1240	0.034
CUA	1.0698	0.0032	325.12	0.000	0.8562	0.1725	6.23	0.000	1.0250	0.0314	32.6419	0.000
AGL	−0.1717	0.0025	−67.18	0.000	−0.1358	0.0489	−3.36	0.001	−0.0493	0.0299	−1.6466	0.100
Constant	−0.8049	0.0238	−33.80	0.000	0.3771	1.335	1.48	0.140	R-squared		0.9931	
SD dependent var		7.685			Wald chi2(5)		132.92		Adjusted R^2		0.9927	
Chi-square		341,456.125			Prob > chi2		0.0000		S.E. of regression		0.0474	

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TABLE 11 Panel Dumitrescu and Hurlin (D-H) causality results.

Null hypothesis:	W-Stat.	Zbar-Stat.	Prob.	Remarks
INT ⇎ FDP	3.82426	6.53211	6.E-11	INT→ FDP
FDP ⇎ INT	1.41432	0.70015	0.4838	
MOBT ⇎ FDP	11.0942	24.1251	0.0000	MOBT ↔ FDP
FDP ⇎ MOBT	2.46339	3.23885	0.0012	
GIN ⇎ FDP	12.0489	26.4353	0.0000	GIN → FDP
FDP ⇎ GIN	1.57222	1.08225	0.2791	
FRT ⇎ FDP	3.49644	5.73879	1.E-08	FRT ↔ FDP
FDP ⇎ FRT	12.3049	27.0550	0.0000	
CUA ⇎ FDP	3.06187	4.68715	3.E-06	CUA ↔ FDP
FDP ⇎ CUA	2.93551	4.38137	1.E-05	
AGL ⇎ FDP	2.20565	2.61514	0.0089	AGL ↔ FDP
FDP ⇎ AGL	3.39336	5.48934	4.E-08	
MOBT ⇎ INT	3.19111	4.99991	6.E-07	MOBT→ INT
INT ⇎ MOB	1.60879	1.17075	0.2417	
GIN ⇎ INT	2.77457	3.99188	7.E-05	GIN ↔ INT
INT ⇎ GIN	0.28053	−2.04359	0.0410	
FRT ⇎ INT	1.18760	0.15148	0.8796	INT→ FRT
INT ⇎ FRT	14.2115	31.6688	0.0000	
CUA ⇎ INT	1.45975	0.81009	0.4179	CUA ⇎ INT
INT ⇎ CUA	1.59779	1.14413	0.2526	
AGL ⇎ INT	2.22536	2.66283	0.0077	AGL ↔ INT
INT ⇎ AGL	4.38422	7.88717	3.E-15	
GIN ⇎ MOBT	3.41626	5.54475	3.E-08	GIN ↔ MOBT
MOBT ⇎ GIN	6.98909	14.1909	0.0000	
FRT ⇎ MOBT	1.57525	1.08959	0.2759	MOBT→ FRT
MOBT ⇎ FRT	7.85577	16.2882	0.0000	
CUA ⇎ MOBT	3.82418	6.53190	6.E-11	CUA ↔ MOBT
MOBT ⇎ CUA	5.15806	9.75984	0.0000	
AGL ⇎ MOBT	0.48206	−1.55588	0.1197	MOBT→ AGL
MOBT ⇎ AGL	3.74089	6.33034	2.E-10	
FRT ⇎ GIN	1.30660	0.43946	0.6603	GIN → FRT
GIN ⇎ FRT	7.05854	14.3589	0.0000	
CUA ⇎ GIN	1.82600	1.69639	0.0898	CUA ↔ GIN
GIN ⇎ LNCA	5.99392	11.7826	0.0000	
AGL ⇎ GIN	0.34424	−1.88942	0.0588	AGL ↔ GIN
GIN ⇎ AGL	3.83917	6.56819	5.E-11	
CUA ⇎ FRT	9.02408	19.1155	0.0000	CUA ↔ FRT
FRT ⇎ CUA	4.10992	7.22340	5.E-13	
AGL ⇎ FRT	17.1869	38.8691	0.0000	AGL ↔ FRT
FRT ⇎ AGL	5.19274	9.84378	0.0000	
AGL ⇎ CUA	1.16116	0.08749	0.9303	CUA → AGL
CUA ⇎ AGL	3.55162	5.87232	4.E-09	

the broader literature that ICT access is associated with higher agricultural productivity and output (Lio and Liu, 2006; Oyelami et al., 2022; Sethi et al., 2024), and it aligns with China-focused evidence showing that Internet use improves agricultural technical performance and efficiency (Chen et al., 2022; Fu and Zhu, 2023).

H2 posits that mobile phone penetration (MOBT) has a positive long-run effect on grain production. The results also support H2: MOBT is positive and statistically significant in the baseline long-run estimates (Table 9), and the robustness checks confirm a positive sign across alternative estimators, with statistical significance in FGLS and FMOLS and marginal significance under MG (Table 10). The causality results further suggest a bidirectional relationship between MOBT and FDP (Table 11), implying that mobile adoption and production outcomes may co-evolve over time. This pattern aligns with earlier findings that mobile technologies can facilitate communication and information access in agricultural activities and are associated with improved agricultural outcomes in developing-country settings (Aker and Mbiti, 2010; Khan et al., 2022; Sethi et al., 2024). This study's conceptual discussion is also consistent with the finding that mobile devices can provide practical, accessible digital tools for agricultural decision-making and service delivery (Ma et al., 2020a).

H3 concerns conventional production factors and predicts positive long-run effects of government investment (H3a), fertilizer use (H3b), and cultivated area (H3c), and a negative effect of agricultural labor (H3d). The estimates are broadly consistent with H3, but the strength of statistical support differs across specifications. Government investment is positive in both models (Tables 7, 9), and it is statistically significant in Model 1 but not in Model 2, indicating that its long-run association with grain output is sensitive to the ICT specification. This finding aligns with previous studies that emphasize the role of public investment in improving agricultural performance (Salim and Islam, 2010; Zhang et al., 2022). Fertilizer use and cultivated area are positive in both models, with cultivated area showing a consistently strong and highly significant association with grain output (Tables 7, 9). These results are consistent with the literature, which shows that fertilizer and land area are key determinants of agricultural production (Pickson et al., 2022). By contrast, agricultural labor shows a negative long-run association in both models. It is statistically significant in the baseline estimates, consistent with structural change and the increasing role of mechanization and technology in modern agricultural systems. This is consistent with previous research that argues that technology adoption and mechanization can reduce the marginal contribution of labor in agriculture (Baig et al., 2024). Taken together, the results suggest that ICT development complements rather than replaces the roles of conventional inputs and public support in sustaining grain production.

Finally, the findings also speak to the broader debate noted in Section 2, namely that ICT effects can be context-dependent in their magnitude. In this study, in the baseline D–K long-run estimates, both ICT channels display positive, statistically significant associations with grain output, and the causality results indicate a clear directionality for Internet access. These patterns are consistent with earlier work emphasizing that ICT can enhance agricultural performance by improving information access and reducing transaction costs (Lio and Liu, 2006; Oyelami et al., 2022),

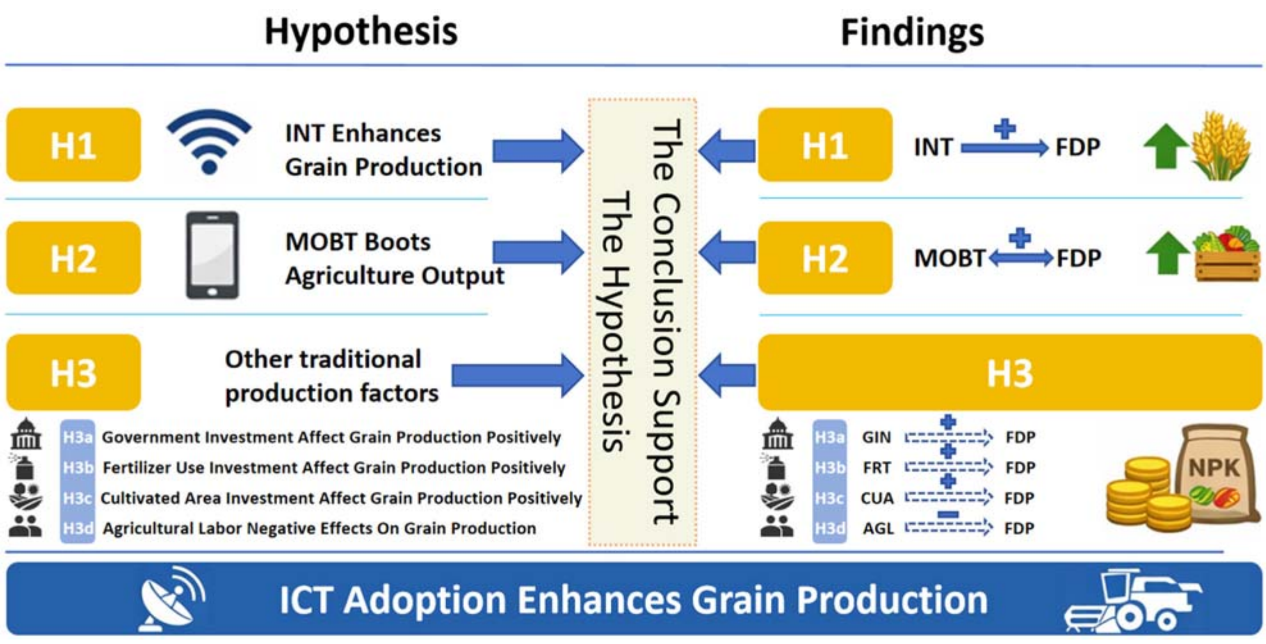

FIGURE 9
Summary of key findings and hypothesis evaluation.

while the province-level long-horizon setting provides additional macro-empirical evidence for China's major grain-producing regions.

5 Conclusion and policy implications

5.1 Conclusion

Using province-level data for China's major grain-producing areas over 2001–2022, this study assesses the long-run relationship between digital adoption, captured by internet connectivity and mobile-phone use, and grain production. This research employed several estimation methods, including the Pesaran CD test to detect CSD, the CADF test to verify variable stationarity, the Westerlund ECM cointegration test to validate long-run equilibrium relationships among variables, and the DKSE regression to determine the long-term impact of digital technologies on grain production. The results from the DKSE model indicate that internet connectivity has a strong, positive impact on long-run grain production. Similarly, mobile phone use in this digitalization period significantly increases grain production in the long run. This suggests that the adoption of digital technologies is a valuable tool for improving grain production and promoting food security in China's major grain-producing regions. The FGLS model findings further confirm the consistency and reliability of the DKSE regression results. Finally, the Dumitrescu and Hurlin causality test results reveal a bidirectional causal connection between Mobile phone use, fertilizer application, cultivated land, and agricultural labor to grain food production. Moreover, the analysis reveals a unidirectional causality running from Internet access and government investment to grain food production.

5.2 Policy implications

Based on the conclusions, the following policy implications are suggested:

- Rural digital infrastructure should be strengthened and better targeted in major grain-producing provinces. The long-run estimates show that both internet connectivity and mobile-phone penetration are positively and significantly associated with grain production, and the panel causality results further indicate that changes in internet access precede changes in grain output. Expanding stable, high-quality, and affordable connectivity can support grain production by improving farmers' access to timely market information, agronomic knowledge, and digital services.
- Digitalization-related measures should be implemented alongside core production-factor policies. The results show that cultivated land has the highest long-run elasticity with respect to grain output, and fertilizer use also shows a positive long-run association. In addition, the causality analysis indicates bidirectional causal relationships between cultivated land and grain production, and between fertilizer use and grain production. Protecting cultivated land, improving land quality, and promoting more scientific fertilizer input management remain essential for sustaining grain output, while ICT development can play a complementary role.
- Public support should focus on improving the effectiveness and targeting of agricultural investment to enable the productive use of ICT. The baseline estimates show a positive association between government investment and grain output, and the causality results suggest that government investment precedes changes in grain production. The stable and well-targeted public spending can reinforce production capacity, mainly when directed toward rural

digital infrastructure and service delivery, agricultural extension and training linked to digital platforms, and complementary physical infrastructure that supports modern production practices.

- Labor-related policies should address the observed negative long-run association between agricultural labor and grain production, which is consistent with ongoing structural change, mechanization, and the aging of the rural workforce. Given the bidirectional causality between agricultural labor and grain output, measures that improve labor productivity are particularly important. Support vocational training, digital-skills upgrading, and the adoption of labor-saving and information-enhancing technologies, so that reductions in agricultural labor do not undermine grain output and the benefits of digitalization can be realized more effectively.

5.3 Limitations and future research

While the province-level analysis identifies a long-run association between ICT diffusion and grain production, future work can examine the underlying mechanisms more directly by incorporating additional variables that capture how farmers obtain information and agricultural knowledge and how production decisions respond to digital access. Future research may adopt stronger identification strategies to address potential endogeneity between ICT expansion and agricultural development. It would be valuable to explore heterogeneity across provinces, since the benefits of internet connectivity and mobile technologies may differ by regional conditions and stages of development. Combining macro-level panel data with more granular data would strengthen causal inference and improve the design of targeted policies for food security.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HZ: Methodology, Conceptualization, Writing – original draft. BY: Methodology, Writing – original draft, Formal analysis. CL: Visualization, Writing – review & editing, Supervision. QH: Writing – review & editing, Formal analysis, Visualization, Supervision. AC: Writing – review & editing, Visualization, Formal analysis.

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Conflict of interest

HZ was employed by Guizhou Planning & Design Institute of Posts & Telecommunications Co., Ltd.

The remaining 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.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. During the preparation of this work, the author(s) used ChatGPT in order to improve the text's language and clarity. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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