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The Role of Digital Finance in Shaping Agricultural Economic Resilience: Evidence from Machine Learning

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Abstract: This study offers detailed recommendations on strengthening government support without harming digital finance benefits, especially in negatively affected areas, which is critical for enhancing the inclusiveness of the digital financial landscape and reducing social disparities. This paper uses year 2011–2022 panel data from China's 31 provinces to empirically analyze digital finance's effects, mechanisms, and heterogeneity on agricultural economy resilience with a two-way, fixed-effect model. It further explores each feature's impacts using machine learning methodologies like the random forest, GBRT, SHAP value method, and ALE plot. The findings show that digital finance boosted agri-economy resilience, varying by food-producing status and marketization. Among all the features analyzed, government input, urbanization level, and planting structure emerged as the most critical factors influencing agri-economy resilience. Notably, government input negatively moderated this relationship. The ALE plot revealed non-linear effects of digital finance and planting structure on agri-economy resilience.

Keywords: digital finance; agricultural economic resilience; machine learning; moderating effects; China

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1. Introduction

Agriculture's vulnerability stems from its long production cycles and dependence on natural conditions. The strengthening of adaptation strategies is essential to mitigate shocks and enhance resilience. Digital finance plays a significant role in the economic development of national agriculture. For an extended period, this issue has been prominent in urban and rural development [1], and the needs of financially vulnerable groups are often unmet by traditional financial services [2]. This gap has led to the transformation of rural finance, evolving from microcredit to inclusive finance and now to digital finance [3]. According to the China Financial Technology and Digital Finance Development Report (2024) released by the Zhongguancun Financial Technology Industry Development Alliance in 2023, as of June 2023, the size of China's rural Internet users reached 301 million, accounting for 27.9% of the overall number of Internet users, and the Internet penetration rate in rural areas was 60.5%, a year-on-year increase of 1.7%. Digital finance, a novel industry, leverages Internet tech to cut costs and reach long-tail groups neglected by traditional finance, especially rural residents and SMEs, addressing info asymmetry and collateral shortage. In this context, dissecting the impact of digital finance on the agricultural economy is critical to addressing the gap between small- and large-scale farmers and enhancing the inclusiveness of digital finance.

Promoting agricultural economic resilience is a rich and complex transformation process, theoretically influenced by multiple factors. Established studies have focused on rural industrial integration [4], digital economy [5], rural population aging [6,7], infrastructure development [8], farm dynamics [9], decoupled subsidies [10], and agricultural policies [11] to illustrate the effects and mechanisms of their influence on the resilience of the agricultural economy. From the perspective of geographical distribution, several studies have pointed out that agricultural economic resilience exhibits spatial characteristics [4,12–14], with agricultural infrastructure and scientific and technological innovation capacity as the primary influencing factors [15]. Although the literature points out that digital finance can improve agricultural production efficiency by breaking down information barriers [16], easing farmers' financial constraints [17], reducing farmers' poverty vulnerability [18], improving financial accessibility for long-tailed groups [19], facilitating factor mobility and technology diffusion [20], and fostering sectoral development [21] to improve agricultural productivity and reduce the urban–rural income gap, there is still very little literature exploring the resilience of the agricultural economy from a digital finance perspective. In particular, most of the current studies on the two are based on the mediating effects of factors, such as urban–rural integration [22,23], agricultural technological innovation [24], and rural industrial integration [22], or on the use of spatial modeling to explore possible spatial spillovers between regions [25]. Methodologically, the relevant studies mainly use traditional econometric methods, significantly enhancing the understanding of agricultural economic resilience. However, they broadly fall into explanatory modeling [26].

Unlike prior work, this paper uses machine learning for the predictive modeling of factors influencing agricultural resilience, complemented by econometric tests for the key factors' moderating effects. The advantages of conducting research using predictive modeling are, first, that, unlike explanatory modeling's emphasis on causality [27], predictive modeling de-emphasizes the unbiased nature of the estimated parameters, thus enabling better prediction of the factors influencing agricultural economic resilience. Secondly, predictive modeling does not presuppose the functional form in advance but rather improves the model's predictive ability by capturing the relationship between the data, reflecting more accurately the abstract relationship between the variables. Thirdly, the wide application of machine learning methods has also led to the rapid development of its interpretable technology, which, to a certain extent, opens the "black box" of machine learning and, at the same time, makes up for the information that is difficult to obtain from interpretive modeling.

Using China's 31-province panel data (2011–2022), this paper tests digital finance's impact on agricultural economic resilience via a two-way, fixed-effect model, examines the control variables' importance, and expands the understanding of digital finance's mechanisms on agri-economy resilience. The marginal contribution of this paper is as follows: (1) it is the first to use multiple machine learning methods to study the problem of agricultural economic resilience, providing evidence from a different perspective and enriching the related research; (2) by adopting random forest (RF) and gradient-boosting regression tree (GBRT), the limitations of explanatory models in the model setting are effectively circumvented, and the complex relationship between variables can be more accurately revealed when exploring the mechanism of action; (3) by using interpretable techniques as SHAP and ALE, the influencing factors on agricultural economic resilience are visualized, and the importance of the impact of different factors on the resilience of the agricultural economy is explored.

2. Methodology and Data

2.1. Empirical Strategies

2.1.1. Two-Way, Fixed-Effect Model

First, this paper constructed the baseline regression model as follows:

$$RL_{i,t} = \alpha_0 + \alpha_1 DIF_{i,t} + \alpha_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

In Equation (1), $RL_{i,t}$ is the level of agricultural economic resilience of province i in period t, $DIF_{i,t}$ is the index of digital financial development level of province i in period t, the vector $Z_{i,t}$ represents a series of control variables, such as the level of urbanization (URB), the level of economic development (lnGDP), the level of transportation infrastructure

(INFR), the level of governmental inputs (GOV), and the planting structure (PS). μ_i denotes individual fixed effects where province i does not vary over time, and δ_t controls for time fixed effects. $\varepsilon_{i,t}$ denotes a random disturbance term.

In addition to the direct effect embodied in Equation (1), in order to discuss the possible role mechanisms of digital finance for the construction of the resilience of the agricultural economy and to verify whether the government financial input can regulate the impact of digital finance on the resilience of the agricultural economy, this paper added the interaction term between digital finance and the government's inputs (DIF × GOV), and constructs the model as follows:

$$RL_{i,t} = \gamma_0 + \gamma_1 DIF_{i,t} + \gamma_2 GOV_{i,t} + \gamma_w DIF_{i,t} \times GOV_{i,t} + \gamma_c Z'_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

In Equation (2), $DIF_{i,t} \times GOV_{i,t}$ is the moderating variable; $Z'_{i,t}$ are the other control variables excluding government inputs.

2.1.2. Machine Learning Methods

(1) Random Forest

Random forest belongs to the type "bagging" (bootstrap aggregating), which arrives at the final prediction by combining the predictions of multiple decision trees [28]. The implementation process of random forest can be summarized in the following main steps:

In the first step, multiple sample sets are randomly selected from the original dataset by means of bootstrapping. Each sample set is usually the same size as the original dataset, but repeated sampling is allowed so that some samples may appear in more than one sample set, while others may not appear at all once. Self-help M samples are obtained, and the "Mth" (number M) autonomous sample is as follows:

$$\{x_i^{*m}, y_i^{*m}\}_{i=1}^{n}, m = 1, \ldots, M \quad (3)$$

In Equation (3), x_i^* and y_i^* are the feature and label, respectively, and n is the sample size of the autonomous sample.

In the second step, a self-help sampling method is used to estimate M mutually exclusive decision trees, and no pruning operation of any kind is performed on these decision trees during this estimation process. The prediction result of the "Mth" tree is marked as follows:

$$\left\{\overline{f}^{*m}(x)\right\}, m = 1, \ldots, M \quad (4)$$

In the third step, the predictions of the M decision trees are averaged to produce the final result $\overline{f}_{bag}(x)$ as follows:

$$\overline{f}_{bag}(x) = \frac{1}{m}\sum_{m=1}^{M} \overline{f}^{*m}(x) \quad (5)$$

Based on the above algorithms, RF reduces the correlation between decision trees in various ways such as self-sampling, selection of feature subsets, randomness of node splitting, and combining multiple decision trees, which improves the accuracy and stability of the model.

(2) GBRT

GBRT continuously optimizes the model through an iterative process to reduce the prediction error in order to progressively improve the model performance. The implementation steps of the GBRT algorithm are specified as in [29].

In the first step, the initial prediction function is set as follows:

$$f_0(x) = argmin_c \sum_{i=1}^{N} L(y_i, c) \quad (6)$$

In Equation (6), c is a constant, $L(\cdot)$ is the loss function, N is the number of samples, and y_i is the true value of the "ith" sample. The purpose of this step is to find a constant c that minimizes the sum of the loss functions of all samples.

In the second step, the process loops for M iterations (m = 1, 2,. . ., M):

First, the residuals are computed: for each sample x_i, the residuals of the current model are computed as $r_{im} = y_i - f_{m-1}(x_i)$, where $f_{m-1}(x_i)$ is the predicted value obtained after the previous iteration.

Next, the residuals are fitted: using the residual r_{im} as the target value, fit a regression tree $h_m(x;\theta_m)$, where θ_m is a parameter of this tree (e.g., the value of a leaf node). This is usually achieved by minimizing the loss function $\sum_{i=1}^{N} L(y_i, f_{m-1}(x_i) + h_m(x_i;\theta_m))$.

Thus, the model is updated: the newly fitted regression tree $h_m(x;\theta_m)$ is added to the model from the previous round to obtain the new model $f_m(x_i) = f_{m-1}(x_i) + \gamma h_m(x_i;\theta_m)$, where γ is a learning rate (or step size) that controls how much each tree contributes to the final model.

In the third step, after the process for M iterations, the final prediction model $f_M(x)$ is output.

In the course of the above, RF and GBRT were employed to train the model using a randomly selected subset of annual data, while the remaining data from the year were used for model validation.

Last but not least, in order to better understand the results of the machine learning modeling, this paper employed interpretable methods of machine learning like the SHAP value method and the ALE plot to analyze the results generated by RF and GBRT.

(3) SHAP Value Method

The SHAP value method provides a specific numerical value (i.e., SHAP value) for each feature to quantify the extent to which the feature contributes to the model's predictive results and ranks the full set of input features in a systematic framework [30]. Therefore, the SHAP value approach is a good choice to measure and compare the importance of different influences on agricultural economic resilience. Specifically, the SHAP value of the "pth" influencing factor is calculated as follows:

$$SHAP_{*}^{p} = \sum_{S \subseteq W \setminus \{p\}} \frac{|S|!(|W| - |S| - 1)!}{|W|!} (v_*(S \cup \{p\}) - v_*(S)) \tag{7}$$

In Equation (7), W represents the full set of influencing factors and $|W|$ is the number of elements in W; the set S does not contain the "pth" influencing factor and the number of elements is $|S|$. $(v_*(S \cup \{p\}) - v_*(S))$ denotes the expected degree of influence of the "pth" influence factor on the predicted value when the combination of influence factors is S. In calculating the expectation $v_*(S)$, this paper adopts the method of Aas et al. [31] to attenuate the effect of variable correlation on the results.

(4) ALE Plot

Further, combining the results of RF, GBRT, and SHAP values, this paper adopted the ALE plot to visualize and interpret the influencing factors of agricultural economic resilience. This is implemented as follows: (1) the selected features are divided into a plurality of intervals (called grids), which can be determined based on the quartiles of the features, equidistant divisions, or other methods. (2) For each interval, the feature values in the original data are replaced using the upper and lower values of the interval and the predictions are rerun. (3) The differences in predicted values between neighboring intervals are calculated and these differences are accumulated. In the fourth step, to ensure the interpretability of the ALE plot, it is usually necessary to center the accumulated differences so that the average effect of the data is zero. The final value of the cumulative local effect of the feature variable x_i is obtained as in Equation (8) below:

$$ALE(x_i) = ALE^*(x_i) - \frac{1}{n} \sum_{i=1}^{n} ALE^*(x_i) \tag{8}$$

2.2. Description of Variables

2.2.1. Explained Variable

The explained variable in this paper is agricultural economic resilience (RL). Given that the current academic community lacks a unified and clear standard framework for constructing an agricultural economic resilience assessment system, this paper drew on the practices of existing studies [32–34] to systematically construct an agricultural economic resilience index system from the three dimensions of resistance capacity, adaptive capacity, and innovative capacity. Meanwhile, tier 2 indicators such as the rural minimum living security expenditure and agricultural meteorological observation stations were added on the basis of previous studies to further enrich the index system. Among them, resistance capacity refers to the ability to effectively mitigate the impact of shocks when faced with unexpected events; adaptive capacity reflects the ability of the agricultural system to quickly recover and return to a stable operating state after being exposed to natural or market risks; and innovative capacity refers to the ability of the agricultural system to innovate and flexibly adjust itself after experiencing shocks, so as to adapt to the new environment or market conditions. This paper used the entropy method to determine the weight of each indicator. The specific indicators are shown in Table 1.

Table 1. Indicators for evaluating the resilience of the agricultural economy.

Tier 1 Indicator	Tier 2 Indicator	Tier 3 Indicator	Direction
Resistance Capacity	Percentage of primary sector	Primary output/regional GDP (%)	+
	Gross power of agricultural machinery	Kilowatt (unit of electric power)	+
	Agricultural fertilizer applications	Application of agricultural fertilizers (10 thousand tons)	+
	Food per capita	Food production/area population (kg/person)	+
	Effective irrigation ratio	Cropland irrigated/cropland area (%)	+
	Engel's coefficient for rural households	Share of food consumption per rural inhabitant (%)	-
	Disaster-stricken condition	Crop damage/area affected (%)	-
	Expenditure on rural minimum subsistence security	Hundred million yuan (RMB)	+
	Agro-meteorological observatory	pcs	+
Adaptive Capacity	Growth rate of value added of primary-sector output	Growth rate of value added of primary production (%)	+
	Percentage of rural retail sales of consumer goods	Rural retail sales/total retail sales (%)	+
	Rural disposable income per capita	Per capita disposable income of rural residents (yuan RMB)	+
	Soil erosion control area	Thousands of hectares	+
	Level of rural labor force	Number of rural population aged 15–64 (person)	+
Innovative Capacity	Advanced industrial structure	Share of primary sector x1 + share of secondary sector x2 + share of tertiary sector x3 (%)	+
	Rural electricity consumption	Rural electricity consumption (kWh)	+
	Investment in fixed assets of rural households in agriculture, forestry, and fisheries	In billions of yuan (RMB)	+
	Expenditures on education for rural residents	Expenditure on education/total consumption expenditure of rural residents (%)	+
	Financial expenditure on agriculture, forestry, and water	In billions of yuan (RMB)	+
	Number of R&D staff	R&D staff full-time equivalent (person)	+

2.2.2. Explanatory Variable

The core explanatory variable of this paper is digital finance (DIF), which is measured using the digital inclusive finance index released by the Digital Finance Research Center of Peking University [35], whose sub-indicator dimensions include breadth of coverage (WID), depth of use (DEP), and degree of digitization (DIG). The construction of this index system employs dimensionless processing as well as hierarchical analysis, which is set up scientifically and reasonably, and is now widely used in academia [36]. The digital finance index and each sub-dimension index used in this paper were quantified by dividing the original data by 100.

2.2.3. Control Variable

In general, the strength of agricultural economic resilience is affected by various factors such as natural, social, and economic factors, and this paper considered the level of urbanization (URB), the level of economic development (lnGDP), the transportation infrastructure (INFR), governmental inputs (GOV), and planting structure (PS) as the control variables. Among them, the urbanization level gauges urban–rural factor mobility, using the urban-to-total population ratio at the year end. The economic development level manages regional disparities, measured by per capita GDP logarithm. Transportation infrastructure is evaluated by highway mileage per million people per province. Government input impacts income distribution, measured by the financial expenditure-to-local GDP ratio. Planting structure is reflected in the ratio of the food crop area to the total sown area. The descriptive statistics of the main variables in this paper are shown in Table 2.

Table 2. Descriptive statistics.

Variable	Definition	Obs	Avg	Std. Dev.	Min	Max
RL	Resilience of agricultural economy	372	0.258	0.111	0.0752	0.517
DIF	Digital finance index	372	2.429	1.076	0.162	4.607
WID	Breadth of digital financial coverage	372	2.260	1.107	0.0196	4.559
DEP	Depth of use of digital finance	372	2.356	1.074	0.0676	5.107
DIG	Degree of digital finance digitization	372	3.118	1.178	0.0758	4.672
URB	Urbanization level	372	0.592	0.130	0.228	0.896
lnGDP	Level of economic development	372	10.900	0.455	9.706	12.16
INFR	Transportation infrastructure	372	2.955	1.257	0.685	7.092
GOV	Government inputs	372	0.280	0.205	0.107	1.379
PS	Planting structure	372	0.655	0.144	0.355	0.971
IV	Spherical distance from provincial capitals to Hangzhou City	372	16.04	7.775	0.000	32.010
DIF × GOV	Digital finance index ×government input	372	−0.0223	0.219	−2.201	0.859

2.3. Data Sources

Given that China implements "one country, two systems" in the special administrative regions in which policies are not synchronized with those of the mainland, several data are not available for these regions. Thus, the samples selected for this paper were 31 provinces (excluding Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province) in China from 2011 to 2022, forming a balanced panel observation of 372 provinces and each year. The data used in this study were all from the China Rural Statistics Yearbook, China Statistical Yearbook, China High-Tech Industry Statistical Yearbook, China Population and Employment Statistical Yearbook, Peking University Digital Inclusive Finance Index, as well as from the statistical yearbooks of each province, and the statistical bulletin of national economic and social development. The statistical yearbooks involved in the study published by China's National Bureau of Statistics, while provincial data came from the official websites of provincial governments and the Department of Agriculture and Rural Affairs. Peking University Digital Inclusive Finance Index published by the Institute of Digital Finance Peking University. For the very few missing data, the interpolation method was used to make up the difference.

3. Empirical Findings

3.1. Baseline Regression Results

The results of the baseline regression from Table 3 show that the digital finance index had a significant contribution to the enhancement of agricultural economic resilience, regardless of whether or not control variables and two-way, fixed effects were added. The development of digital finance enables capital to flow more flexibly as well as freely into the agricultural sector, facilitating technological innovation and industrial upgrading. Through digital means, digital finance promotes the optimal allocation and efficient use of agricultural resources. The development of digital finance has also further promoted the mobility of talents and the dissemination of knowledge in the agricultural sector, provided more employment opportunities and entrepreneurial platforms, promoted the dissemination and sharing of agricultural knowledge, enhanced the overall quality and competitiveness of the agricultural economy, and strengthened its adaptability and resilience in the face of external shocks.

Table 3. Baseline regression results.

Variable	(1) RL	(2) RL	(3) RL
DIF	0.021 *** (0.005)	0.021 *** (0.001)	0.024 *** (4.65)
URB			−0.980 *** (−14.09)
lnGDP			1.668 *** (6.70)
INFR			0.012 *** (2.78)
GOV			−0.418 *** (−18.88)
PS			0.158 *** (5.54)
Constant	0.207 *** (0.014)	0.208 *** (0.002)	−3.223 *** (−5.77)
Observations	372	372	372
R-squared	0.039	0.589	0.571
Province/year FE	NO	YES	YES

Note: *** denotes 1% significance levelwith robust standard errors in parentheses, similarly hereinafter.

3.2. Robustness Test

In order to verify the above regression results, we chose to replace the core explanatory variables, exclude the data of municipalities, and replace the baseline regression model for the robustness test. The test results are shown in Table 4. Columns (1), (2), and (3) show the results of replacing the core explanatory variables of digital finance with the three sub-dimension indicators of the breadth of coverage, depth of use, and degree of digitization of digital finance, and the results were significant at the 1% level, which means that the level of the development of digital finance significantly promoted agricultural economic resilience in terms of the breadth of coverage, the depth of use, and the degree of digitization. Column (4) shows the regression results after excluding municipalities, and the results remained robust.

Table 4. Robustness test results.

Variable	(1) Replacing Explanatory Variables	(2) Replacing Explanatory Variables	(3) Replacing Explanatory Variables	(4) Excluding Municipalities	(5) Instrumental Variable Method
IV					0.001 ** (2.24)
DIF				0.022 *** (4.20)	
WID	0.022 *** (0.005)				

Table 4. *Cont.*

Variable	(1) Replacing Explanatory Variables	(2) Replacing Explanatory Variables	(3) Replacing Explanatory Variables	(4) Excluding Municipalities	(5) Instrumental Variable Method
DEP		0.028 ***			
		(0.005)			
DIG			0.015 ***		
			(0.004)		
URB	−0.992 ***	−0.968 ***	−0.993 ***	−1.010 ***	−1.039 ***
	(0.070)	(0.070)	(0.071)	(−10.39)	(−14.75)
lnGDP	0.156 ***	0.137 ***	0.172 ***	0.160 ***	0.192 ***
	(0.023)	(0.023)	(0.022)	(7.35)	(9.18)
INFR	0.012 ***	0.013 ***	0.013 ***	0.025 ***	0.013 ***
	(0.004)	(0.004)	(0.004)	(4.51)	(2.92)
GOV	−0.419 ***	−0.416 ***	−0.418 ***	−0.421 ***	−0.420 ***
	(0.022)	(0.022)	(0.022)	(−16.60)	(−18.17)
PS	0.161 ***	0.161 ***	0.151 ***	0.184 ***	0.155 ***
	(0.029)	(0.028)	(0.029)	(6.91)	(5.29)
_cons	−0.927 ***	−0.759 ***	−1.097 ***	−1.006 ***	−1.262 ***
	(0.213)	(0.216)	(0.203)	(−4.83)	(−6.40)
N	372	372	372	372	372
Adj. R^2	0.559	0.571	0.552	0.608	0.549
Province/year FE	YES	YES	YES	YES	YES

Note: *** and **, denote 1% and 5% significance levels.

3.3. Endogenous Discussion

Further, with reference to the study of Zhang et al. [37], this paper used the latitude and longitude information of provincial capital cities (municipalities directly under the central government) obtained from the National Center for Basic Geographic Information (NCBGI) of China. It employed these as instrumental variables, measuring the distances of these cities from Hangzhou city, the origin of digital finance in China, to address endogeneity. Assuming Hangzhou's digital finance lead, closer cities are expected to have higher development. Hangzhou-centric distances as instrumental variables have proven effective in a wide range of related studies [36,37]. As the DIF varies annually while distances (lnKM) are fixed, this paper interacted the lnKM with the annual DIF nationally to create a dynamic IV. The specific formula is as follows:

$$IV = \beta_0 + \beta_1 \ln KM_{i,j} + \beta_2 DIF_{i,t} + \beta_c Z_{i,t} + \varepsilon_{i,t} \quad (9)$$

$$RL_{i,t} = \lambda_0 + \lambda_1 IV_{i,t} + \lambda_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (10)$$

where IV represents the newly generated core explanatory variables; $\ln KM_{i,j}$ represents the geographical distance between provincial capitals and Hangzhou; $DIF_{i,t}$ is the original core explanatory variable of the level of digital financial development; and $Z_{i,t}$ is the control variable. As can be seen from Column (5) of Table 4, the coefficients were significantly positive after excluding the effect of the endogeneity problem of the core explanatory variables on the regression results, which verifies the robustness of the previous regression results.

3.4. Heterogeneity Analysis

To investigate digital finance's varied influence on agricultural economy resilience across provinces, this paper divided China's 31 provinces into 13 major and 18 non-major grain-producing regions. Additionally, considering marketization's impact on resource allocation and growth-mode transition [38], the provinces were categorized into high and low marketization levels based on the median of the marketization index from the China Provincial Marketization Index Report (2023). The regression results are shown in Table 5.

Table 5. Heterogeneity regression results.

Variable	(1) Major Grain-Producing Region	(2) Non-Major Grain-Producing Region	(3) High Marketization Level	(4) Low Marketization Level
DIF	−0.120 ***	0.038 *	0.036	−0.074 ***
	(0.029)	(0.020)	(0.030)	(0.027)
URB	−0.414 **	0.257 ***	0.377 ***	−0.398 ***
	(0.194)	(0.084)	(0.114)	(0.130)
lnGDP	0.091 ***	0.012	0.029	0.034 **
	(0.025)	(0.019)	(0.027)	(0.017)
INFR	−0.001	−0.004	0.002	−0.002
	(0.007)	(0.004)	(0.006)	(0.004)
GOV	−0.165	0.042	0.191	0.038
	(0.105)	(0.044)	(0.119)	(0.037)
PS	−0.215 ***	−0.014	−0.068	−0.156 ***
	(0.074)	(0.045)	(0.055)	(0.051)
_cons	−0.220	−0.114	−0.308	0.136
	(0.260)	(0.205)	(0.290)	(0.174)
N	156	216	186	186
Adj. R^2	0.700	0.644	0.527	0.733
Province/year FE	YES	YES	YES	YES

Note: ***, **, and * denote 1%, 5%, and 10% significance levels.

In major food-producing areas, digital finance and planting structure hinder agricultural economy resilience, likely due to the low profitability of food crops vital for national security. The digital divide exacerbates, hindering some farmers without digital skills, while risks from digital finance spread, impacting traditional finance access and economic resilience. Conversely, in non-food areas, digital finance fosters resilience, diversifying production, raising market value, and enabling precise management, thereby improving production quality, breaking sales constraints, and driving agricultural growth.

In highly marketized regions, digital finance's impact on agri-economy resilience is limited due to complete financial systems, abundant resources, and digital–traditional finance integration. Its marginal benefit may diminish with increasing marketization. Conversely, in low-marketized regions, digital finance inhibits resilience due to scarce resources, limited traditional finance, weak digital infrastructure, and homogeneous economies with low-tech agriculture. It may cause resource mismatches and widen urban–rural and wealth gaps, and policy lags can further weaken its role.

4. Results Based on Machine Learning Methods

4.1. Two-Way, Fixed-Effect Model Versus Machine Learning Models

The goodness of fit can be used to assess how well a model fits the observational data. In this paper, the goodness of fit of the two-way, fixed-effect model in traditional econometric models was compared with machine learning methods such as RF and GBRT to investigate the degree of fit of different models to existing data. As can be drawn from Table 6, the goodness of fit under two-way, fixed-effect model, RF, and GBRT were, respectively, 0.571, 0.819, and 0.806, with obvious improvement on using machine learning models.

Table 6. Goodness of fit under two-way, fixed-effect model, RF and GBRT.

Model	Goodness of Fit
Two-way, fixed-effect model	0.571
RF	0.819
GBRT	0.806

4.2. SHAP Value Method Calculations

To delve deeper into feature impacts on agricultural economic resilience, this paper employed SHAP values to assess the predictive power. Table 7 compares random forest (RF) and gradient-boosting regression tree (GBRT), ranking the features by importance. The top five features aligned: government inputs, urbanization, planting structure, digital finance depth, and transport infrastructure. The RF and GBRT results concurred, confirming the conclusion's robustness. This paper also conducted a regression by excluding GOV, URB, and PS from the baseline regression results, respectively (Table 8), and the results show that the model goodness-of-fit decreased by 73.86%, 40.35%, and 6.32%, respectively, once again verifying the reliability of the machine learning results. This paper highlights the government inputs' pivotal role in agricultural economy resilience. Lower-ranked features still matter. The SHAP values gauge marginal contribution per prediction, not overall impact. Complex interactions may amplify some features' effects when combined. Based on that, this paper further explored the moderating effect of digital finance on government inputs' role in agricultural resilience.

Table 7. Importance of characterization variables based on SHAP value approach.

Ranking	RF		GBRT	
	Variable	**|SHAP|**	**Variable**	**|SHAP|**
1	GOV	0.04388410	GOV	0.04557499
2	URB	0.02452443	URB	0.03869038
3	PS	0.01143754	PS	0.01822471
4	DEP	0.00794909	DEP	0.01261587
5	INFR	0.00761693	INFR	0.00971452
6	DIG	0.00456230	DIG	0.00850498
7	DIF	0.00198884	WID	0.00482080
8	lnGDP	0.00193550	lnGDP	0.00283562
9	WID	0.00173762	DIF	0.00274505

Table 8. Comparison of regression results for the top 3 importance-ranked feature variables.

Variable	(1) Baseline Regression	(2) Excluding PS	(3) Excluding URB	(4) Excluding GOV
DIF	0.024 ***	0.024 ***	0.039 ***	0.015 **
	(4.78)	(4.66)	(6.48)	(2.16)
URB	−0.979 ***	−0.943 ***		−0.454 ***
	(−13.94)	(−12.97)		(−5.01)
lnGDP	0.150 ***	0.118 ***	−0.091 ***	0.113 ***
	(6.58)	(5.16)	(−4.93)	(3.54)
INFR	0.013 ***	0.020 ***	0.006	0.006
	(2.89)	(4.79)	(1.17)	(0.98)
GOV	−0.419 ***	−0.425 ***	−0.297 ***	
	(−18.90)	(−18.44)	(−11.79)	
PS	0.158 ***		0.121 ***	0.182 ***
	(5.53)		(3.44)	(4.55)
Constant	−0.876 ***	−0.472 **	1.135 ***	−0.877 ***
	(−4.11)	(−2.26)	(5.84)	(−2.93)
Observations	372	372	372	372
R-squared	0.570	0.534	0.340	0.149
Province/year FE	YES	YES	YES	YES

Note: *** and **, denote 1% and 5% significance levels.

4.3. The Moderating Effect of Government Input

This paper examined how the government input moderates digital finance's impact on agri-economy resilience. Adding their interaction boosted digital finance's significance from 5% to 1%. The −0.014 interaction coefficient ($p < 0.01$) confirmed the government input's moderating role. See Table 9. The reasons may lie in, first, lack of complementarity. The government input's goals may clash with digital finance's, crowding out its space. Short-term policies versus digital finance's long-term needs reduce synergy. Secondly, excessive intervention distorts market signals and hinders digital finance's innovation and competitiveness, weakening its positive impact. Thirdly, the lack of effective coordination between government input and digital finance hampers synergy, causing negative effects. Information asymmetry also hinders the government's ability to support digital finance appropriately.

Table 9. The moderating effect of government inputs.

Variable	**(1)** **RL**	**(2)** **RL**
DIF	0.015 **	0.009 ***
	(2.16)	(2.84)
GOV		−0.034
		(−1.00)
DIF × GOV		−0.014 ***
		(−2.92)
URB	−0.454 ***	0.115 **
	(−5.01)	(2.01)
lnGDP	0.113 ***	0.017
	(3.54)	(1.33)
INFR	0.006	0.005 *
	(0.98)	(1.94)
PS	0.182 ***	−0.047
	(4.55)	(−1.42)
_cons	−0.877 ***	0.003
	(−2.93)	(0.02)
N	372	372
Adj. R^2	0.149	0.663
Province/year FE	YES	YES

Note: ***, **, and * denote 1%, 5%, and 10% significance levels.

4.4. ALE Plot: Predictive Model of Agricultural Economy Resilience by the Main Features

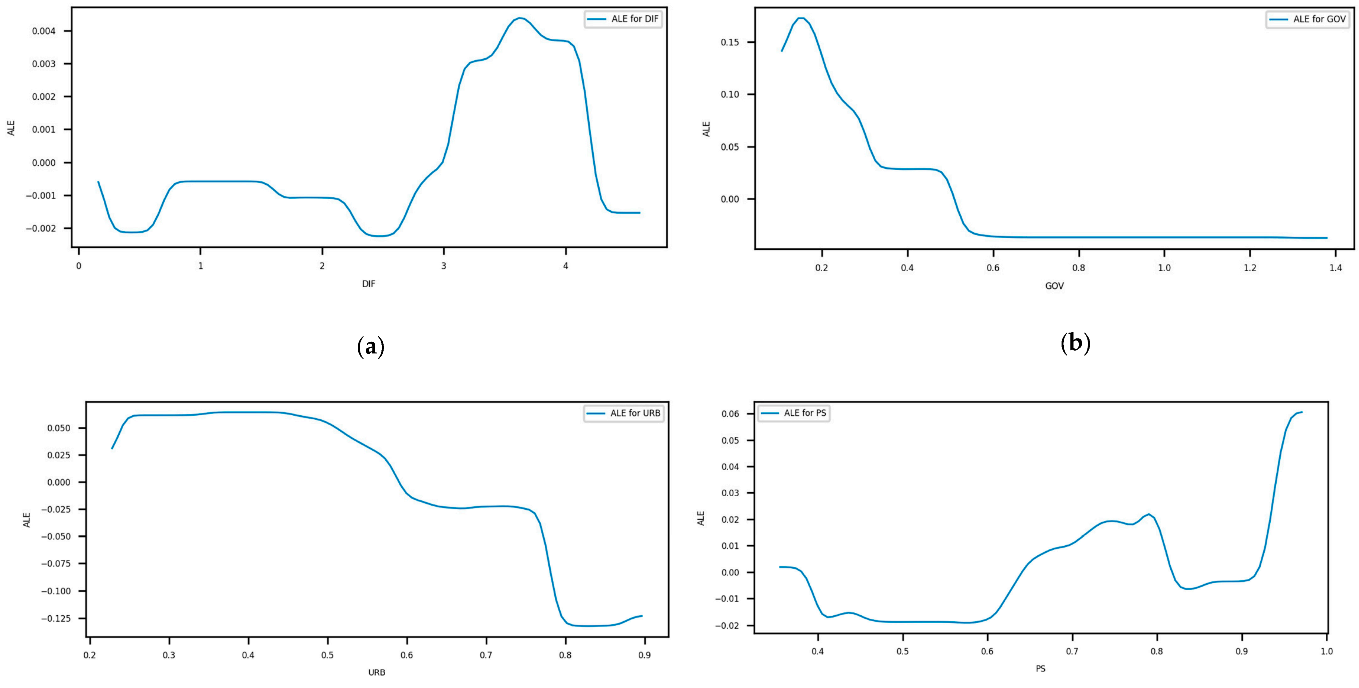
This paper used an ALE plot to highlight the key features affecting agri-economy resilience and show predictive patterns. The variables GOV, URB, PS (top three important), and DIF (core) were analyzed. The X-axis shows feature value ranges; the Y-axis quantifies their cumulative impact on predictions. Positive Y values mean rising predictions with higher feature values, and vice versa. The Y-axis height/depth shows influence strength and direction. The slopes indicate how feature changes affect predictions, positive/negative for positive/negative influence. Larger-slope absolute values mean greater impact. The specific prediction model is shown in Figure 1.

4.4.1. Level of Digital Finance Development

When the digital finance index is located below four, it positively impacts agri-economic resilience. Conversely, it becomes negative. This may be due to provinces like Shanghai or Jiangsu, with indices higher than four having a strong digital economy but limited agriculture due to resource constraints. Digital finance's surge may divert resources, affecting stability. Yet, in less-developed areas, digital finance spreads widely, boosting agri-economy resilience. Optimized digital finance offers tailored products, meeting agri-production needs.

4.4.2. Government Input

The government input positively impacted agri-economic resilience below 0.2, suppressing it from 0.2 to 0.6 and then having a limited effect. The possible reasons are as follows: in the early stage, government input boosts the development of infrastructure, technology, equipment, and incentives, spurring growth. Later on, overinvestment may lower efficiency, foster farmer dependency, and hinder innovation. Market distortions, policy lags, as well as environmental pressure also contribute to negative impacts.



(**a**) (**b**) (**c**) (**d**)

Figure 1. Predictive model of the main features DIF (**a**), GOV (**b**), URB (**c**), PS (**d**).

4.4.3. Level of Urbanization

Urbanization generally negatively impacts agri-economic resilience. This may because of the following: First, demand shifts reduce traditional crop cultivation, hurting diversity and stability. Secondly, agricultural industrialization lacks the necessary support, hindering progress. Thirdly, market expansion intensifies competition, raising risks and volatility. Fourthly, urban-biased policies and institutional barriers limit rural-urban migration and land use, affecting sustainable development and resilience.

4.4.4. Planting Structure

Figure 1 shows the planting structure's impact on agri-economic resilience: slow rise, slight decline, then rapid rise. Initially, farmers and enterprises adjust to higher-value crops, boosting resilience. Efficiency gains from new tech and varieties strengthen resilience. However, the initial adjustments are slow due to natural limits and market information gaps. Later, costs from new tech and varieties may offset the benefits. Market volatility and environmental pressures can erode early gains, turning the impact negative if the costs outweigh the benefits. Eventually, the planting structure stabilizes, enhancing market competitiveness, product value, and tech innovation, thereby strengthening agri-economic resilience.

4.5. Social Disparities Faced: Small-Scale Versus Large-Scale Farmers

Based on the analysis of the SHAP value method, it is evident that the main focus should be on the four aspects mentioned in Section 4.4, in eliminating the social disparity between small- and large-scale farmers.

In terms of government support, smallholders receive limited assistance. Their knowledge and management experience are insufficient, leading to chaotic operations and ineffective cooperatives. Consequently, government investment in them is less effective. By contrast, the government prefers supporting large-scale farmers due to lower administrative costs and potential mutual benefits, granting them more advantages in subsidies, loans, and technical support.

Regarding urbanization, smallholders often reside in backward rural areas with limited income from agriculture, breeding, and part-time jobs. Poor consumer attitudes, education, and medical resources further hinder their development. In contrast, large-scale farmers, often in urban–rural fringes or accessible areas, benefit from urban resources like culture, education, and healthcare, enhancing their competitiveness.

As far as planting structure is concerned, smallholders tend to be more homogeneous, focusing on traditional crops, leading to irrational planting structures and poor yields due to lack of market understanding and technical support. In contrast, large-scale farmers diversify their crops based on the market demand and have easier access to technology, improving product yield and quality.

As far as digital finance is concerned, smallholders have limited access to digital finance due to lack of knowledge, trust, and digital skills. In contrast, large-scale farmers widely use digital finance, trust digital products, and benefit from support services, reducing costs and improving capital efficiency.

5. Conclusions and Policy Recommendations

Using China's 31-province panel data from 2011 to 2022, this paper examined digital finance's impact on agri-economic resilience via a fixed-effect model and machine learning models (RF, GBRT, SHAP, ALE). This research found that digital finance boosted resilience, while urbanization and government input hindered it. The level of economic development, infrastructure, and planting structure aided resilience. In major grain-producing regions, digital finance and planting structure hindered resilience; while in non-major grain-producing region, positive impacts from digital finance and urbanization were seen. Low-marketized regions showed negative impacts from digital finance, urbanization, and planting structure and positive ones from economic growth. The machine learning analysis highlighted the government input's negative influence, moderating digital finance's effects. The ALE plot showed digital finance and planting structure's non-linear impacts on agri-economy resilience.

The policy insights drawn from this paper are as follows: firstly, policy coordination with digital finance must be strengthened to align government support with development goals, paths, and priorities in agri-economy. Policy variability across major and non-major grain-producing regions should match local needs: major regions prioritize digital finance for food production efficiency, stability, and technological advancement; non-major regions focus on diverse agri-industry growth. Secondly, the government should optimize resource allocation, minimize market intervention, and foster digital finance innovation in the agri-sector. Marketized regions enjoy flexible policies tailored to demand, while less-marketized ones can leverage policy incentives to engage financial institutions and tech firms, despite financial constraints. Former policies emphasize market-driven resource allocation while the latter emphasize government-led support. Last but not least, policymakers must adopt a nuanced strategy to ensure that government interventions stabilize the agricultural economy while preserving digital finance benefits. In regions with advanced digital finance, targeted support, like special funds for agricultural tech innovation and rural e-commerce, should be prioritized over blanket funding. Resources should focus on rural infrastructure and talent cultivation. Digital finance should undergo rigorous risk assessment and monitoring, with support for sustainable agricultural projects. A risk warning and response system is crucial for informed decision-making. For bridging the gap between small- and large-scale farmers, the main focus should be on improving the inclusiveness of the digital financial landscape. Specifically, digital infrastructure should be strengthened to reduce the digital divide, financial education should be popularized to improve the financial literacy and digital skills of farmers, digital financial product design should be optimized for small-scale farmers, and a large-scale farmer-led approach should be adopted to promote coordinated regional development.

This paper used macro data for study, and there are still deficiencies in examining within provinces or among farmers. Future research could focus on specific regions or business entrepreneurs for microanalysis. In addition, the findings of this paper can be used in the future to dig deeper into the non-linear effects of digital finance and planting structure on agricultural economic resilience.

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