

# Theoretical Mechanisms Linking the Digital Economy and Agricultural Economic Resilience: Construction and Analysis Based on a Quantitative Spatial Equilibrium Model

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**Abstract:** This study aimed to construct a Quantitative Spatial Equilibrium (QSE) model that integrates digital factors and agricultural infrastructure, providing a unified theoretical framework for analyzing the underlying mechanisms of agricultural economic resilience. The model embedded a three-dimensional resilience system—resistance–adaptation–transformation—into consumer preferences and production functions. Within the agricultural context, it depicted the generation, exchange, and enabling mechanisms of data as a novel production factor, and elucidated its synergistic interaction pathways with both traditional and digital infrastructures. By incorporating the hat algebra approach, the model enabled counterfactual simulations of policy shocks in multi-regional and multi-sector economic systems, effectively mitigating parameter identification challenges. The theoretical contributions of this research lay in extending the application of quantitative spatial economics to the agricultural domain, identifying the sectoral heterogeneity of data-factor diffusion effects, and providing a formal analytical tool to explore the micro-foundations of how “digital–infrastructure” synergies enhance agricultural economic resilience. These findings established a methodological basis for subsequent empirical investigations and policy evaluations.

**Keywords:** Digital Economy; Agricultural Economic Resilience; Quantitative Spatial Equilibrium (QSE) Model; Data as a Production Factor; Digital–Infrastructure Synergy

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## 1.Introduction

The deep integration of the digital economy and agricultural modernization has been reshaping agricultural production methods and rural economic structures, injecting new momentum into enhancing agricultural resilience and sustainable development. According to the 2023 Report of the Ministry of Agriculture and Rural Affairs, the informatization rate of agricultural production in China had exceeded 25%, and the scale of the agricultural digital economy had reached 2.8 trillion yuan, demonstrating a remarkable annual growth rate<sup>[1,2]</sup>. Against this backdrop, digital technologies empowered agricultural production, distribution, services, and consumption, thereby significantly strengthening the resilience of the agricultural economic system<sup>[3]</sup>. At the policy level, since 2022, successive No.1 Central Policy Documents have emphasized the promotion of digital villages and the digital transformation of the entire agricultural value chain, aiming to systematically enhance agricultural economic resilience and sustainability. Theoretically, the digital economy—with its pervasive,

synergistic, and inclusive characteristics—has laid the micro-foundation for improving agricultural resilience<sup>[4,5]</sup>. Data, as a critical new production factor, optimized agricultural resource allocation, improved total factor productivity, and strengthened the system's capacity for shock resistance and adaptive response through information integration and intelligent decision-making<sup>[6,7]</sup>. Meanwhile, agricultural infrastructure—particularly digitalized facilities such as information networks and cold-chain logistics—served as essential physical carriers for digital empowerment. According to quantitative spatial economics, infrastructure played a central role in enhancing adaptability and recoverability by reducing factor mobility costs, improving spatial allocation efficiency, and strengthening regional connectivity<sup>[8,9]</sup>.

However, existing research primarily focused on empirical verification and lacked a unified theoretical framework that integrated digital factors, infrastructure, and resilience. In particular, few studies clearly characterized the unique economic attributes of data factors and their synergistic mechanisms with infrastructure<sup>[10]</sup>. To fill this theoretical gap, this study constructed a Quantitative Spatial Equilibrium (QSE) model incorporating digital factors and agricultural infrastructure, aiming to formally analyze the formation mechanisms of agricultural economic resilience from the three dimensions of resistance–adaptation–transformation.

The theoretical contributions of this study were threefold. First, it explicitly incorporated data factors into the agricultural production function, defining their non-rivalry nature and dynamic accumulation process. Second, it calibrated infrastructure elasticity within a structural model to support counterfactual simulations. Third, it uncovered three core mechanism pathways—technological progress, resource allocation, and institutional adaptation—thus providing a robust theoretical foundation for enhancing agricultural resilience and promoting high-quality development through coordinated “digital–infrastructure–institutional” policies.

## **2. Empirical Characteristics of Agricultural Economic Resilience and Digital Economy Development in China**

To provide an empirical foundation for the theoretical model, this section briefly outlines and analyzes the key characteristics of China's agricultural digitalization and economic resilience.

### **2.1 Regional Concentration and Structural Imbalance of Agricultural Digital Talent**

Agricultural digital talent serves as the core carrier for the application of digital technologies. Following the classification proposed by Sun Jiulin et al.<sup>[11]</sup>, this study defined such talent as rural employees engaged in occupations related to digital technology application, agricultural data analysis, and the operation of intelligent agricultural machinery. The analysis revealed that between 2014 and 2024, the overall proportion of agricultural digital talent in China increased steadily, yet the regional distribution remained highly uneven. The share in eastern regions rose rapidly from 3.8% to 9.2%, significantly ahead of the central (5.6%) and western (3.4%) regions. Although grain-producing regions exhibited a higher proportion of digital talent than non-grain regions, their growth rate was relatively modest. This pronounced regional imbalance reflected substantial differences in the depth of digital technology adoption in agriculture and suggested the emergence of a “digital dividend divide,” a phenomenon consistent with patterns of skill-biased technological change observed in other developing economies<sup>[12]</sup>. Consequently, it underscored the necessity of incorporating regional heterogeneity into the theoretical model.

### **2.2 Pronounced Spatial Disparities in Digital Infrastructure Development**

Digital infrastructure constitutes the fundamental prerequisite for the functioning of digital factors. Based on a composite index constructed from indicators such as rural broadband access rates and 5G base station coverage, the national average value of China's digital infrastructure index reached only 0.52 in 2024, with striking regional disparities—0.78 in the east, 0.51 in the center, and 0.32 in the west. Notably, the spatial distribution of this index exhibited a strong positive correlation ( $r = 0.83$ ) with the agricultural economic resilience index, and the regional gap had widened since 2018. This pattern of infrastructure divergence and its economic consequences aligns with findings on the digital divide in other contexts<sup>[13]</sup>.

The eastern region experienced rapid improvement, driven by “digital village” pilot policies, while the western region lagged behind due to natural and economic constraints. This sharp contrast in baseline conditions represents a critical exogenous constraint that must be accounted for in constructing a multi-regional spatial equilibrium model.

## 2.3 Efficiency and Structural Issues in Agricultural Infrastructure Investment

Although total investment in agricultural infrastructure continued to grow, its efficiency exhibited a downward trend. The increase in total factor productivity (TFP) per unit of investment declined from 0.32 in 2014 to 0.18 in 2024. Meanwhile, structural imbalances in investment allocation became evident: the return elasticity of investment in rural road transport and storage logistics facilities was relatively high (0.24 and 0.21, respectively), whereas that of traditional irrigation facilities remained low (only 0.07). This underscores the importance of not just the volume but the type of infrastructure investment, a factor critical for growth and resilience<sup>[14]</sup>.

This pattern revealed both the urgency of upgrading traditional infrastructure and the crucial role of digital transformation in enhancing investment efficiency. It also implied that the type of infrastructure and the degree of its digitalization were key determinants of its enabling efficiency. These findings provided a strong empirical rationale for distinguishing between traditional and digital infrastructures in the theoretical model and for analyzing their complementary relationship, particularly in building adaptive capacity to climate shocks<sup>[15]</sup>.

## 3. Model Specification

This study constructed a multi-regional monopolistic competition general equilibrium model within the theoretical framework of Quantitative Spatial Economics (QSE). The model incorporated digital factor inputs, agricultural infrastructure, and intersectoral production linkages, building on foundational spatial equilibrium theories<sup>[16]</sup>. It aimed to characterize an economic system consisting of  $N$  regions, each containing an agricultural sector—further disaggregated into grain production ( $a_1$ ), cash crops ( $a_2$ ), and livestock & fisheries ( $a_3$ )—a local non-agricultural services sector ( $s$ ), and an external market.

The model featured three core innovations. First, it embedded the multidimensional “resistance–adaptation–transformation” framework of agricultural economic resilience into both consumer preferences and production functions, reflecting a growing emphasis on resilience in economic modeling<sup>[17]</sup>. Second, it explicitly modeled the generation, trading, and enabling mechanisms of agricultural data factors, while distinguishing between the dual roles of traditional and digital infrastructure. Third, it accounted for factor mobility and technological spillovers both within the agricultural sector and between agricultural and non-agricultural sectors, thereby enabling a more comprehensive simulation of the spatial general equilibrium effects of policy shocks<sup>[18]</sup>.

### 3.1 Generation and Accumulation of Agricultural Data Factors

This paper treated data as an accumulable and essential production factor, recognizing its unique economic properties<sup>[19]</sup>. In region  $i$  and period  $t$ , the data stock of the agricultural sector (representative subindustry  $g$ ), denoted as  $D_{it}$ , comprised two components: self-collected data ( $D^{\text{coll}}_{it}$ ), generated automatically during agricultural operations via IoT devices and e-commerce platforms; and externally purchased data ( $D^{\text{buy}}_{it}$ ) acquired from data markets.

Data, characterized by non-rivalry and replicability, followed the dynamic accumulation process. The amount of data collected ( $D^{\text{coll}}_{it}$ ) was positively related to the level of digital technology ( $A_{it}$ ) and the scale of agricultural activities ( $X_{k,it}$ ). Government agencies or enterprises could purchase external data at price  $p_{\text{buy},it}$  in data markets. The non-rival nature of data allowed its simultaneous use in local production (e.g., precision fertilization) and interregional trade.

### 3.2 Consumer Preferences and Resilience Evaluation System

Agricultural economic resilience was incorporated into the consumer utility function to capture preferences for system stability and sustainability. Following recent advances in welfare measurement under uncertainty<sup>[20]</sup>, the resilience index of region  $i$  in period  $t$  ( $R_{it}$ ) was defined as a composite CES function of three dimensions: resistance ( $R_{\text{res},it}$ ), adaptation ( $R_{\text{adj},it}$ ), and transformation ( $R_{\text{inno},it}$ ). The final utility of consumers depended on agricultural product consumption ( $C_{it}$ ) and resilience level ( $R_{it}$ ).

### 3.3 Production Function and Data-Driven Enabling Mechanism

Agricultural production followed a nested CES–Cobb–Douglas structure, integrating data factors as a new input alongside traditional factors such as labor and capital. The representative firm in sector  $g$  of region  $i$  produced output accordingly. The parameter  $\delta$  captured the data-driven enabling effect: a higher  $\delta$  indicated a stronger enhancement of productivity through digital technologies, thereby improving the system’s capacity to withstand external shocks, a mechanism increasingly

documented in the literature on technology and productivity (18).

### 3.4 Composite Mechanism of Agricultural Infrastructure

Agricultural infrastructure (Git) was modeled as a composite form comprising traditional infrastructure (Gtra,it), such as irrigation, transport, and storage, and digital infrastructure (Gdig,it), such as 5G networks and IoT systems. These components were combined through a CES function. Infrastructure influenced agricultural economic resilience through multiple channels, including reducing transportation costs, enhancing information transparency, and optimizing resource allocation<sup>[21]</sup>. The transportation cost for agricultural goods between regions *i* and *j* ( $\tau_{ijt}$ ) was assumed to be inversely related to the infrastructure level.

### 3.5 Factor Mobility and Policy Intervention

Rural labor was assumed to be mobile across agricultural and non-agricultural sectors as well as across regions. Migration decisions depended on expected utility differentials and migration costs, consistent with spatial equilibrium models<sup>[22]</sup>. Government intervention influenced agricultural resilience through taxation, subsidies, and infrastructure investment.

### 3.6 Equilibrium Conditions and Resilience Feedback Mechanism

The model achieved closure through the simultaneous clearing of product, labor, data, and infrastructure markets. Agricultural economic resilience (Rit) was not treated as exogenous; instead, it dynamically influenced production efficiency, investment performance, and consumer confidence, forming a positive feedback loop, a feature central to understanding path-dependent development outcomes<sup>[23]</sup>. By calibrating provincial-level parameters for China and conducting counterfactual simulations, the model quantitatively evaluated the contributions and transmission mechanisms of the digital economy and infrastructure to agricultural economic resilience.

## 4. Theoretical Analysis

To elucidate the underlying mechanisms through which the digital economy and agricultural infrastructure influence agricultural economic resilience, this study adopted the “Hat Algebra” approach proposed by Dekle et al. to transform the above general equilibrium model into a system expressed in relative changes<sup>[24]</sup>. Let the observed variable be  $x$ , and its counterfactual value be  $x'$ ; then, the relative change is defined as  $\hat{x} = x'/x$ . By taking this differential form, the method effectively eliminates constant parameters, highlights the structural variations induced by policy shocks, and reduces the number of parameters requiring estimation, thereby improving model identification. Within this framework, this section theoretically derives the core mechanisms through which digital factors and infrastructure affect agricultural economic resilience.

### 4.1 Impact of the Digital Economy on Agricultural Total Factor Productivity

Starting from the producer’s equilibrium condition and based on the production function described above, the relative change in agricultural Total Factor Productivity (TFP) primarily depends on the relative change in data input and its output elasticity:

$$\widehat{TFP}_{it} \propto \hat{D}_{it}^{\delta} \quad (11)$$

Since the output elasticity of data input ( $\delta > 0$ ) was positive, agricultural TFP responded positively to the increase in data factor investment. This indicated that the application of digital technologies became a key pathway for improving agricultural TFP by optimizing decision-making, enabling precision input, and reducing production volatility<sup>[25]</sup>. The non-rivalrous nature of data further amplifies these productivity effects across different agricultural applications<sup>[1,26]</sup>.

### 4.2 Impact of Digital Infrastructure on the Three Dimensions of Agricultural Resilience

The relative change in the three-dimensional capacities of agricultural resilience can be expressed as a function of the relative change in the stock of digital infrastructure:

$$\hat{R}_{res} = \eta_{res} \cdot \hat{G}_{dig}, \quad \hat{R}_{adj} = \eta_{adj} \cdot \hat{G}_{dig}, \quad \hat{R}_{inno} = \eta_{inno} \cdot \hat{G}_{dig} \quad (11)$$

where  $\eta_{res}$ ,  $\eta_{adj}$ ,  $\eta_{inno}$  (all  $> 0$ ) denote the elasticities of digital infrastructure with respect to resistance, adaptation, and transformation capacities, respectively.

This demonstrated that digital infrastructure enhanced agricultural economic resilience through three pathways: improving information accessibility, reducing transaction costs, and promoting technological innovation<sup>[21]</sup>. Theoretically, the elasticity coefficient for innovation and transformation ( $\eta_{inno}$ ) was typically the largest, implying that digital infrastructure was

particularly effective in driving long-term structural transformation by enabling new business models and facilitating knowledge spillovers across the agricultural value chain<sup>[23,27]</sup>.

#### 4.3 Synergistic Mechanism between Agricultural Infrastructure and Resilience Enhancement

Traditional and digital infrastructures exhibited a complementary relationship. The marginal contribution of composite infrastructure stock to agricultural output could be decomposed as follows:

$$\frac{\partial \hat{Y}_{ig}}{\partial \hat{G}_{it}} = \underbrace{\frac{\partial \hat{Y}_{ig}}{\partial \hat{G}_{it}}}_{\text{Direct effect}} + \underbrace{\frac{\partial \hat{Y}_{ig}}{\partial \hat{R}_{it}} \cdot \frac{\partial \hat{R}_{it}}{\partial \hat{G}_{it}}}_{\text{Indirect toughness effect}} \quad (12)$$

This indicated that infrastructure not only directly promoted agricultural growth but also indirectly enhanced output stability and sustainability by strengthening economic resilience<sup>[28,29]</sup>. The synergistic effect depended on the elasticity of substitution ( $\rho$ ) and the composite weight ( $\pi$ ) between traditional and digital infrastructures. Such complementarity is particularly crucial in developing country contexts where infrastructure gaps persist<sup>[21]</sup>.

#### 4.4 Heterogeneous Effects under Different Scenarios

The theoretical model suggested significant sectoral and regional heterogeneity in the effects of the digital economy and infrastructure on resilience. For instance:

Major grain-producing regions: Given the relatively high stock of traditional infrastructure, marginal improvements in digital infrastructure exerted a stronger influence on adaptive capacity (Radj), as digitalization more effectively optimized the allocation efficiency of existing resources<sup>[22]</sup>.

Economically developed regions: Digital infrastructure had a more pronounced effect on innovative and transformative capacity (Rinno), as these regions possessed more mature market ecosystems and stronger innovation capabilities to absorb and convert disruptive digital technologies<sup>[13]</sup>.

This heterogeneity warranted close examination in subsequent counterfactual simulations.

#### 4.5 Integrated Effects of Multidimensional Resilience on Agricultural Growth

Agricultural economic resilience affected agricultural value added through three channels—stabilizing production, optimizing resource allocation, and promoting innovation. The relative change in total output could be decomposed into changes in factor inputs and TFP variations induced by resilience:

$$\hat{Y}_{ig} \approx \hat{L}_{ig}^{\beta} \cdot \hat{K}_{ig}^{\gamma} \cdot \hat{D}_{it}^{\delta} \cdot \hat{R}_{it}^{\zeta} \quad (13)$$

where  $\zeta$  denoted the elasticity of resilience with respect to output. This indicated that improvements in agricultural economic resilience independently contributed to agricultural output growth. Particularly under external shocks, resilience helped maintain system stability and mitigate output volatility<sup>[17]</sup>. This theoretically demonstrated the long-term value of investing in resilience-building, especially in the context of increasing climate variability and market disruptions<sup>[3]</sup>.

### 5. Quantitative Methodology and Parameter Calibration

The theoretical model developed in this study was ultimately applied to real-world economic analysis through quantitative implementation. The key analytical strength of the model lay in its capacity for calibration and counterfactual simulation. This section elaborates on the quantitative realization strategy and the calibration procedures for the core structural parameters.

#### 5.1 Counterfactual Simulation Based on the Hat Algebra Method

To effectively assess the impacts of policy shocks, this study adopted the Hat Algebra approach proposed by Dekle et al.<sup>[24]</sup>, transforming the multi-sector general equilibrium framework into a computable system of equations expressed in relative changes, defined as  $\hat{x} = x'/x$ . The advantages of this approach were threefold:

Avoidance of over-parameterization — it did not require full calibration of deeply unobservable structural parameters such as absolute productivity levels;

Data-driven structure — it directly utilized empirically observed baseline equilibrium data such as trade flows and factor shares;

Shock tracing capability — it allowed direct computation of the relative changes in endogenous variables resulting from

exogenous shocks, such as increases in digital infrastructure investment.

$$\{\pi_{ait}, \Psi_{ait}, \varpi_{ait}, L_{ait}, w_{ait}, Y_{ait}, G_{dig,it}, G_{tra,it}\}$$

Given a set of baseline observations and the exogenous specification of:

digital infrastructure investment shocks,

changes in agricultural data-factor inputs, and external market variations<sup>[31]</sup>, the model solved for the endogenous system of relative changes under a pre-specified set of deep structural parameters.

$$\{\delta, \beta, \gamma, \rho, \sigma, \theta, \kappa, \eta_{res}, \eta_{adj}, \eta_{inno}\}$$

$$[\hat{w}_{ait}, \hat{L}_{ait}, \hat{\pi}_{ait}, \hat{R}_{res,it}, \hat{R}_{adj,it}, \hat{R}_{inno,it}, \hat{Y}_{ait}]$$

This approach accurately captured the dynamic responses of the agricultural economic system to digital technology shocks and effectively mitigated systemic bias arising from structural economic changes.

## 5.2 Parameter Calibration Strategy

To enable numerical simulation, the model's structural parameters required careful calibration. This study employed a hybrid approach combining structural estimation and literature-constrained calibration.

### (1) Literature-Constrained Parameters

Several key parameters were directly drawn from established studies and adjusted to reflect the characteristics of China's agricultural economy:

Output elasticity of data factors ( $\delta$ : 0.08–0.12<sup>[1,8,32]</sup>;

Elasticities of digital infrastructure with respect to the three resilience dimensions:

$$\eta_{res} \in [0.05, 0.15]$$

$$\eta_{adj} \in [0.06, 0.18]$$

$$\eta_{inno} \in [0.10, 0.25]^{[21,33]};$$

Output elasticity of traditional agricultural infrastructure ( $\xi$ : 0.12<sup>[28]</sup>;

Labor output elasticity ( $\beta$ ): 0.28 (reference value from related empirical research<sup>[34,35]</sup>;

Intermediate input elasticity ( $\gamma$ ): determined from the structure of regional input–output tables<sup>[36]</sup>.

### (2) Fitted Parameters

The remaining parameters were obtained through a residual-minimization fitting process, formulated as the following optimization problem:

$$\min_{\theta_k} \sum_i \sum_t [Y_{it}^{model}(\theta_k) - Y_{it}^{data}]^2 + \lambda_k \sum_k (\theta_k - \bar{\theta}_k)^2 \quad (14)$$

where

$Y_{it}^{model}$ : model represents the model-predicted agricultural output,

$Y_{it}^{data}$ : the observed output,

$\theta_k$ : the vector of estimated parameters,

$\lambda_k$ : the constraint weight, and

$\bar{\theta}_k$ : the reference values derived from prior literature.

This calibration procedure ensured that the model could reproduce the observed evolution of agricultural economic resilience in China while maintaining parameter consistency with economic theory, thereby providing a reliable baseline for counterfactual analysis.

## 5.3 Stock Computation and Data Processing

The agricultural data-factor stock ( $D_{it}$ ) was computed using the perpetual inventory method (PIM). The initial stock was estimated based on agricultural data-resource surveys, while the depreciation rate followed the benchmark for ICT capital, set at 15%<sup>[37]</sup>. Similarly, both digital and traditional infrastructure stocks were constructed using investment series and corresponding depreciation rates under the perpetual inventory framework.

## 5.4 Summary

Through the hybrid calibration strategy that integrated literature constraints and fitted estimation, this study ensured both the

economic plausibility and empirical relevance of the parameterization. Consequently, the theoretical model evolved into a quantitative analytical tool capable of conducting policy experiments and counterfactual evaluations tailored to the realities of China's agricultural economy.

## 6. Conclusion and Policy Implications

This study developed a Quantitative Spatial Equilibrium (QSE) model that integrated digital factors and agricultural infrastructure to provide a unified analytical framework for understanding the formation mechanism of agricultural economic resilience along three dimensions—resistance, adaptation, and transformation. The theoretical contribution lay in explicitly incorporating data factors as a non-rival and novel production input into the production function and formally characterizing their synergistic interaction with both traditional and digital infrastructures<sup>[19,21]</sup>. This approach revealed the intrinsic logic of “digital empowerment–infrastructure support–resilience enhancement.”

### 6.1 Main Findings

#### 1) Applicability of the Theoretical Framework

This study extended the application of Quantitative Spatial Economics (QSE) to the agricultural domain. The constructed model effectively captured multi-regional, multi-sectoral, and multi-factor interactions, providing a formalized analytical tool for exploring spatial equilibrium and resilience responses within the agricultural economic system<sup>[16]</sup>.

#### 2) Core Mechanism of Data Factors

The theoretical derivation demonstrated that data factors directly enhanced agricultural economic resilience by increasing total factor productivity (TFP). Their non-rivalry and cumulative characteristics implied decreasing marginal costs and additive efficiency effects, forming the microeconomic foundation for their role as a primary driver of resilience enhancement<sup>[19]</sup>.

#### 3) Synergistic Amplification Effects of Infrastructure

The model revealed that infrastructure contributed to agricultural performance through both direct and indirect channels—it reduced transaction and logistics costs while simultaneously amplifying economic resilience<sup>[9]</sup>. The relationship between traditional and digital infrastructure was complementary rather than substitutive, governed by the elasticity of substitution ( $\rho$ ). Their effective integration emerged as the key to maximizing resilience improvement.

4) Theoretical Significance of Heterogeneity

The model's endogenous regional and sectoral heterogeneity indicated that identical policy shocks—such as increased investment in digital infrastructure—generated heterogeneous impacts across regions and industries. This theoretical finding underscored the limitations of “one-size-fits-all” policy approaches and highlighted the necessity of tailoring policies to local factor endowments and economic structures (Bryan & Morten, 2019).

### 6.2 Theoretical Insights and Policy Implications

#### 1) Treating Data-Factor Accumulation as a Long-Term Strategy

Policymakers should move beyond perceiving digital technologies merely as instrumental tools and instead treat them as core production factors requiring systematic development. This entails establishing an agricultural data resource system that is well-defined in ownership, open and shareable, and securely managed, thereby laying the institutional foundation for data accumulation and market-based exchange<sup>[5]</sup>.

#### 2) Strengthening Synergistic Investment between Digital and Physical Infrastructure

The findings suggested that the enabling effect of digital technologies critically depended on the modernization of traditional infrastructure. Policies should promote integrated infrastructure investment, such as embedding IoT sensors during the construction of high-standard farmland or integrating smart logistics networks when upgrading rural transportation systems, to maximize synergistic investment effects<sup>[38]</sup>.

#### 3) Designing Policies According to the Heterogeneity of Resilience Dimensions

The theoretical model indicated that digital technologies exerted the strongest influence on transformational capacity, while their impact on resistance capacity was comparatively limited. Consequently, in regions vulnerable to natural shocks, policymakers should not rely solely on digital technologies but complement them with hard infrastructure such as water

conservancy and disaster prevention facilities, forming a combined approach of “digital early warning + engineering defense”<sup>[10]</sup>.

#### 4) Providing a Quantitative Tool for Policy Evaluation

The proposed quantitative spatial equilibrium model, coupled with the Hat Algebra approach<sup>[24]</sup>, offered a scalable analytical framework and quantitative tool for assessing the macroeconomic and spatial spillover effects of digital agriculture policies, including subsidies, pilot programs, and infrastructure investments.

### 6.3 Summary

In summary, this study provided theoretical evidence for the feasibility and significance of the synergistic interaction between the digital economy and agricultural infrastructure in enhancing agricultural economic resilience. Future research could extend this framework through empirical estimation and counterfactual simulations using more granular datasets, thereby offering more precise policy insights to promote high-quality agricultural development and advance the goal of building a strong agricultural nation.

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