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ARTICLE

# COMPETITIVE INTELLIGENCE-DRIVEN AGRICULTURAL DIGITALIZATION AND GREEN PRODUCTIVITY TRANSFORMATION: EVIDENCE FROM CHINA'S PROVINCIAL AGTFP DYNAMICS

## DIGITALIZAÇÃO AGRÍCOLA ORIENTADA PELA INTELIGÊNCIA COMPETITIVA E TRANSFORMAÇÃO DA PRODUTIVIDADE VERDE: EVIDÊNCIAS DA DINÂMICA DA PRODUTIVIDADE TOTAL DOS FATORES VERDE AGRÍCOLA (AGTFP) NAS PROVÍNCIAS DA CHINA

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**ABSTRACT**

**Purpose:** This study investigates whether competitive intelligence (CI) driven agricultural digitalization enhances Agricultural Green Total Factor Productivity (AGTFP) across China's 30 provinces. Three research questions guide the inquiry: (1) does digitalization significantly improve AGTFP? (2) through which institutional mechanisms digital financial inclusion and land transfer—does this impact operate? and (3) do the effects exhibit regional heterogeneity and nonlinear dynamics that generate paradoxical outcomes under certain conditions?

**Methodology/approach:** A composite agricultural digitalization index is constructed via the entropy-weighting method. AGTFP is measured using an input-oriented Slack-Based Measure (SBM) model with undesirable outputs. Within a two-way fixed-effects panel framework, this study applies mediation analysis, moderation and threshold tests, quantile regression, and regional subgroup regressions.

**Originality/Relevance:** By integrating competitive intelligence theory with green productivity analysis, this paper develops a unified 'mechanism-context' framework to explain how identical digital investments produce divergent efficiency outcomes across regions. The study extends digital agriculture theory beyond technology adoption narratives toward ecosystem-level structural transformation.

**Key findings:** Digitalization exerts a significant positive effect on AGTFP (β = 0.495, $p < 0.05$) under the preferred two-way fixed-effects specification. Digital financial inclusion mediates this relationship more effectively (indirect effect = 0.051) than land transfer (indirect effect = 0.002). Moderate fiscal support amplifies digitalization effectiveness while excessive intervention weakens it. Regional analysis reveals strong positive effects in eastern China but adverse outcomes in the central region, suggesting transitional inefficiency. Quantile regression confirms that the productivity-enhancing effect is strongest among lower-performing provinces.

**Theoretical/methodological contributions:** The study contributes a multidimensional digitalization index, an SBM-based green productivity measure, a staged nonlinear modernization trajectory, and a conditioned policy-effectiveness framework to digital agriculture and green productivity literature.

**Keywords:** Agricultural Total Factor Productivity. Digital Agriculture. Green Productivity. Financial Inclusion. Panel Data. China.



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## RESUMO

**Objetivo:** Este estudo investiga se a digitalização agrícola impulsionada pela Inteligência Competitiva (CI) melhora a Produtividade Total dos Fatores Verde Agrícola - AGTFP nas 30 províncias da China. Três questões de pesquisa orientam a investigação: (1) a digitalização melhora significativamente a AGTFP? (2) por meio de quais mecanismos institucionais inclusão financeira digital e transferência de terras esse impacto ocorre? e (3) os efeitos apresentam heterogeneidade regional e dinâmicas não lineares capazes de gerar resultados paradoxais sob determinadas condições?

**Metodologia/Abordagem:** Foi construído um índice composto de digitalização agrícola utilizando o método de ponderação por entropia. A AGTFP foi mensurada por meio de um modelo Slack-Based Measure (SBM) orientado para insumos, incorporando outputs indesejáveis. Em uma estrutura de painel com efeitos fixos bidirecionais, o estudo emprega análise de mediação, testes de moderação e limiar (threshold), regressão quantílica e regressões por subgrupos regionais.

**Originalidade/Relevância:** Ao integrar a teoria da Inteligência Competitiva à análise da produtividade verde, este artigo desenvolve uma estrutura unificada de "mecanismo–contexto" para explicar como investimentos digitais idênticos podem produzir resultados distintos de eficiência entre diferentes regiões. O estudo amplia a teoria da agricultura digital para além das narrativas centradas na adoção tecnológica, direcionando a análise para processos de transformação estrutural em nível de ecossistema.

**Principais Resultados:** A digitalização exerce efeito positivo e significativo sobre a AGTFP ($\beta = 0{,}495$; $p < 0{,}05$) na especificação preferencial de efeitos fixos bidirecionais. A inclusão financeira digital medeia essa relação de forma mais expressiva (efeito indireto = 0,051) do que a transferência de terras (efeito indireto = 0,002). Um nível moderado de apoio fiscal amplia a eficácia da digitalização, enquanto intervenções excessivas reduzem seus efeitos positivos. A análise regional revela impactos fortemente positivos no leste da China, mas resultados adversos na região central, sugerindo ineficiências transitórias. A regressão quantílica confirma que o efeito de aumento da produtividade é mais intenso entre as províncias com menor desempenho.

**Contribuições Teóricas/Metodológicas:** O estudo contribui para a literatura sobre agricultura digital e produtividade verde ao propor um índice multidimensional de digitalização, uma medida de produtividade verde baseada no modelo SBM, uma trajetória de modernização não linear em estágios e uma estrutura analítica condicionada para avaliar a efetividade de políticas públicas.


**Palavras-chave:** Produtividade Total dos Fatores Agrícola. Agricultura Digital. Produtividade Verde. Inclusão Financeira. Dados em Painel. China.

# 1 INTRODUCTION

Global agriculture faces mounting resource and environmental pressures, recurrent climate shocks, rural labor outmigration, and exhaustion of traditional extensive growth models. In this context, enhancing Agricultural Total Factor Productivity (AGTFP) has emerged as a critical pathway toward sustainable and high-quality agricultural development (Zeng et al., 2024; Wei & Baharudin, 2025).

China is one of the world's largest agricultural economies, and quality improvement, green development, and digital empowerment are core issues on its modernization agenda (Xu et al., 2022). The 14th Five-Year Plan and subsequent Central No.1 Documents highlight digital villages, smart agriculture, and market-oriented use of production factors. However, regional differences in rural financial access and digital infrastructure, rigidities in factor markets, and weak capacities to transfer and disseminate new technologies and practices remain. As an input-driven growth pattern nears its end, the question is how to attain efficiency gains while simultaneously complying with ecological red lines and limited resources (Xu et al. 2024). Digital technologies, ranging from big data to artificial intelligence and the Internet of Things, and remote sensing to cloud platforms, are revolutionizing the agricultural value chain (Javaid et al., 2022).

However, empirical findings indicate a potential disconnect between digital investments and the resulting productivity gains, or even a "productivity paradox" where technology investments may be made but do not yield a proportional increase in productivity (Mi, Chen, Nanseki & Chomei, 2021; Prakasha, Singh & Sharma, 2024). Competitive intelligence (CI) is a strategic analytical tool that helps decision-makers gather, study, and act on environmental data to facilitate adaptive decision-making (Cai & Han, 2024).

CI frameworks can assist governments and enterprises in recognizing investment opportunities, forecasting structural constraints, and designing policy actions given the changing productivity dynamics. This study sees the CI-led approach to agricultural digitalization as embedding data-driven intelligence systems in the agricultural production and governance value chain in a way that can take us towards more agile and evidence-based agricultural modernization.

Despite the growing literature on agricultural digitalization and green productivity, existing studies predominantly conceptualize digital transformation as a technological adoption process rather than as an intelligence-enabled governance capability. Most prior studies emphasize infrastructure investment, digital finance, and technological diffusion while paying insufficient attention to how agricultural institutions collect, process, disseminate, and operationalize strategic intelligence for adaptive decision-making. Consequently, the Competitive Intelligence (CI) dimension of agricultural digitalization remains theoretically underdeveloped. This study addresses this gap by conceptualizing agricultural digitalization as a CI-driven governance architecture that transforms digital information into actionable intelligence supporting sustainable agricultural modernization and AGTFP enhancement (Singh et al., 2024).

Competitive Intelligence (CI) has traditionally been conceptualized as a systematic process through which organizations collect, process, disseminate, and utilize environmental information to support strategic decision-making and long-term competitiveness (Aguilar, 1967; Gilad, 1988; Calof & Wright, 2008). While CI originated within corporate strategic management, recent studies increasingly recognize its relevance in public-sector governance and digital ecosystem management, where intelligence capabilities enable adaptive responses to complex environmental conditions.

Within agricultural modernization, CI should not be interpreted merely as information availability or technological adoption. Rather, it represents an institutional capability that transforms dispersed digital information into actionable intelligence supporting resource allocation, environmental management, and sustainable productivity enhancement. In this perspective, agricultural digitalization functions as the technological infrastructure through which intelligence capabilities are developed and deployed.

This study conceptualizes CI capability through four interconnected dimensions:

**Intelligence Acquisition**

Collection of production, market, weather, and environmental information through digital infrastructure, sensors, IoT devices, remote sensing systems, and agricultural databases;

**Intelligence Processing**

Analytical transformation of raw data into usable knowledge through digital platforms, artificial intelligence systems, predictive analytics, and decision-support mechanisms;

**Intelligence Dissemination**

Transmission of intelligence across agricultural actors through digital financial services, extension systems, e-commerce platforms, and government information networks;

**Intelligence Utilization**

Application of intelligence to production decisions, resource optimization, policy interventions, environmental management, and strategic adaptation.

Accordingly, agricultural digitalization is viewed as a CI-enabled governance architecture rather than a purely technological phenomenon. Green productivity improvements emerge not solely from technology adoption but from the capability of agricultural institutions to convert information into strategic intelligence and actionable decisions.

## 1.1 Research Significance

This study contributes at three interconnected levels. Theoretically, it integrates the chain of "digital technology–institutional environment–factor allocation–efficiency outcomes" within a unified framework, examining direct and indirect effects together with contextual moderation by broadband penetration and fiscal support (Chen et al., 2023; Li et al., 2023). Methodologically, it introduces a multidimensional entropy-weighted digitalization index and an SBM model incorporating agricultural non-point source pollution and carbon emissions. At the policy level, identification of mediating and moderating effects clarifies the key levers for realizing the digital dividend–efficiency enhancement nexus, providing actionable guidance for China's rural digitalization programs.

RQ1: How does Competitive Intelligence-enabled agricultural digitalization influence Agricultural Green Total Factor Productivity across Chinese provinces?

RQ2: Through which intelligence dissemination and coordination mechanisms does Competitive Intelligence capability affect green productivity outcomes?

RQ3: How do intelligence governance conditions influence the effectiveness of Competitive Intelligence systems in promoting agricultural sustainability?

RQ4: Do differences in regional intelligence capability generate heterogeneous productivity outcomes?

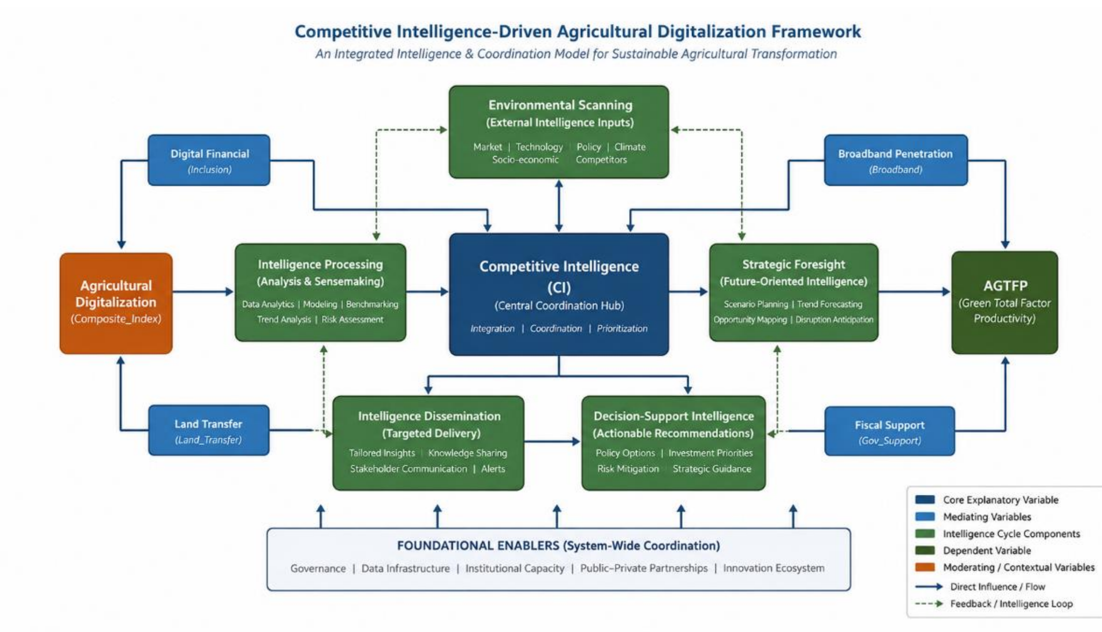


**Figure 1:** Theoretical Framework – CI-Driven Agricultural Digitalization and AGTFP

## 2 LITERATURE REVIEW AND HYPOTHESES

### 2.1 Competitive Intelligence and Agricultural Digitalization

Within the broader context of agricultural modernization, digital technology has emerged as a central driver of informatization, profoundly reshaping production processes and resource allocation. Applications encompass big data, artificial intelligence, the Internet of Things (IoT), remote sensing, blockchain, and e-commerce. Agricultural digitalization refers to the extent to which such technologies penetrate different stages of agricultural production, operation, management, and service delivery (Zhou, Chen, & Zhang, 2023). The competitive intelligence dimension emphasizes that strategic use of agricultural data—market intelligence, production analytics, weather forecasting—enables farmers and institutions to make superior decisions, creating differential productivity advantages (Liu et al., 2024).

From a global perspective, advanced economies have entered a systematized stage of smart agriculture. The United States has proposed the 'Agriculture 5.0' strategy building full-cycle intelligent systems through sensor–algorithm–actuator loops (Taha & Mao, 2025). The EU emphasizes digital agricultural platforms and sustainable regulatory mechanisms (Micheni et al., 2022). In China, agricultural digitalization shows a 'transaction-heavy and production-light' path dependency, with digital technologies concentrated in circulation domains such as rural e-commerce, smart logistics, and product traceability (Zeng et al., 2024). Penetration into production processes remains constrained by smallholder structures, infrastructure deficits, and uneven digital literacy (Cai & Han, 2024; Chen & Jiang, 2024). Modern agricultural systems increasingly operate under conditions characterized by environmental uncertainty, climate volatility, technological disruption, and rapidly changing market structures. Under such circumstances, the capacity to generate, interpret, and utilize strategic intelligence becomes a critical determinant of sustainable competitiveness. Competitive Intelligence provides an institutional mechanism through which agricultural actors can identify emerging opportunities, anticipate risks, coordinate resources, and support evidence-based decision-making.

## 2.2 Theoretical Foundations

Three theoretical perspectives underpin the analytical framework. Productivity growth theory emphasizes that technological progress and efficiency improvements drive long-term economic growth. Digital technologies can boost agricultural efficiency by optimizing resource allocation, improving information access, and reducing transaction costs (Li et al., 2023; Xu et al., 2024). Technology diffusion and innovation adoption theory highlights that diffusion pathways are shaped by market structure, institutional environments, user capacity, and information dissemination speed. Digital diffusion in Chinese agriculture exhibits 'staged' and 'regionalized' characteristics (Zeng, Zhou, & Wei, 2024). The agricultural–ICT integration theory argues that embedding information technologies into agricultural systems enhances responsiveness, optimizes production structures, and strengthens market adaptability (Chen et al., 2023).

### Competitive Intelligence Governance and Dynamic Capability Theory

Competitive Intelligence theory emphasizes the systematic collection, analysis, dissemination, and strategic utilization of environmental information to support organizational adaptability and long-term competitiveness. Traditionally developed within corporate strategic management, CI has increasingly expanded into public governance and digital ecosystem management contexts. Within agricultural modernization, CI-driven governance involves environmental scanning, intelligence dissemination, strategic foresight, and evidence-based adaptive coordination among governments, producers, financial institutions, and digital platform ecosystems.

From a dynamic capability perspective, agricultural digitalization enhances institutional sensing, learning, and reconfiguration capacities. Digital infrastructures—including sensor networks, remote monitoring systems, digital finance platforms, and agricultural databases—function not merely as technological tools but as intelligence-generation architectures enabling real-time decision support. Consequently, green productivity improvements emerge not solely from technological adoption itself, but from the institutional capability to transform dispersed digital information into actionable intelligence for resource optimization, environmental governance, and sustainable agricultural coordination.

### 2.3 Research Hypotheses

Drawing on the theoretical framework and prior empirical evidence, four hypotheses are proposed:

H1: CI-driven agricultural digitalization has a significant positive effect on AGTFP.

H2a: Digital inclusive finance mediates the effect of digitalization on AGTFP.

H2b: Agricultural land transfer mediates the effect of digitalization on AGTFP.

H3: Fiscal support moderates the digitalization–AGTFP relationship nonlinearly, with moderate support amplifying and excessive support weakening the effect.

## 3 DATA SOURCES AND METHODOLOGY

### 3.1 Study Area and Data

The study employs a balanced panel dataset covering 30 Chinese provinces (mainland China, excluding Tibet, Hong Kong, Macao, and Taiwan) for 2012–2021, yielding 300 province-year observations. The timeframe coincides with China's accelerated push for agricultural digitalization following the mid-12th Five-Year Plan period. Data are drawn from the China Statistical Yearbook, the China Agricultural and Rural Statistical Yearbook, the Ministry of Industry and Information Technology, the Peking University Digital Finance Research Center, and provincial statistical yearbooks. Outliers are winsorized at the 1% and 99% levels; missing values are treated via multiple imputation. The Hausman test ($\chi^2 = 18.4$, $p < 0.01$) rejects random effects, validating the two-way fixed-effects specification.

### 3.2 Measurement of Agricultural Digitalization (Composite_Index)

Agricultural digitalization is operationalized as a multidimensional composite index spanning four first-level dimensions: digital infrastructure, production digitalization, business and circulation digitalization, and service digitalization. Table 1 presents the complete indicator system. Raw data are standardized to [0,1] via min–max normalization; entropy values are computed for each indicator; entropy weights are derived as $w_j = (1-e_j)/\Sigma(1-e_j)$; and the composite index is the weighted sum. Higher values indicate broader and deeper digital penetration across the agricultural value chain.

**Table 1:** Agricultural Digitalization Indicator System

| First-Level Dimension | Second-Level Indicator | Third-Level Indicator | Measurement |
|---|---|---|---|
| Digital Infrastructure | Internet coverage | Internet penetration rate | Internet users / population |
| | Communication facilities | Mobile phone ownership | Mobiles per 100 households |
| | Fiber-optic density | Fiber length per km² | km/km² |
| | Information service investment | Fixed asset investment in info services | 100 million yuan |
| Production Digitalization | Electrification | Agri. value-added / rural electricity | yuan/kWh |
| | Monitoring facilities | Number of agrometeorological stations | Count |
| | Digital agricultural bases | Number of Taobao villages | Count |
| Business Digitalization | E-commerce participation | Share of firms in e-commerce | % |
| | Online sales | Goods & services sold online | 100 million yuan |
| | Online purchases | Goods & services purchased online | 100 million yuan |
| Service Digitalization | Digital finance | Inclusive Finance Investment Index | PKU index |
| | Postal coverage | Village postal access share | % |
| | Communication expenditure | Household spending on communication | % of income |

**Note:** Source: Authors' construction based on national statistical yearbooks, 2012–2021.

### 3.3 Measurement of AGTFP

This study adopts an input-oriented SBM model with undesirable outputs (Tone, 2001;

Bao et al., 2023) to measure provincial AGTFP. Inputs encompass agricultural labor, total sown area, total agricultural machinery power, and fertilizer consumption. Desirable output is agricultural output value at current prices. Undesirable output is total agricultural carbon emissions covering energy use, fertilizer application, livestock production, and straw treatment, calculated following IPCC guidelines. The SBM efficiency scores are further extended through a Malmquist–Luenberger productivity index to decompose AGTFP into efficiency change (Effch) and technological change (Techch), revealing distinct sources of green productivity growth over time.

### 3.4 Variable Specification

Table 2 summarizes all variables. The core explanatory variable is the Composite_Index. Mediators are digital financial inclusion (DFI, Peking University index) and land transfer rate. Moderators are broadband access users and fiscal support intensity. Controls include per capita GDP, government expenditure ratio, agricultural structure, disaster rate, and urbanization rate.

**Table 2:** Variable Definitions and Data Sources

| Variable | Type | Definition | Unit | Expected Sign |
|---|---|---|---|---|
| AGTFP | Dependent | SBM green TFP with undesirable outputs | Index | — |
| Composite_Index | Core explanatory | Entropy-weighted digitalization index | [0–1] | + |
| Digital_Finance (DFI) | Mediator | PKU digital inclusive finance index (aggregated) | Score | + |
| Land_Transfer | Mediator | Transacted farmland / total cultivated land | % | + |
| Broadband | Moderator | Number of broadband access users | 100m HH | + |
| Fiscal_Support | Moderator | Local fiscal expenditure / GDP | % | ± |
| PGDP | Control | Per capita regional GDP | 10k CNY | + |
| Disaster_Rate | Control | Disaster-affected farmland / total sown area | % | − |
| Urban_Rate | Control | Urban population share | % | ± |

**Note:** Sources: National Bureau of Statistics; China Agricultural and Rural Statistical Yearbook; Peking University Digital Finance Database; Ministry of Industry and Information Technology.

### 3.5 Empirical Model

The baseline two-way fixed-effects model is: $AGTFP_{it} = \alpha + \beta_1 Composite\_Index_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$, where i indexes provinces, t indexes years, $X_{it}$ is the vector of control variables, $\mu_i$ captures province fixed effects, $\lambda_t$ captures year fixed effects, and $\varepsilon_{it}$ is the idiosyncratic error term. Standard errors are clustered at the provincial level. Mediation analysis follows the Baron–Kenny three-step procedure with bootstrap confidence intervals. Moderation is tested via interaction terms, with threshold estimation using fiscal support tertile splits. Quantile regression examines distributional heterogeneity, and cubic polynomial specifications test for nonlinear development dynamics.

## 4 RESULT AND DISCUSSION

### 4.1 Descriptive Statistics and Temporal Trends

Table 3 presents descriptive statistics. AGTFP shows a mean of 1.408 (SD = 0.400; range 0.649–3.131), indicating substantial variation in green agricultural efficiency. The Composite_Index averages 0.174 but is highly right-skewed (skewness = 2.067), reflecting China's pronounced digital inequality. Over the sample period, AGTFP rose from 1.056 (2012) to 2.201 (2021), a 108% improvement. The Composite_Index increased from 0.106 to 0.250 (+136%), and DFI surged from 100.7 to 360.2, reflecting China's fintech revolution. Regional analysis confirms eastern provinces average 0.213 on the Composite_Index versus 0.138 in the west, with corresponding DFI means of 273.7 versus 231.2.

**Table 3:** Descriptive Statistics of Main Variables (N = 300)

| Variable | N | Mean | Std. Dev. | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| AGTFP | 300 | 1.408 | 0.400 | 0.649 | 3.131 | 1.630 | 3.416 |
| Composite_Index | 300 | 0.174 | 0.111 | 0.046 | 0.780 | 2.067 | 5.851 |
| Land_Transfer | 300 | 0.334 | 0.164 | 0.039 | 0.911 | 0.795 | 0.642 |
| DFI | 300 | 249.19 | 86.03 | 61.47 | 453.75 | −0.127 | −0.764 |
| Fiscal_Support | 300 | 0.263 | 0.113 | 0.105 | 0.758 | 1.709 | 4.224 |
| PGDP (10k CNY) | 300 | 5.823 | 2.917 | 1.895 | 18.753 | 1.693 | 3.217 |
| Disaster_Rate | 300 | 0.137 | 0.109 | 0.006 | 0.696 | 1.435 | 2.704 |
| Urban_Rate | 300 | 0.603 | 0.118 | 0.363 | 0.896 | 0.760 | 0.290 |

**Note:** Source: Authors' own calculations. DFI = Digital Financial Inclusion index (Peking University). AGTFP measured via SBM model with undesirable outputs.

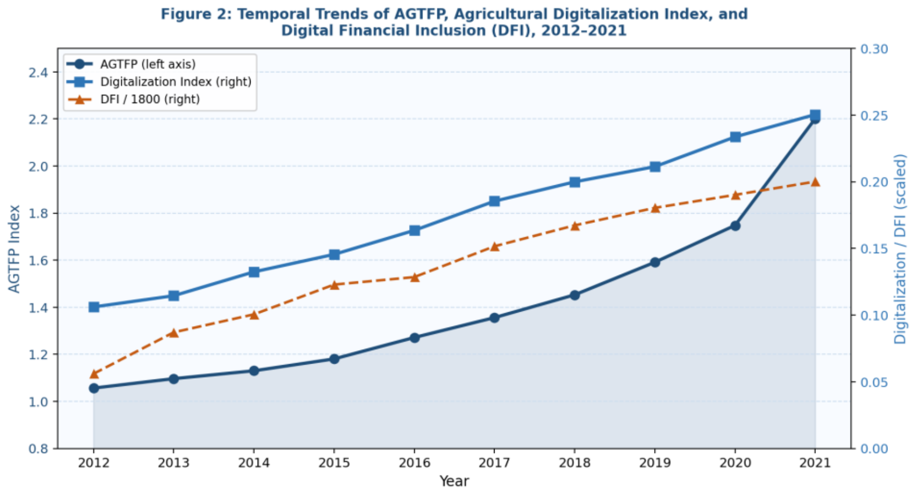


**Figure 2:** Temporal Trends of AGTFP, Agricultural Digitalization Index, and DFI, 2012–2021

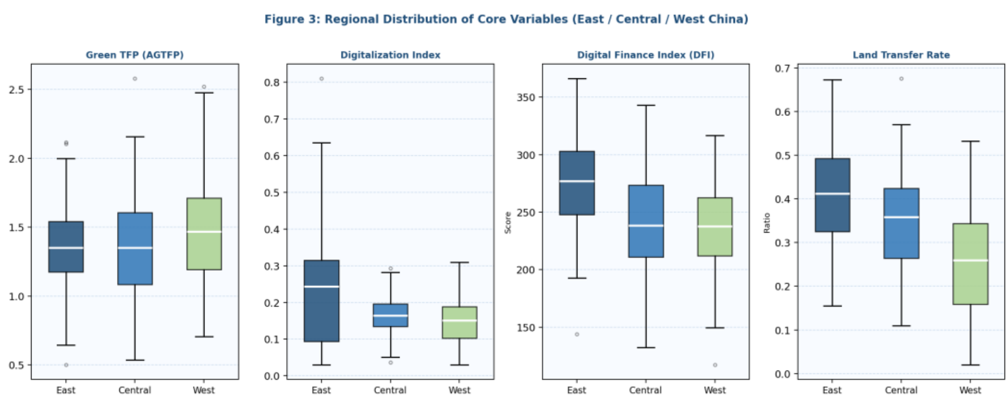


**Figure 3:** Regional Distribution of Core Variables Across East, Central, and West China

### 4.2 Baseline Regression Results

Across five model specifications—pooled OLS, individual fixed effects, time fixed effects, two-way fixed effects (preferred), and random effects—agricultural digitalization maintains a consistently positive coefficient. Under the two-way fixed-effects model, the coefficient is 0.495 ($p < 0.05$), indicating that a one-unit increase in the Composite_Index is associated with a 0.495-unit increase in AGTFP after controlling provincial and temporal heterogeneity. The individual fixed-effects estimate is larger (0.647), while the random-effects estimate (0.397) is directionally consistent. These results confirm H1. Among control variables, urbanization consistently shows a positive and significant effect (coefficient = 3.027 in the two-way FE model), reflecting how structural transformation facilitates labor reallocation and modernization. Government expenditure is negatively associated with AGTFP, likely reflecting compensatory concentration in structurally disadvantaged provinces rather than a direct adverse effect.

### 4.3 Robustness and Quantile Regression

Six robustness checks—lagged specification, logarithmic transformation, winsorization, COVID-year exclusion, alternative control transformations, and rolling-window estimation—confirm that the digitalization coefficient remains positive and stable (range: 0.466–0.495), ruling out outlier, temporal, or scaling drivers. Quantile regression reveals important distributional heterogeneity: the digitalization coefficient is 0.363 ($p < 0.01$) at the 25th percentile, declining to 0.190 at the median and −0.069 at the 75th percentile (both insignificant). This diminishing marginal-return pattern is consistent with the competitive intelligence hypothesis that intelligence-driven digital investment yields the highest returns where informational and coordination inefficiencies are most severe. From a Competitive Intelligence perspective, the positive baseline coefficient ($\beta = 0.495, p < 0.05$) is consistent with the proposition that provinces functioning as more developed intelligence-processing ecosystems — where digital data flows are systematically converted into governance signals and decision-support outputs — yield structurally higher green agricultural productivity. The larger coefficient under individual fixed effects (0.647) compared with the two-way specification reflects the role of time-invariant provincial CI governance capacity, which is absorbed once province fixed effects are included. This pattern is consistent with CI theory's argument that intelligence capability is a durable organizational asset rather than a transient technological advantage.

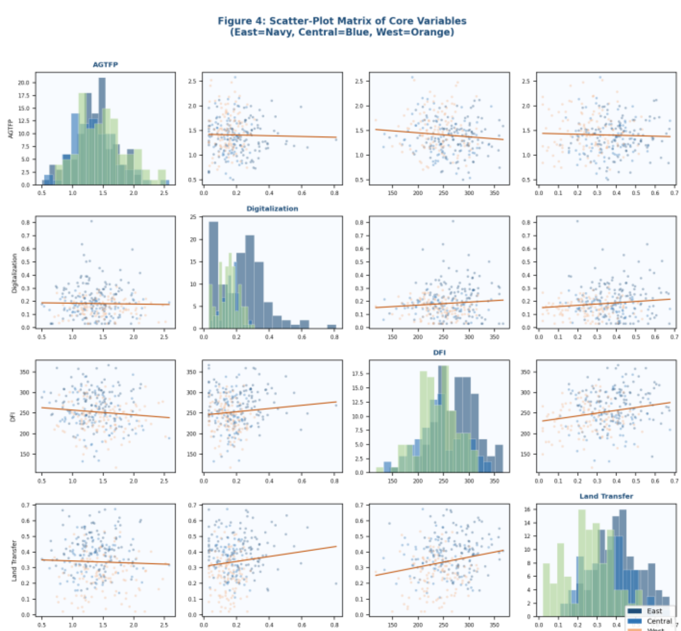


**Figure 4:** Scatter-Plot Matrix of Core Variables (East = Navy, Central = Blue, West = Orange)

## 4.4 Mechanism Analysis: Mediation Effects

The parallel mediation framework tests DFI and land transfer as transmission channels. The total effect is 1.162 ($p < 0.01$); the direct effect after introducing both mediators is 1.111. The indirect effect via land transfer is only 0.0021 (mediation ratio: 0.18%), while the indirect effect through DFI is 0.051 (ratio: 4.36%). The DFI mediation path operates as follows: digitalization expands financial accessibility by reducing information asymmetry and transaction costs ($a_1 = 15.342$, $p < 0.1$), which improves producers' financing capacity, investment in productivity-enhancing technology, and risk management, ultimately raising AGTFP ($b_1 = 0.003$, $p < 0.05$). These findings confirm H2a. The negligible land transfer effect (H2b not supported) reflects institutional rigidities in China's rural land governance system—regulatory complexity, collective ownership arrangements, and the slower pace of structural land adjustment relative to digital ecosystem development. From a CI theory perspective, the dominance of DFI as a mediation channel (indirect effect ratio: 4.36% versus 0.18% for land transfer) reflects the role of digital financial inclusion as an intelligence dissemination architecture. DFI reduces informational fragmentation across agricultural ecosystems by improving the circulation of financial and production-relevant signals among producers, lenders, and platform operators. This finding aligns with CI theory's intelligence dissemination construct (Marceau & Sawka, 2001), wherein competitive advantage accrues not merely from data collection but from the institutional mechanisms that distribute actionable intelligence to decision-making actors at the point of productive use. The negligible land transfer channel further suggests that physical-factor reallocation, without accompanying informational coordination mechanisms, generates limited productivity returns — a finding consistent with the CI proposition that structural transformation requires intelligence-enabled coordination, not merely resource redistribution.

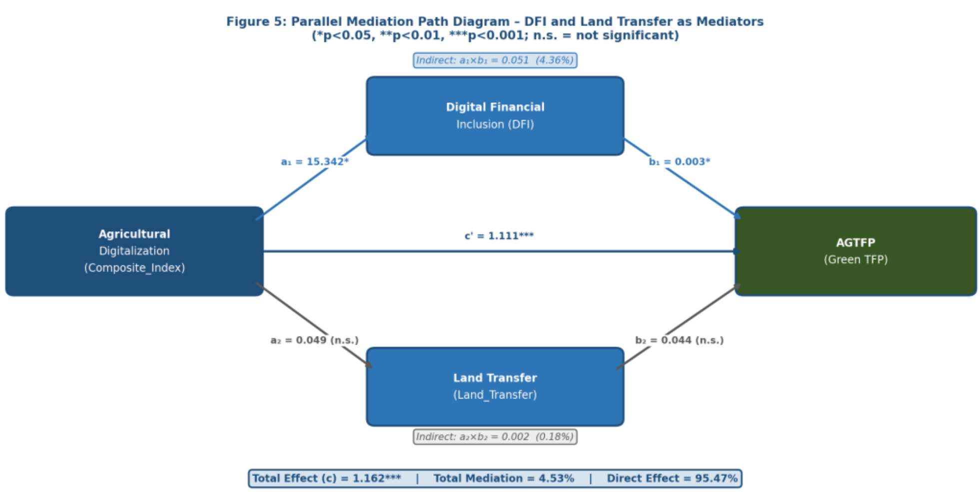


**Figure 5:** Parallel Mediation Path Diagram – Digital Financial Inclusion and Land Transfer as Mediators

### 4.5 Moderation, Threshold, and Heterogeneity Analysis

The interaction between moderation and fiscal support (Composite_Index × Fiscal_Support) results in a positive coefficient (β = 3.323), indicating that fiscal support is a positive factor in enhancing the productivity impact of digitalization. The digitalization coefficient shows a nonlinear inverted U shape (0.660 for low support, $p < 0.05$, 1.129 for moderate support, and −1.149 for high support). This confirms H3. Too much intervention can be seen to undermine the efficiency mechanism of the CI and foster "subsidy dependence." The mediation–threshold interaction: DFI mediation is strongest in the mediation–threshold interaction in the presence of moderate fiscal support (indirect effect = 0.038); virtually absent in the presence of high fiscal support (indirect effect = 0.001), suggesting that policy context influences the overall effect as well as the internal transmission architecture. The area shows high intra-regional variability. The eastern region has a coefficient of 1.012 ($p < 0.01$), indicating the presence of mature digital ecosystems and high absorptive capacity. The coefficient of the central region is highly negative, as expected in the case of transitional inefficiency: −3.252 ($p < 0.01$). The west region comes up with a near-zero insignificant result (−0.201) due to structural constraints. The low-AGTFP group benefits the most (0.927, $p < 0.001$ vs. 0.644, n.s. for high-AGTFP), further supporting the catch-up interpretation. The nonlinear cubic specification recognizes a three-phase curve consisting of a quick initial gain, deceleration during a transition period, and acceleration again once digital ecosystems reach their maturity – a curve that is difficult to reconcile with the idea of linear modernization. These heterogeneity results carry direct implications for CI governance theory. The eastern coefficient (1.012, $p < 0.01$) reflects mature intelligence dissemination architectures — institutional environments in which digital data generated through sensor networks, e-commerce platforms, and digital finance systems is systematically interpreted and operationalized into agricultural management decisions. The central region's negative coefficient (−3.252, $p < 0.01$) exemplifies the 'data-rich, insight-poor' condition documented in corporate CI literature (Fuld, 1995; Fleisher & Bensoussan, 2007): digital infrastructure investment has outpaced the development of analytical capacity and institutional governance routines needed to convert data flows into productive intelligence outputs. The western near-zero coefficient reflects a pre-scanning stage, where even the environmental scanning infrastructure required to initiate an intelligence cycle remains

## 5 FINAL CONSIDERATIONS

### 5.1 CI-Driven Digitalization as Structural Modernization

The steady positive baseline reading is an indication that CI-based digital transformation plays a significant role in the structural modernization of Chinese agriculture. This is no longer just technological substitution but a reconfiguration of the ecosystem: digitalization influences the functioning of information, the coordination of production, the functioning of the market, and the accessibility of institutions. In terms of competitiveness, agricultural information is the most restrictive information constraint in agriculture and can be addressed by the systematic use of data to optimize agricultural decisions (David, 2005; Liu et al., 2024). Reducing information asymmetry is particularly crucial for agricultural green productivity, where there is a need to improve both productive efficiency and environmental performance. Economic and ecological goals are achieved by using digital monitoring systems, precision agriculture systems, and data-driven management, which reduce unnecessary inputs.

A closer examination of this mechanism indicates that digitalization takes place via three overlapping structural change mechanisms. The first is the information efficiency channel: enabling smallholder producers to access integrated information on time – weather, pests, agronomics – through the urban decision-support system. This access directly benefits the quality of production decisions: planting time, amount of fertilizer use, type of pest management, etc., which are related to output and undesirable environmental side effects. The second channel is the reduction of transaction costs in intermediaries. Traditional agricultural value chains struggle with several layers of intermediaries based on information asymmetries rather than value addition. These platforms can disintermediate these layers, enabling producers to retain more of the price premium from consumers and minimizing food waste and emissions from transportation in the supply chain (Zeng, Zhou, & Wei, 2024). Thirdly, there is organizational modernization, in which digital management technologies such as cloud-based farm records, remote sensing dashboards, and digital cooperatives slowly change the logic of how agricultural production units operate towards capital-efficient, knowledge-intensive units.

Together, these three channels account for the robustness of the digitalization effect in this study across various robustness specifications, such as excluding years with COVID and estimating the effect through a rolling window. More importantly, this transformation represents the emergence of intelligence-enabled agricultural governance systems in which digital infrastructures function as mechanisms for environmental scanning, intelligence processing, and adaptive strategic coordination. Agricultural data generated through sensor networks, remote monitoring systems, digital finance platforms, and e-commerce ecosystems become strategically valuable only when institutional actors possess the capability to transform dispersed information into actionable intelligence supporting resource optimization and sustainable agricultural decision-making.

This is further enriched by the nonlinear cubic trajectory identified in the extended analysis. A key part of the first phase of large increases in marginal returns is the period when the most critical informational barriers are being overcome as basic connectivity is expanded – in other words, the first-time producers are brought into the modern information economy. The middle deceleration phase concerns adaptations that producers, institutions, and actors along the supply chain need to make before higher-order digital applications can create efficiency gains: The operating procedures of producers and institutions must be restructured, complementary human capital must be acquired, and contractual relationships must be renegotiated. The late re-acceleration phase is the ecosystem maturity with interoperable platforms, data-sharing protocols, and integrated digital financial services that generate multiplicative returns, which are larger than the early adoption gains. This three-phase architecture is similar to more general theories of the diffusion of general-purpose technology, in which the implementation of a set of transformative productivity-enhancing technologies does not occur until a complementarity investment cycle has been completed (David, 2005; Falki, 2023).

These findings suggest that agricultural digitalization should be interpreted as an intelligence-enabled governance transformation rather than merely technological modernization. The productivity gains associated with digitalization emerge because digital ecosystems improve the capability of agricultural institutions to collect, interpret, disseminate, and operationalize strategic intelligence across production, financial, and policy systems.

### 5.2 Financial Inclusion as the Dominant Transmission Channel

The dominance of DFI over land transfer as a mediation channel carries significant theoretical implications. It suggests that modernization bottlenecks in China's agricultural sector are increasingly institutional–accessibility constraints rather than physical-factor constraints. Agricultural modernization is investment-intensive, and conventional rural financial systems have historically excluded many producers through collateral requirements, geographic barriers, and high transaction costs. Digital financial inclusion directly addresses this bottleneck by expanding access to credit, mobile payment systems, fintech lending, and broader financial connectivity—creating a more immediate pathway between digitalization and productive investment. The structural compatibility between digital transformation and digital finance—where improvements in connectivity, mobile technology, and data systems directly expand inclusive finance—creates synergies absent from land market reform, which requires deeper institutional change (Yang & Meseretchanie, 2024; Xu et al., 2024).

The magnitude of the DFI effect relative to the land transfer effect also reflects an important temporal dynamic. Land market reform in China is a multi-decade process shaped by constitutional constraints on collective ownership, local government incentives, and village-level power structures. Even where digital platforms improve the matching efficiency of land transactions, the underlying legal and institutional framework constrains how rapidly reallocation can materialize. By contrast, digital financial services—mobile wallets, online microcredit, algorithmic credit scoring—can be deployed and adopted within a single agricultural season, generating financing effects that interact with productive investment in near real-time. This temporal asymmetry means that within a ten-year observational window, the financial channel will naturally dominate even if the land channel is equally important in the long run. Future studies using longer panels or higher-frequency data may reveal a more balanced distribution of mediation effects as land market institutions gradually liberalize.

It is also worth noting that DFI mediates the digitalization–AGTFP relationship through risk management as well as credit provision. Rural households that gain access to digital insurance products, price-hedging platforms, and diversified savings instruments become more willing to invest in higher-risk, higher-return agricultural technologies. This behavioral channel—willingness to bear productive risk—is an underappreciated dimension of financial inclusion's contribution to productivity. When producers cannot insure against crop failure or price volatility, rational risk aversion leads to conservative input choices and foregone investments in precision technology. Digital finance reduces this risk-induced underinvestment, contributing to AGTFP gains that would not appear in analyses that examine credit access alone (Li et al., 2023; Li, 2025).

From a Competitive Intelligence perspective, digital financial inclusion operates as an intelligence dissemination mechanism that reduces informational fragmentation across agricultural ecosystems. By improving the circulation of financial and production-related information, DFI enhances the capability of agricultural actors to respond adaptively to market uncertainty, environmental volatility, and investment risk. Consequently, the productivity effect of DFI reflects not merely expanded financing access, but the strengthening of intelligence-enabled coordination capability across agricultural governance systems.

### 5.3 Policy Complementarity and the Limits of Fiscal Intervention

The findings of the nonlinear fiscal threshold pattern indicate that digital transformation that introduces CI is not self-sustaining; it needs to be supported by an appropriate institution. Moderate fiscal intervention enhances digitalization by creating enabling infrastructure, lowering use barriers, and increasing institutional coordination. Over-interference can alter incentives and stifle market innovations. Competitive intelligence value in the eyes of competitive intelligence can be maximised when intelligence systems are integrated to adaptive governance structures rather than to the replacement of market response. Therefore, a good policy should be one that helps to enable ecosystem capacity rather than replace structural modernization processes. The conclusion that an overly generous fiscal policy may have a negative effect on the link between digitalization and AGTFP should be interpreted with caution, as it contradicts the policy reflex that the higher the fiscal support, the better the development results. The negative high support effect may occur through several mechanisms. First, provinces with the highest baseline market institutions, digital readiness, and production fragmentation – conditions known to limit the productivity returns on any technological input, whether digital or otherwise – are also the provinces receiving the highest fiscal agricultural support. The negative coefficient under high support might thus be partly due to selection bias: fiscal resources are directed to structurally less successful areas, which leads to a combination of an intervention effect and an adverse structural baseline. Second, when fiscal expenditure is in the form of input subsidies, machinery grants, and/or direct income support (as opposed to investment in infrastructure and training), it can create dependency without the capacity to absorb and effectively use digital tools. Third, a significant amount of public spending can also reduce the competitive pressure that would otherwise stimulate adoption and innovation, leaving the agricultural sector comfortable and unchanging, as digital transformation would entail structural changes from the inside out (Hu, 2023; Cai & Han, 2024). The threshold effect further demonstrates that Competitive Intelligence systems require governance adaptability rather than purely financial expansion. Moderate fiscal intervention strengthens institutional intelligence-processing capacity by supporting data integration, technical training, inter-agency coordination, and digital dissemination infrastructures. However, excessive intervention may weaken adaptive intelligence responsiveness by reducing market-based feedback mechanisms and organizational learning incentives.

### 5.4 Regional Heterogeneity and Development Trajectories

The dramatic differences between the impacts of digitalization in different parts of China, as shown above, are not just the result of infrastructure inequality, but rather the manifestation of China's stance on the three-phase nonlinear modernization path as described in Section 4.5. The digitalization coefficient of these eastern provinces is around 1.012, indicating that they are mostly in the late-acceleration zone. Digital ecosystems are more well-developed, and with further improvements in connectivity, platform integration, and data governance, there are multiplier effects that benefit digital finance, precision agriculture, and supply-chain optimization in complementary ways.

The middle (negative) coefficient phase appears to be the phase that the central provinces are currently undergoing. Investments in digitalization have led to changes in traditional production arrangements, forcing informal intermediaries out of production, changing labor allocations, and restructuring input markets. However, institutional and organizational complements are still needed to generate efficiency benefits. This transitional inefficiency should not be interpreted as a failure of digitalization in central China; it is a common phenomenon in the literature on general-purpose technology diffusion and is predicted to result in a productivity valley during the transition from early adoption to full digitalization ecosystem integration.

A third challenge is presented by the western provinces. The near-zero coefficient is not a result of transitional disruption but rather a structural issue: a lack of fundamental digital infrastructure to even enter the adoption phase. Information efficiency gains and financial inclusion effects from investments in agricultural digitalization can only be realized with reliable broadband connection, functional digital payment systems, and accessible online agricultural services. Given this, and the fact that fewer than half of these areas are served by basic infrastructure for digital finance, foundation-building investments in fiber-optic and mobile network deployment, promoting digital literacy, and basic infrastructure in the field of fintech should be prioritized before more advanced CI-based applications can be meaningfully introduced. Building a region-specific digitalization roadmap with properly sequenced interventions, taking western China as a lower bound and eastern China as a target trajectory, instead of using a set of national technological templates that may not be suitable for the areas on either end of the spectrum, is recommended (Zhao et al., 2024).

## 5.5 Implications for Competitive Intelligence Theory and Practice

This research also has empirical implications for the field of agricultural economics, as well as specific implications for the theory and practice of competitive intelligence and its use in public sector governance environments. The core idea of CI theory is that by systematically collecting, analyzing, and distributing information about the competitive landscape, organizations can proactively identify threats and opportunities, thereby making better strategic decisions in the future. This theory was first developed in the context of corporate strategies (Cai & Han, 2024; Liu et al., 2024). The current study shows that at the national level of agricultural governance, digital data infrastructure—sensor networks, databases of e-commerce transactions, satellites tracking crop monitoring, and digital financial records—can be viewed as an analog of CI systems, providing the potential to create more responsive, evidence-based agricultural policy and management at the national level. The productivity dividend' is a key aspect of the positive ‘AGTFP' impacts of digitalization, in part because of the ability to operate at a level of governance that is more information rich.

The threshold and heterogeneity results qualify this CI-theory extension: the productivity benefits of agricultural intelligence infrastructure depend on the institutional capacity for data analysis and action based on the data collected. In provinces with high support, where investment in digital infrastructure is strong but organizational routines, technical skills, and governance agility in the use of digital data for actionable agricultural management decisions are low, large amounts of agricultural data may be generated with only limited strategic value. This is similar to the documented fact in the corporate CI literature of 'data rich, insight poor' – the case of excessive investment in information collection, but no investment in the analysis and interpretation of that information or in the integration of that information into decision making. In addition to data infrastructure, investments in the development of human analytical capacities, inter-institutional data-sharing arrangements, and governance processes that connect the outputs of CI to policy design cycles are needed for sustainable agricultural CI. The results of this study showing that moderate, capability-based fiscal support is superior to under-investment in both situations and over-intervention, are entirely in line with the CI theory's focus on the quality and adaptability of the processes used for intelligence, rather than the amount of information or funding (Falki, 2023). The findings also suggest that the effectiveness of agricultural digitalization depends fundamentally on intelligence governance capability. Provinces possessing stronger institutional mechanisms for intelligence dissemination, cross-agency coordination, strategic foresight, and evidence-based adaptive policymaking are significantly more capable of converting digital infrastructures into sustainable productivity gains. This finding aligns closely with Competitive Intelligence theory, which argues that competitive advantage emerges not from information abundance itself, but from the organizational capability to transform environmental information into actionable strategic intelligence. Consequently, agricultural modernization should increasingly be understood as an intelligence-capability development process rather than merely a technological modernization process.

## 6 CONCLUSION

This study examines the effect of competitive intelligence–based agricultural digitalization on AGTFP in 30 provinces in China from 2012 to 2021. The major findings are as follows: (1) the digitalization of agriculture has a significant positive impact on AGTFP ($\beta = 0.495$, $p < 0.05$ (TWO-WAY FE)); H1 is supported; (2) digital financial inclusion has a significant mediating effect on the relationship between digitalization and AGTFP, which stands at 4.36% (indirect effect ratio); H2a is supported, whereas H2b is not supported; (3) digitalization is facilitated by moderate fiscal support but is constrained by heavy fiscal support, supporting H3; and (4) regional heterogeneity is observed: the effect is greatest in the eastern provinces, with a transitional inefficiency in the central provinces or areas, and a structural constraint in the western provinces. The policy implications are as follows: investing in digital infrastructure first in less developed regions; increasing digital financial inclusion in the countryside as a digital farming policy tool; setting digitalization support levels to moderate enabling intervention and not too much substitution; using region-specific digitalization policies depending on the level of development; and implementing long-term digital agricultural ecosystem governance instead of short-term metrics of deployment. The main limitations are at the provincial level (hiding micro-behavioral dynamics) and the inbuilt simplifications of the composite index measurement. Further studies are needed at the micro level using agricultural household information, formal spatial econometric models, comparative international analysis, and other mechanisms to explore the dimensions of human capital development, supply chain modernization, and institutional quality.

Overall, this study demonstrates that agricultural digitalization contributes to green productivity not simply through technological penetration, but through the development of Competitive Intelligence capability embedded within agricultural governance systems. The findings therefore reposition digital agriculture as an intelligence-based institutional transformation process in which environmental scanning, strategic foresight, intelligence dissemination, and adaptive policy coordination collectively shape sustainable agricultural competitiveness.

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