Has Digital Financial Inclusion Improved Agricultural Green Total Factor Productivity? Considering Agricultural Industrialization and Technological Innovation in China

Recebimento dos originais: 09/03/2024
Aceitação para publicação: 17/03/2025

Ao Yang
PhD in Accounting and Finance
Institution: Graduate School of Management,Management and Science University, Shah Alam 40100, Selangor, Malaysia
E-mail: yangao@stu.haut.edu.cn

Mao Yang, Prof. Dr.
(Corresponding author)
Institution: School of Business , Sias University, Zhengzhou 451100, China
E-mail: yangmao20022002@163.com

Peixu Wang
PhD in Management and Business
Institution: Graduate School of Management,Management and Science University, Shah Alam 40100, Selangor, Malaysia
E-mail: wangpeixu0506@163.com

Aza Azlina Md Kassim, Prof. Dr.
Institution: Graduate School of Management,Management and Science University, Shah Alam 40100, Selangor, Malaysia
E-mail: aza_azlina@msu.edu.my

Abstract

Digital Finance Inclusive (DFI) represents big data and agriculture-friendly finance development. Agricultural Green Total Factor Productivity (AGTFP) describes the development of a green economy and agricultural modernization. This paper used the Slack Based Measure (SBM) model to calculate AGTFP based on Chinese provincial data from 2011 to 2022. At the same time, with the help of the Mediating Effect Model and the Spatial Durbin Model (SDM), tested the influence of DFI on AGTFP. The main research conclusions include: (1) DFI, the coverage breadth of digital financial inclusion (DIFB), and the degree of digitization (DIG) can significantly improve AGTFP. (2) The intermediary effect model proves that DFI can increase AGTFP by improving agricultural industrialization and technological innovation. (3) The heterogeneity test found that the DFI of the provinces in the central and western regions has a more substantial promotion effect on AGTFP. (4) SDM found that AGTFP and DFI have a positive spillover spatial effect. In addition, DFI can significantly increase the local AGTFP and reduce the AGTFP in the surrounding area. The research results will help to enrich the relevant research on the application of DFI to AGTFP and provide empirical evidence for better implementation of rural revitalization and construction of a beautiful China.

Keywords: Digital financial inclusion. Agricultural green total factor productivity. Agricultural industrialization. Technological innovation. Beautiful china initiative.

1.Introduction

Since World War II, with the continuous progress of modern science and technology, the world has gradually entered a period of agricultural modernization (Kirkendall, 1986). As a primary industry, agriculture provides excellent means of production and living for human society. However, at the same time, modern agricultural production has also caused severe damage to the ecological environment (Dent, Edwards-Jones & McGregor, 1995), such as soil erosion, environmental pollution, and species reduction. Therefore, the green development of agriculture has gradually become a new driving force for the reconstruction of the global agricultural economic order and ecological governance in the new era and has attracted extensive attention from the academic community.

As a predominantly agricultural country, China's agricultural output has always been at the top level, feeding 22% of the world's population with 7% of the world's arable land (Zhao et al., 2010). According to data released by the World Bank, China's total agricultural output value will reach US$1.288 trillion in 2021, accounting for 32.4% of the world's total. The grain output is 683 million tons, accounting for 24.4% of the world's total (Piao et al., 2008). The per capita income of Chinese farmers has also increased from 134 yuan at the beginning of the reform and opening up to 18,931 yuan in 2021, an increase of 141 times. Although China's agriculture has made remarkable achievements, there are still severe problems, such as environmental pollution and waste of resources in the production process. From the environmental pollution perspective, the extensive use of agricultural chemical products has caused severe environmental pollution (Duru, Therond & Fares, 2015). For example, China's fertilizer consumption has increased from 8.84 million tons in 1978 to 51.91 million tons in 2021, an increase of nearly six times. According to China's second national survey on pollution sources in 2017, agricultural pollution is one of the primary sources of environmental pollution. From the perspective of resource waste, the inefficient use of agricultural production materials has caused a severe waste of agricultural resources. For example, according to data released by the Ministry of Water Resources of China in 2016, the effective utilization rate of agricultural irrigation water in China is only 47%. Therefore, modern agriculture's development goal is to ensure the balance between the supply and demand of agricultural products under the rigid constraints of resources and to fully consider the carrying capacity of resources and environmental protection (Carey, 1993). How to effectively promote the green development of modern agriculture has become a major practical problem to be solved urgently in China's agriculture. AGTFP refers to incorporating the emergence and accumulation of environmental pollution into the research framework based on traditional total factor productivity, which can more accurately reflect the comprehensive level of green agricultural development (Liu, Zhu & Wang, 2021).

Inclusive finance is a significant strategic move for the development of the financial industry. It refers to providing appropriate and effective financial services to all social classes and groups needing financial services at an affordable cost based on the requirements of equal opportunity and the principle of sustainable business (Corrado & Corrado, 2017). China's banking institutions cover over 98% of townships, and essential financial services cover all administrative villages. As of the end of 2021, the balance of national inclusive small and micro-enterprise loans was 19.1 trillion yuan, and the balance of inclusive agriculture-related loans was 8.9 trillion yuan. DFI is a more convenient, accurate, and reliable new digital financial service formed recently with the help of new digital technologies such as the Internet, big data, cloud computing, and artificial intelligence (Wang & He, 2020). DFI strengthens the construction of financial infrastructure and deepens the development of inclusive financial services, thereby affecting the input and output of agricultural production factors (Liu, Liu & Zhou, 2021). Under the current background of building a new development pattern, how to use DFI development to promote the green development of agriculture is an important research topic.

Compared with traditional financial services, DFI can broaden the sources of funds for agricultural production and alleviate the problems of financing difficulties and high thresholds in the agricultural sector (Ozturk & Ullah, 2022). In addition, DFI can accelerate the introduction and application of advanced agricultural technologies, accelerate the transformation of agricultural production methods, and achieve green and sustainable agricultural development (Guo et al., 2022). Existing studies primarily focus on the impact of DFI on rural residents' income, consumption, and upgrading of industrial structure (Ji et al., 2021, Wang, He & Li, 2023, Ren, Zeng & Gozgor, 2023). However, the research on the relationship between DFI and AGTFP is relatively weak. Based on the above analysis, this paper uses panel mediation and spatial econometric models to test DFI's impact on AGTFP. The possible marginal contributions of this study include: First, based on the dual attributes of agricultural carbon emissions and carbon uptake, use the SBM model to measure AGTFP. Second, using agricultural industrialization and technological innovation as intermediary variables, the mechanism by which DFI affects AGTFP is discussed. Third, divide the research sample into eastern, central, and western regions to explore the regional heterogeneity of the impact of DFI on AGTFP. Fourth, use the spatial Durbin model to test the spatial spillover effect of the impact of DFI on AGTFP.

The rest of the paper is organized as follows: Section 2 is the literature review and theoretical hypotheses; Section 3 elaborates on data sources, empirical models, and variable selection; Section 4 presents the results of the empirical analysis; Section 5 focuses on the research conclusions and policy suggestions. Literature Review and Research Hypotheses

2. Literature Review and Research Hypotheses

Agriculture is the basis for the birth and development of human civilization (Li et al., 2006). Human society has entered the stage of modern development, and green development has become a significant trend (Shen et al., 2020). AGTFP is an organic combination of agricultural total factor productivity and ecological environment factors, which can promote the green development of agriculture (Huang et al., 2022). As the core of modern economic development (Komal & Abbas, 2015), the penetration of finance into the agricultural industry has an important impact on agricultural GTFP (Li et al., 2023). The coverage, depth of use, and degree of digitalization of digital financial inclusion have gradually increased the impact on AGTFP (Lin et al., 2022). The study found that existing literature studies mainly focus on the impact of digital financial inclusion on total factor productivity and green agriculture.

From the perspective of the impact on green total factor productivity: Under the dual constraints of resources and the environment, improving green total factor productivity is an inevitable choice to achieve green development (Ma & Stern, 2008). Digital inclusive finance is characterized by flexibility, convenience, precision, and efficiency. It can improve green total factor productivity by reducing cost risks, alleviating resource misallocation, and optimizing factor distortions (Wang et al., 2022). In addition, reducing the financing constraints of innovative enterprises is conducive to encouraging enterprises to increase investment in green technology (Yang & Wang, 2022) and increase the production and consumption of green high-tech products (Li et al., 2023). These will have a positive impact on GTFP. From the perspective of the impact on agricultural total factor productivity: Improving agricultural total factor productivity will help accelerate the transformation of agricultural economic structure and promote the stable development of rural areas (Li et al., 2023). Research results show that financial development can significantly increase agricultural total factor productivity Mo, Sun & Zhang, 2023, Lin & Ma, 2022). The improvement of agricultural total factor productivity depends on the progress of modern agricultural technology and equipment and the popularization of agricultural knowledge by the Internet (Zheng, Zhu & Jia, 2022). With the continuous advancement of Internet technology, digital financial inclusion can provide rural enterprises and residents with lower-cost, broader, and more efficient financial services (Yang & Zhang, 2020). The optimal allocation of production factors among industries and regions further enhances agricultural technology progress and agriculture's sustainable development (Li et al., 2023). From the perspective of the impact on the green development of agriculture: green agriculture has the following characteristics: long production cycle, slow return on investment, and low investment efficiency(Ge et al., 2022). Therefore, financial instruments are essential to its development. Due to financing constraints, traditional financial services are difficult to meet the needs of green agricultural production (Northrup, et al., 2023). DFI can significantly enable green technologies (Xiao et al., 2023) and services to be applied to agricultural production (Ding et al., 2021). The reduction of pollution and the efficient use of resources promote the low-carbon development of agriculture (Zhang et al., 2023). In addition, breaking market information barriers reduces the operational risks of green agricultural production entities (Ji et al., 2021). Based on the above discussion, this paper proposes the first research hypothesis:

Hypothesis 1: DFI can promote the improvement of AGTFP.

Research manuscripts reporting large datasets that are deposited in a publicly available database should specify where the data have been deposited and provide the relevant accession numbers. If the accession numbers have not yet been obtained at the time of submission, please state that they will be provided during review. They must be provided prior to publication. The upgrading of industrial structure is one of the fundamental driving forces of modern economic development (Li et al., 2022). With the improvement of the financial system, financial services can effectively alleviate the problems of information asymmetry and transaction costs. Increase the availability of monetary funds to provide reasonable financial support for industrial restructuring (Tang et al., 2022). Capital accumulation is conducive to technological innovation and industrial structure optimization (Su, Su & Wang, 2021). The transformation and upgrading of industrial structures will further enhance the green total factor productivity (Hu et al., 2023). DFI can effectively improve the efficiency of agricultural resource allocation (Hong, Tian & Wang, 2022) and further promote the development of agricultural industrialization. Therefore, DFI can promote agricultural development and increase AGTFP by improving agricultural industrialization (Zhang, Zhang & Song, 2022). Based on the above discussion, this paper puts forward the second hypothesis:

Hypothesis 2: DFI promotes the increase of AGTFP by improving agricultural industrialization.

The breakthrough innovation of digital technology accelerates the deep integration of finance and technology and drives the digital transformation of traditional industries (Yang & Masron, 2022). It is conducive to the green development of the economy and the improvement of green total factor productivity (Jia, 2023). As a primary industry, the core of agricultural development lies in the sustainable development and promotion of AGTPP (Liu, Zhu & Wang, 2021). Finance is the core of modern economic resource allocation, and DFI has achieved breakthrough development in terms of coverage, depth of use, and degree of digitization (Zhang & Chen, 2023). Therefore, it can provide vital financial support for mechanized agricultural production, scientific research and development, and achievement transformation (Wang & Fu, 2022). DFI improves agricultural total factor productivity by promoting technological progress (Zhu, Zhang & Piao, 2022). Based on the above discussion, this paper proposes a third hypothesis:

Hypothesis 3: DFI promotes the improvement of AGTFP through technological innovation.

3.Research Methods and Data Sources

3.1. Data sources

Considering data availability, this paper excludes Hong Kong, Macao, Taiwan, and Tibet and retains 30 provinces in China as research samples. DFI is a new product, so the research time of the samples started from 2011. Secondly, due to the impact of COVID-19, China's economic data has been missing. The paper uses linear interpolation to supplement the missing data. Therefore, the time range of the sample in this paper is 2011-2022. The independent variable data in this paper comes from the Institution of Digital Finance Peking University, and the data of other variables come from the China Stock Market Accounting Research (CSMAR), the official website of the National Bureau of Statistics of China, and the statistical yearbooks of various provinces over the years. In addition, according to the usual practice of domestic scholars, the country is divided into three regions: East, middle, and West.

3.2. Variable definitions

Dependent variable: There are many ways to measure agricultural total factor productivity, and the evaluation is based on the Data Envelopment Analysis (DEA) model. The measurement methods in the existing literature only consider agricultural carbon emissions as an undesired output but ignore that agriculture has the attribute of carbon sequestration. Agriculture produces carbon dioxide while growing crops that absorb it. Based on the realistic background of carbon peaking and carbon neutrality, this paper calculates agricultural carbon uptake as a desired output and agricultural carbon emissions as an undesired output. Finally, the SBM model in unexpected production is used to measure AGTFP. The model takes environmental pollution as an undesired output into the model to calculate AGTFP and can effectively measure the comprehensive efficiency of economic growth, environmental pollution, and resource consumption. Equation 1 shows the model setup. Suppose there are n decision-making units (DMUs) at time t, and each DMU has m types of inputs X, s types of expected outputs Y, and t types of undesired outputs B. Finally, the SBM model calculates the AGTFP of the province "i" in period "t." In the formula, ρ is AGTFP; s_r^+ is the expected output deficit; s_p^+ is the undesired output redundancy; s_j^- is the input redundancy.

$$\text{Min } \rho = \frac{1-\frac{1}{m}\sum_{j=1}^{m}\frac{s_j^-}{x_{ji}}}{1+\frac{1}{s+t}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{ri}}+\sum_{p=1}^{t}\frac{s_p^+}{b_{pi}}\right)} \quad (1)$$

$$\text{S.t.} \sum_{i=1}^{n}\lambda_i x_{ji} + s_j^- = X_0, j = 1,2\cdots m \quad (2)$$

$$\sum_{i=1}^{n}\lambda_i y_{ri} - s_r^+ = Y_0, r = 1,2\cdots s \quad (3)$$

$$\sum_{i=1}^{n}\lambda_i b_{pi} + s_p^+ = B_0, p = 1,2\cdots t \quad (4)$$

$$s_j^- \geq 0, s_r^+ \geq 0, s_p^+ \geq 0, \lambda_i \geq 0 \quad (5)$$

The index calculation system of AGTFP is as follows:

Input indicators: 7 indicators of the labour force, cultivated area, agricultural machinery, chemical fertilizer application amount (converted into scalar amount), agrarian irrigation area, agricultural film coverage area, and pesticide application amount.

Undesired output indicators: sum of carbon emissions from fertilizers, agriculture, mulch, diesel, and irrigation; soil nitrous oxide emissions (converted to carbon dioxide); livestock carbon emissions; rice field methane emissions (converted to carbon dioxide).

Expected output indicators: ① Based on the agricultural output value (real GDP) in 2000. ② Agricultural carbon absorption mainly includes rice, wheat, corn, beans, potatoes, peanuts, rapeseed, sugar cane, cotton, melons, vegetables, and other crops.

Independent variables: This paper uses the DFI in the *Peking University Digital Financial Inclusion Index of China* as an independent variable. In addition to DFI, the three latitudes of coverage (DFIB), depth of use (DFID), and digitalization (DIG) are selected at the same time to investigate their impact on AGTFP. Peking University and Ant Financial jointly compile the indicator, and most scholars in China use this data to measure the level of DFI development. Therefore, the data is reliable, extensive, and scientific. Considering the difference in data dimension, this paper takes the logarithm of the original DFI and its sub-dimension data.

Mediating variable: level of agricultural industrialization and technological innovation. Agricultural industrialization represents the situation of industrial development in rural areas. This paper uses the entropy method to fit five variables into the agricultural industrialization index. The index variables include the number of farmers' professional cooperatives, the per capita output of major farm products, the proportion of farmers' non-agricultural income, rural electricity consumption, and the per capita total output value of the agricultural and sideline products processing industry. The scientific and technological innovation level reflects whether specialized development activities are active. The greater the number of invention patents, the higher the innovation capability of society and the more vitality the organization has. Due to the timeliness of China's invention patent applications, "the number of domestic patent applications" is selected as an indicator to measure the level of technological innovation.

Control variables: In order to make the regression results more accurate and realistic, this paper selects the following six control variables based on the existing literature and the actual economic and social conditions: Agricultural Economic Development (AGDP), Government Environmental Expenditure (GOV), and Rural Employment Level (JOB), Rural Education Level (EDU), Road Infrastructure Construction (ROAD) and Internet Development Level (INTE). Table 1 shows the codes and measurement methods for each variable.

Table 1: Variable codes and definitions

Variable Type	Variable Name	Variable Code	Variable Definitions
Dependent Variables	Carbon Emissions Intensity	AGTTP	SBM model calculated
Independent Variables	Digital Financial Inclusion	DFI	*Peking University Digital Financial Inclusion Index of China*
	The Breadth of DFI	DFIB	
	The Depth of Use of DFI	DFID	
	Degree of Digitization	DIG	
Mediating variable:	Agricultural industrialization	AGROI	Calculated by the entropy method
	Technological Innovation	INV	The logarithm of the number of invention patent applications
Control Variables	Agricultural Economic Development	AGDP	Ratio of Agricultural GDP to GDP
	Government Environmental Expenditure	GOV	Government environmental expenditure as a percentage of total fiscal expenditure
	Rural Employment Level	JOB	The ratio of agricultural employment population to the total population of the province
	Rural Education Level	EDU	The logarithm of the number of people with a high school degree or above in rural areas
	Road Infrastructure Construction	ROAD	The logarithm of highway mileage in the whole province
	Internet Development Level	INTE	The logarithm of the number of Internet users in the province

3.3. Model design

In order to explore the impact of DFI on AGTFP, this paper constructs a benchmark panel regression model:

$$AGTTP_{i,t} = \beta_0 + \beta_1 \ln DFI_{i,t} + \beta_2 \sum control_{i,t} + \theta_i + \emptyset_t + \varepsilon_{i,t} \quad (6)$$

$AGTTP_{i,t}$ represent agricultural green total factor productivity, and $\ln DFI_{i,t}$ include the

DFI index and its three sub-dimensions. The subscripts i and t represent individual provinces and representative years; $\mathrm{control}_{i,t}$ represent the set of control variables. θ_i and $\emptyset_t$ represent unobservable provincial fixed effects and time fixed effects; $\varepsilon_{i,t}$ represents a random interference item (obeys normal distribution).

Secondly, to explore the mechanism of DFI affecting AGTFP, this paper constructs the following mediation effect model. Formula 7 and Formula 8 combined with Formula 6 above constitute the mediation effect model of the three-step regression method.

$$M_{i,t} = \partial_0 + \partial_1 \mathrm{lnDFI}_{i,t} + \partial_2 \sum \mathrm{control}_{i,t} + \theta_i + \emptyset_t + \varepsilon_{i,t} \quad (7)$$

$$\mathrm{AGTFP}_{i,t} = \beta_0 + \beta_1 \mathrm{lnDFI}_{i,t} + \beta_2 M_{i,t} + \beta_3 \sum \mathrm{control}_{i,t} + \theta_i + \emptyset_t + \varepsilon_{i,t} \quad (8)$$

Among them, $M_{i,t}$ represent an intermediary variable. According to the above research hypothesis, agricultural industrialization and technological innovation are selected as intermediary variables, and the meanings of other variables are the same as above.

Finally, this paper constructs the following spatial econometric model to explore the spatial spillover effect of DFI on agricultural total factor productivity. First, the GEODA software was used to construct Chinese provinces' spatial geographic weight matrix (W), as shown in Equation 9. Second, a spatial econometric model is constructed, as shown in Equation 10.

$$W_{mn} = \begin{cases} 1/d_{mn}, m \neq n \\ 0, m = n \end{cases} \quad (9)$$

$$\mathrm{AGTTP}_{i,t} = W * \partial + W * \beta_1 \mathrm{lnDFI}_{i,t} + W * \beta_2 \sum \mathrm{control}_{i,t} + \varepsilon_{i,t} \quad (10)$$

Among them, m and n represent two different provinces. d_{mn} is to calculate the distance between two provinces using latitude and longitude data. W is the constructed spatial weight, and the meanings of other variables are the same as above.

3.4. Descriptive Statistics for Variables

The descriptive statistics of the variables are shown in Table 2. China has vast land and abundant resources, and uneven regional development leads to significant differences in AGTFP, DFI, agricultural industrialization, and technological innovation. The variable correlation test in Table 3 proves a significant positive correlation between DFI and AGTFP. Other control variables, except for the level of agricultural employment, are also significantly positively correlated with AGTFP, which is consistent with the preliminary research hypothesis of this paper. The direct correlation coefficients of each variable are less than 0.7, and there is no multicollinearity in theory.

Table 2: Descriptive statistics for variables

VARIABLES	N	mean	sd	min	max
AGTFP	360	0.778	0.153	0.123	1
DFI	360	5.151	0.670	2.909	6.017
DFIB	360	4.995	0.827	0.673	5.952
DFID	360	5.133	0.646	1.911	6.087
DIG	360	5.458	0.716	2.026	6.136
AGROI	360	0.204	0.107	0.0459	0.637
INV	360	6.649	1.869	0	11.21
AGDP	360	0.091	0.052	0.002	0.277
GOV	360	0.029	0.009	0.011	0.068
JOB	360	0.437	0.115	0.142	0.613
EDU	360	9.194	0.888	7.514	12.80
ROAD	360	11.60	0.827	9.440	12.98
INTE	360	6.467	0.907	3.728	8.243

Table 3: Correlation test of variables

	AGTFP	DFI	AGDP	GOV	JOB	EDU	ROAD	INTE
AGTFP	1							
DFI	0.268***	1						
AGDP	0.115*	-0.195***	1					
GOV	0.013**	0.059	-0.105*	1				
JOB	-0.262***	-0.123**	0.661***	-0.033	1			
EDU	0.305***	0.306***	-0.519***	0.097	-0.654***	1		
ROAD	0.120**	0.132**	-0.131**	-0.315***	0.092	-0.131**	1	
INTE	0.295***	0.443***	-0.232***	-0.174***	-0.144**	0.135**	0.688***	1

Note: *, **, *** indicate significant at 10%, 5% and 1% levels respectively.。

4. Analysis of Empirical results
4.1. Benchmark panel regression results

The empirical part of this article uses the software STATA 15.1 for regression analysis. The regression analysis using fixed effects was proved to be more efficient by the Hausman test. The elastic coefficient of DFI is 0.028, which is significant at the 1% level, indicating that DFI can significantly increase AGTFP. The elasticity coefficient of DFIB is 0.018, which is significant at the 5% level, indicating that DFIB can significantly increase AGTFP. DFID has a significant impact on AGTFP, indicating that the effect of DFI in depth use in rural areas could be better, and the effect of DFID on improving AGTFP is not strong. The elastic coefficient of DIG is 0.018 and is significant at the 5% level, indicating that DIG can significantly increase AGTFP. Overall, DFI can significantly improve AGTFP. Therefore, hypothesis 1 holds.

From the regression results of the control variables: agricultural economic development, government environmental expenditure, rural education level, infrastructure construction and Internet development level all significantly increase AGTFP. Improving the total value of agricultural production means that more capital elements are invested in agricultural production, easing the financial constraints of agricultural production. The government's environmental expenditure increases the financial sector's support for green agricultural development, which can optimize the environment and conditions of agricultural production. The rural education level represents high-quality human capital in rural areas. More talents can enhance the influence of DFI on AGTFP and maximize the value of financial resources. Infrastructure construction increases the flow of factors in rural areas and further creates a material basis and product market for agricultural development. The development level of the Internet has promoted agricultural technology development, further promoting the growth of the agricultural economy and the optimization of agricultural production structure. The level of agricultural employment significantly suppressed AGTFP. Agriculture is a primary industry. The more people employed in agriculture, the smaller the number of people employed in higher industries such as industry and services. More agricultural employment means a lower level of agricultural mechanization can reduce AGTFP.

Table 4: DFI affects the regression results of AGTFP

	(1)	(2)	(3)	(4)
VARIABLES	AGTFP	AGTFP	AGTFP	AGTFP
DFI	0.028***			
	(2.69)			
DFIB		0.018**		
		(2.16)		
DFID			0.016	
			(1.49)	
DIG				0.023***
				(3.05)
AGDP	1.106***	1.106***	0.993***	1.064***
	(3.57)	(3.52)	(3.19)	(3.51)
GOV	1.259**	1.249**	1.294**	1.367**
	(2.21)	(2.18)	(2.25)	(2.43)
JOB	-0.800***	-0.793***	-0.812***	-0.867***
	(-4.39)	(-4.32)	(-4.40)	(-4.81)
EDU	0.050**	0.042**	0.041*	0.053**
	(2.32)	(1.98)	(1.86)	(2.49)
ROAD	0.061**	0.063**	0.051*	0.055*
	(2.07)	(2.07)	(1.70)	(1.90)
INTE	0.130***	0.125***	0.115***	0.121***
	(8.09)	(7.80)	(7.27)	(8.75)
Constant	-1.072**	-0.977**	-0.809**	-1.027**
	(-2.58)	(-2.33)	(-1.97)	(-2.58)
Observations	360	360	360	360
R-squared	0.436	0.430	0.425	0.441
Number of pro	30	30	30	30
F test	0	0	0	0
r2_a	0.349	0.342	0.336	0.355
F	25.78	25.15	24.55	26.29

Note: T statistics are in brackets; *, **, *** indicate significant at 10%, 5% and 1% levels respectively.

4.2. Robustness test

This paper uses three methods for robustness checking to verify the robustness of the benchmark regression results above. Table 5 shows the results of the robustness test. The first way is to adjust the sample size. Since the urban economic development of the municipalities directly under the central government in China is relatively early, there is a bias in the impact on AGTFP, so the four municipalities directly under the central government, Beijing, Shanghai, Tianjin, and Chongqing, are considered to be regressed. The second method is to replace the evaluation model of the dependent variable. In this paper, other scholars often use the SBM-ML model to re-calculate AGTFP and perform regression analysis. The third method uses the Generalized Method of Moments (GMM) to estimate the relationship between variables. Considering the timeliness of environmental impact, and the previous AGTFP on the current impact, the dependent variable with a lag of one period was added to the regression model for testing. Table 4 shows the results of the robustness checks. The three methods all show that the impact of DFI on AGTFP is significantly positive, thus demonstrating the establishment of Hypothesis 1 again.

Table 5: Results of robustness tests

	Adjust Sample Size	Replace the Dependent Variable	Change Estimation Method
VARIABLES	AGTFP	SBM-ML	AGTFP
L.AGTFP			0.681***
			(9.94)
DFI	0.023**	0.024***	0.040**
	(2.24)	(3.24)	(2.25)
AGDP	1.023***	-0.245	0.501*
	(3.26)	(-1.05)	(1.71)
GOV	1.008	0.076	0.592
	(1.37)	(0.18)	(1.15)
JOB	-0.629***	-0.104	-0.503***
	(-3.11)	(-0.76)	(-2.92)
EDU	0.032	0.039**	0.066***
	(1.24)	(2.38)	(3.40)
ROAD	0.065**	-0.019	-0.000
	(2.10)	(-0.85)	(-0.01)
INTE	0.122***	0.026**	0.088***
	(7.04)	(2.12)	(4.74)
Constant	-0.794*	0.901***	-0.547
	(-1.92)	(3.05)	(-1.48)
Observations	312	360	330
R-squared	0.453	0.082	0.663
Number of pro	26	30	30
F test	0	0	0
r2_a	0.366	0.061	0.601

F	23.78	2.989	49.68

Note: T statistics are in brackets; *, **, *** indicate significant at 10%, 5% and 1% levels respectively.

4.3. Regional heterogeneity test

The descriptive statistical analysis of variables shows regional differences in DFI and AGTFP in various regions of China, so it is necessary to consider the impact of DFI on AGTFP from the perspective of regional heterogeneity. Table 6 reports the impact of DFI on AGTFP in the eastern, central, and western regions of China. From the regression results of the eastern region: the elastic coefficient of DFI is 0.022, which is significant at the 10% level. From the perspective of the central region: the elastic coefficient of the DFI pair is 0.031 and is significant at the 1% level. From the perspective of the western region: the elastic coefficient of DFI is 0.038, which is significant at the 1% level. Therefore, in the three major regions, DFI can significantly increase AGTFP, again demonstrating the establishment of Hypothesis 1. Overall, the promotion effect of DFI on AGTFP is as follows: "West>Central>East". This situation may be due to the unbalanced development of China's regional economy, production factors, and policy support differences. The eastern provinces have a higher level of economic growth and agricultural ecological environment construction, and the marginal effect of DFI on AGTFP will be minor. The central and western provinces have the characteristics of poor resource endowment and ecological environment, which have the potential to increase AGTFP.

Table 6: Regional heterogeneity test of DFI affecting AGTFP

Region	East	Central	West
VARIABLES	AGTFP	AGTFP	AGTFP
DFI	0.022*	0.031***	0.038***
	(1.91)	(2.69)	(2.76)
AGDP	-0.508	0.808**	3.382***
	(-0.70)	(2.50)	(3.73)
GOV	1.939***	-0.652	1.060
	(2.89)	(-0.61)	(0.61)
JOB	-1.697***	-0.197	-1.415**
	(-6.58)	(-0.91)	(-2.25)
EDU	0.018	0.069**	0.055
	(0.61)	(2.04)	(1.09)
ROAD	0.122***	-0.021	-0.053
	(2.99)	(-0.46)	(-0.70)

INTE	0.107***	0.117***	0.198***
	(4.30)	(4.56)	(5.94)
Constant	-0.770	-0.204	0.050
	(-1.32)	(-0.35)	(0.06)
Observations	144	120	96
R-squared	0.683	0.485	0.588
Number of pro	12	10	8
F test	0	0	0
r2_a	0.619	0.372	0.487
F	27.39	12.81	11.62

Note: T statistics are in brackets; *, **, *** indicate significant at 10%, 5% and 1% levels respectively.

4.4. Mediating effect test

The above literature review analyzes that DFI promotes AGTFP by improving agricultural industrialization and technological innovation. Table 7 shows the regression results of the mechanical test. Column (1) is the basic regression of the first step, columns (2) and (3) are the test of the mediation effect of agricultural industrialization, and columns (4) and (5) are the test of the mediation effect of technological innovation. The impact coefficient of DFI on agricultural industrialization is 0.031, which is significant at the 1% level. After adding agricultural industrialization to the model, the elastic coefficients of DFI and agricultural industrialization on AGTFP are 0.025 and 0.379 and are significant at the 1% level. The impact coefficient of DFI on technological innovation is 0.315, which is significant at the 1% level. After adding technological innovation to the model, the elastic coefficients of DFI and technological innovation on AGTFP are 0.021 and 0.016 and are significant at the 1% level. The SOBEL test results of the two mediating variables are more effective than 0.97, and the mediation effect is relatively substantial. Specifically, the mediating effect of agricultural industrialization on DFI on AGTFP is 10.24%; the mediating effect of technological innovation on DFI on AGTFP is 8.29%.

The mediation effect test proves that DFI promotes AGTFP by improving agricultural industrialization and technological innovation. First, DFI can provide financial support and financial services for more farmers to participate in agricultural production and operation and promote the application of more scientific and practical production methods. Therefore, DFI can increase AGTFP by improving the level of agricultural industrialization. Secondly, DFI brings information payment and big data technology to farmers' production and promotes the innovation of green agricultural technology. Therefore, DFI can increase AGTFP by increasing the level of technological innovation. Based on the above results and discussions, Hypothesis 2 holds.

Table 7: Mediating effect test of DFI affecting AGTFP

	Primary Regression	Agricultural Industrialization		Technological Innovation	
VARIABLES	AGTFP	AGROI	AGTFP	INV	AGTFP
DFI	0.028***	0.031***	0.025***	0.315***	0.021***
	(2.91)	(3.22)	(-2.87)	(3.87)	(3.15)
AGROI			0.379***		
			(4.18)		
INV					0.016***
					(3.27)
AGDP	1.106***	0.150	1.073***	-2.682	1.105***
	(3.57)	(1.39)	(3.45)	(-1.02)	(3.55)
GOV	1.259**	-0.451**	1.358**	-8.231*	1.255**
	(2.21)	(-2.28)	(2.36)	(-1.71)	(2.19)
JOB	-0.800***	-0.398***	-0.712***	-0.864	-0.800***
	(-4.39)	(-6.28)	(-3.62)	(-0.56)	(-4.38)
EDU	0.050**	0.000	0.050**	-0.112	0.050**
	(2.32)	(0.03)	(2.32)	(-0.61)	(2.31)
ROAD	0.061**	0.018*	0.057*	0.607**	0.062**
	(2.07)	(1.76)	(1.92)	(2.42)	(2.05)
INTE	0.130***	0.035***	0.122***	0.358***	0.130***
	(8.09)	(6.24)	(7.05)	(2.64)	(7.96)
Constant	-0.882**	-0.054	-0.870**	-2.425	-0.883**
	(-2.25)	(-0.40)	(-2.23)	(-0.73)	(-2.25)
Observations	360	360	360	360	360
R-squared	0.503	0.422	0.506	0.459	0.503
Number of pro	30	30	30	30	30
F test	0	0	0	0	0
r2_a	0.427	0.333	0.428	0.375	0.427
F	33.74	24.29	29.74	28.19	33.74
SOBEL test		Z=3.84>0.97 The mediating effect is significant.		Z=3.02>0.97 The mediating effect is significant.	
Mediating Effect		The mediation effect accounts for 10.24% of the total effect.		The mediation effect accounts for 8.29% of the total effect.	

Note: T statistics are in brackets; *, **, *** indicate significant at 10%, 5% and 1% levels respectively.

4.5. Spatial panel regression results

Table 8 shows the calculation results of Moran's index. Except for 2011 and 2014, Moran's index of AGTTP is significantly positive, indicating that China's AGTFP has an incredibly positive spatial correlation. The Moran indices of DFI are all quite positive, meaning that DFI has a positive spatial spillover effect. In addition, the Moran index has risen significantly in recent years, indicating that the spatial dependence of AGTFP and DFI is gradually increasing.

Table 8: Global Moran Index for AGTTP and DFI

Year	AGTFP			DFI		
	Moran's I	Z	P-value	Moran's I	Z	P-value
2011	0.065	1.206	0.228	0.105	3.922	0.000
2012	0.032	2.641	0.006	0.130	4.710	0.000
2013	0.014	1.829	0.067	0.127	4.628	0.000
2014	0.079	0.294	0.769	0.126	4.592	0.000
2015	0.008	3.225	0.001	0.097	3.790	0.000
2016	0.084	2.119	0.002	0.124	4.566	0.000
2017	0.101	3.147	0.002	0.131	4.764	0.000
2018	0.154	3.168	0.002	0.142	5.041	0.000
2019	0.145	4.161	0.001	0.145	5.129	0.000
2020	0.133	4.098	0.002	0.138	4.728	0.000
2021	0.148	4.762	0.001	0.157	5.135	0.000
2022	0.158	4.981	0.002	0.162	5.152	0.000

This paper selects the fixed effect spatial Durbin model (SDM) for the model selection through the LM, Hausman, Wald, and LR tests. Table 9 shows the regression results of the SDM. From the results of the primary regression, the elastic coefficient of DFI is 0.015 and is significant at the 1% level, so the development of DFI significantly increases the local AGTFP. In addition, the agricultural economic development, rural education level, road facilities construction, and Internet development level can dramatically improve the local AGTFP. Rural employment can significantly reduce the province's AGTFP. After adding spatial weights, the regression coefficient of W*dfi is -0.044. It is significant at the 1% level, indicating that the development of DFI in adjacent areas has significantly reduced the AGTFP of the province. This situation is due to the "Siphonage" of financial resources in provinces with a higher level of DFI development, which is not conducive to economic catch-up in lagging regions. Secondly, the government is under the pressure of environmental protection policies, and the transfer of agricultural and ecological pollution to surrounding areas will often occur. The rural education level of neighbouring provinces significantly increases the

AGTFP of the region. Improving rural education can strengthen the application of inclusive finance in rural areas and help farmers reasonably apply inclusive rural finance to agricultural production management activities, thereby increasing AGTFP. Therefore, the level of education in rural areas can increase the AGTFP of the local and adjacent provinces.

Table 9: Regression Results of Spatial Durbin Model

Primary Regression		Spatial Weight	
VARIABLES	AGTFP	VARIABLES	AGTFP
DFI	0.015***	W*DFI	-0.044**
	(2.98)		(2.21)
AGDP	1.131***	W*AGDP	-0.463
	（4.04）		(-1.00)
GOV	0.284	W*GOV	0.561
	(0.52)		(-0.03)
JOB	-0.527***	W*JOB	0.207
	(-3.06)		(-1.02)
EDU	0.031**	W*EDU	0.018**
	(2.15)		(2.03)
ROAD	0.067**	W*ROAD	0.016
	(2.23)		(1.06)
INTE	0.078***	W*INTE	0.035**
	(2.61)		(2.31)
Observations		360	
R-squared		0.384	
Spatial rho		0.079*** (3.22)	
Variance sigma2_e		0.019*** (11.61)	

Note: T statistics are in brackets; *, **, *** indicate significant at 10%, 5% and 1% levels respectively.

5. Conclusion and Recommendations

This paper uses the SBM model of unexpected output to calculate AGTFP based on the local data of China from 2011 to 2022. At the same time, with the help of Mediating Effect Model and SDM, tested the influence of DFI on AGTFP. The main research conclusions include: (1) DFI, DIFB and DIG can significantly improve AGTFP. (2) DFI improves AGTFP by improving agricultural industrialization and technological innovation. (3) The DFI of provinces in the central and western regions has a more substantial promotion effect on AGTFP. (5) Both AGTFP and DFI have significant positive spatial spillover effects.

In addition, DFI can significantly increase the local AGTFP and considerably reduce the AGTFP in the surrounding area. Based on the above discussion, the relevant suggestions put forward in this paper are as follows:

First, vigorously promote the development of DFI, especially the coverage and digitalization of DFI, and further comprehensively improve AGTFP. Second, promote technological progress and agricultural industrial structure adjustment. On the one hand, increase investment in scientific research and promote agricultural technology innovation. On the other hand, further, adjust and optimize the structure of the agricultural industry, guide the flow of funds to high-value-added emerging agricultural industries, and improve the efficiency of factor allocation. Third, adhere to the nationwide development idea of "adapting measures to local conditions and making overall plans and coordination". On the one hand, it is necessary to continue to strengthen the support of DFI in the central and western regions and maintain its benign effect on AGTFP. On the other hand, optimize and adjust the DFI in the eastern region, and increase AGTFP in multiple ways. Fourth, improving AGTFP requires coordination among regions. It is necessary to improve the DFI supervision mechanism further and coordinate the agricultural green development mechanism among adjacent provinces. Finally, it is necessary to control the specific areas and directions of DFI support, implement relevant service policies and measures in a targeted manner, and avoid waste and irrational use of financial resources.

6. References

CAREY, D. I. Development based on carrying capacity: A strategy for environmental protection. *Global Environmental Change*, Vol. 3, n. 2, p. 140-148. https://doi.org/10.1016/0959-3780(93)90002-3 . 1993.

CORRADO, G.; CORRADO, L. Inclusive finance for inclusive growth and development. *Current opinion in environmental sustainability*, Vol. 24, p. 19-23. https://doi.org/10.1016/j.cosust.2017.01.013 . 2017.

DENT, J. B.; EDWARDS-JONES, G.; MCGREGOR, M. J.Simulation of ecological, social and economic factors in agricultural systems. *Agricultural systems*, Vol. 49, n. 4, p. 337-351. https://doi.org/10.1016/0308-521X(95)00029-5 . 1995.

DING, C.; LIU, C.; ZHENG, C.; LI, F. Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. *Sustainability*, Vol. 14, n. 1, 216. https://doi.org/10.3390/su14010216 . 2021.

DURU, M.; THEROND, O.; FARES, M. Designing agroecological transitions; a review. *Agron Sustain Dev* . Vol. 35, p. 1237–1257. https://doi.org/10.1007/s13593-015-0318-x . 2015.

GE, H.; LI, B.; TANG, D.; XU, H.; BOAMAH, V. Research on digital inclusive finance promoting the integration of rural three-industry. *International Journal of Environmental Research and Public Health*, Vol. 19, n. 6, 3363. https://doi.org/10.3390/ijerph19063363 . 2022.

GUO, H.; GU, F.; PENG, Y.; DENG, X.; GUO, L. Does digital inclusive finance effectively promote agricultural green development?—A case study of China. *International Journal of Environmental Research and Public Health*, Vol. 19, n. 12, 6982. https://doi.org/10.3390/ijerph19126982 . 2022.

HONG, M.; TIAN, M.; WANG, J. Digital inclusive finance, agricultural industrial structure optimization and agricultural green total factor productivity. *Sustainability*, Vol. 14, n. 18, 11450. https://doi.org/10.3390/su141811450 . 2022.

HU, G.; WANG, J.; FAHAD, S.; LI, J. Influencing factors of farmers' land transfer, subjective well-being, and participation in agri-environment schemes in environmentally fragile areas of China. *Environmental Science and Pollution Research*, Vol. 30, n. 2, p. 4448-4461. https://doi.org/10.1007/s11356-021-16292-1 . 2023.

HUANG, X.; FENG, C.; QIN, J.; WANG, X.; ZHANG, T. Measuring China's agricultural green total factor productivity and its drivers during 1998–2019. *Science of The Total Environment*, 829, 154477. https://doi.org/10.1016/j.scitotenv.2022.154477 . 2022.

JI, X.; WANG, K.; XU, H.; LI, M. Has digital financial inclusion narrowed the urban-rural income gap: The role of entrepreneurship in China. *Sustainability*, Vol. 13, n. 15, 8292. https://doi.org/10.3390/su13158292 . 2021.

JIA, X. Digital Economy, Factor Allocation, and Sustainable Agricultural Development: The Perspective of Labor and Capital Misallocation. Sustainability, 15(5), 4418. https://doi.org/10.3390/su15054418 . 2023.

KIRKENDALL, R. S. The agricultural colleges: Between tradition and modernization. *Agricultural History*, Vol. 60, n. 2, p. 3-21. https://www.jstor.org/stable/3743427 . 1986.

KOMAL, R.; ABBAS, F. Linking financial development, economic growth and energy consumption in Pakistan. *Renewable and sustainable energy reviews*, Vol. 44, p. 211-220. https://doi.org/10.1016/j.rser.2014.12.015 . 2015.

LI, B.; JIANG, F.; XIA, H.; PAN, J. Under the background of AI application, research on the impact of science and technology innovation and industrial structure upgrading on the sustainable and high-quality development of regional economies. *Sustainability*, Vol. 14, n. 18, 11331. https://doi.org/10.3390/su141811331 . 2022.

LI, G.; JIA, X.; KHAN, A. A.; KHAN, S. U.; ALI, M. A. S.; LUO, J. Does green finance promote agricultural green total factor productivity? Considering green credit, green investment, green securities, and carbon finance in China. *Environmental Science and Pollution Research*, Vol. 30, n. 13, p. 36663-36679. https://doi.org/10.1007/s11356-022-24857-x . 2023.

LI, Y. Y.; WILLIS, K. J.; ZHOU, L. P.; CUI, H. T. The impact of ancient civilization on the northeastern Chinese landscape: palaeoecological evidence from the Western Liaohe River Basin, Inner Mongolia. *The Holocene*, Vol. 16, n. 8, p. 1109-1121. https://doi.org/10.1177/095968360606940 . 2006.

LI, Y.; CHEN, C.; LIU, F.; WANG, J. Analysis method of agricultural total factor productivity based on stochastic block model (SBM) and machine learning. *Journal of Food Quality*, 2022. https://doi.org/10.1155/2022/9297205 . 2022.

LI, Y.; WANG, M.; LIAO, G.; WANG, J. Spatial Spillover Effect and Threshold Effect of Digital Financial Inclusion on Farmers' Income Growth—Based on Provincial Data of China. *Sustainability*, Vol. 14, n. 3, 1838. https://doi.org/10.3390/su14031838 . 2022.

LIN, B.; MA, R. How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective. *Journal of environmental management*, 320, 115833. https://doi.org/10.1016/j.jenvman.2022.115833 . 2022.

LIN, Q.; CHENG, Q.; ZHONG, J.; LIN, W. Can digital financial inclusion help reduce agricultural non-point source pollution?—An empirical analysis from China. *Frontiers in Environmental Science*, 10, 2473. https://doi.org/10.3389/fenvs.2022.1074992 . 2022.

LIU, D.; ZHU, X.; WANG, Y. China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. *Journal of Cleaner Production*, 278, 123692. https://doi.org/10.1016/j.jclepro.2020.123692 . 2021.

LIU, Y.; LIU, C.; ZHOU, M. Does digital inclusive finance promote agricultural production for rural households in China? Research based on the Chinese family database (CFD). *China Agricultural Economic Review*, Vol. 13, n. 2, p. 475-494. https://doi.org/10.1108/CAER-06-2020-0141 . 2021.

MA, C.; STERN, D. I. Biomass and China's carbon emissions: A missing piece of carbon decomposition. *Energy Policy*, Vol. 36, n. 7, p. 2517-2526. https://doi.org/10.1016/j.enpol.2008.03.013 . 2008.

MO, Y.; SUN, D.; ZHANG, Y. Green Finance Assists Agricultural Sustainable Development: Evidence from China. *Sustainability*, Vol. 15, n. 3, 2056. https://doi.org/10.3390/su15032056 . 2023.

NORTHRUP, D. L.; BASSO, B.; WANG, M. Q.; MORGAN, C. L.; BENFEY, P. N. Novel technologies for emission reduction complement conservation agriculture to achieve negative emissions from row-crop production. *Proceedings of the National Academy of Sciences*, Vol. 118, n. 28, e2022666118. https://doi.org/10.1073/pnas.2022666118 . 2021.

OZTURK, I.; ULLAH, S. Does digital financial inclusion matter for economic growth and environmental sustainability in OBRI economies? An empirical analysis. *Resources, Conservation and Recycling*, Vol. 185, 106489. https://doi.org/10.1016/j.resconrec.2022.106489 . 2022.

PIAO, S.; CIAIS, P.; HUANG, Y.; SHEN, Z.; PENG, S.; LI, J. ...; FANG, J. The impacts of climate change on water resources and agriculture in China. *Nature*, Vol. 467, n. 7311, p. 43-51. https://doi.org/10.1038/nature09364 . 2010.

REN, X.; ZENG, G.; GOZGOR, G. How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management*, Vol. 330, 117125. https://doi.org/10.1016/j.jenvman.2022.117125 . 2023.

SHEN, J.; ZHU, Q.; JIAO, X.; YING, H.; WANG, H.; WEN, X.; ...; ZHANG, F. Agriculture green development: A model for China and the world. *Frontiers of Agricultural Science and Engineering*, Vol. 7, n. 1, p. 5-13. https://doi.org/10.15302/J-FASE-2019300 . 2020.

Su, J.; Su, K.; Wang, S. Does the digital economy promote industrial structural upgrading?—A test of mediating effects based on heterogeneous technological innovation. *Sustainability*, Vol. 13, n. 18, 10105. https://doi.org/10.3390/su131810105 . 2021.

TANG, X.; DING, S.; GAO, X.; ZHAO, T. Can digital finance help increase the value of strategic emerging enterprises?. *Sustainable Cities and Society,* Vol. 81, 103829. https://doi.org/10.1016/j.scs.2022.103829 . 2022.

WANG, S.,;ZHU, J.; WANG, L.; ZHONG, S. The inhibitory effect of agricultural fiscal expenditure on agricultural green total factor productivity. *Scientific Reports*, Vol. 12, n. 1, 20933. https://doi.org/10.1038/s41598-022-24225-2 . 2022.

WANG, W.; HE, T.; LI, Z. Digital inclusive finance, economic growth and innovative development. *Kybernetes*, Vol. 52, n. 9, p. 3064-3084. https://doi.org/10.1108/K-09-2021-0866 . 2023.

WANG, X.; FU, Y. Digital financial inclusion and vulnerability to poverty: Evidence from Chinese rural households. *China agricultural economic review,* Vol. 14, n. 1, p. 64-83. HTTPS://DOI.ORG/10.1108/CAER-08-2020-0189 . 2022.

WANG, X.; HE, G. Digital financial inclusion and farmers' vulnerability to poverty: Evidence from rural China. *Sustainability*, Vol.12, n. 4, 1668. https://doi.org/10.3390/su12041668 . 2020.

XIAO, Q.; WANG, Y.; LIAO, H.; HAN, G.; LIU, Y. The impact of digital inclusive finance on agricultural green total factor productivity: A study based on China's provinces. *Sustainability*, Vol. 15, n. 2, 1192. https://doi.org/10.3390/su15021192 . 2023.

YANG, C.; MASRON, T. A. Impact of digital finance on energy efficiency in the context of green sustainable development. *Sustainability*, Vol. 14, n. 18, 11250. https://doi.org/10.3390/su141811250 . 2022.

YANG, L.; WANG, S. Do fintech applications promote regional innovation efficiency? Empirical evidence from China. Socio-Economic *Planning Sciences*, Vol. 83, 101258. https://doi.org/10.1016/j.seps.2022.101258 . 2022.

YANG, L.; ZHANG, Y. Digital financial inclusion and sustainable growth of small and micro enterprises—evidence based on China's new third board market listed companies. *Sustainability*, Vol. 12, n. 9, 3733. https://doi.org/10.3390/su12093733 . 2020.

ZHANG, H.; LI, Y.; SUN, H.; WANG, X. How Can Digital Financial Inclusion Promote High-Quality Agricultural Development? The Multiple-Mediation Model Research. *International Journal of Environmental Research and Public Health*, Vol. 20, n. 4, 3311. https://doi.org/10.3390/ijerph20043311 . 2023.

ZHANG, H.; ZHANG, J.; SONG, J. Analysis of the threshold effect of agricultural industrial agglomeration and industrial structure upgrading on sustainable agricultural development in China. *Journal of Cleaner Production,* Vol. 341, 130818. https://doi.org/10.1016/j.jclepro.2022.130818 . 2022.

ZHANG, X.; CHEN, N. Does financial institutions assure financial support in a digital economy for energy transition? Empirical evidences from Markov chain and DEA technique. *Environmental Science and Pollution Research*, Vol. 30, n. 23, 63825-63838. https://doi.org/10.1007/s11356-023-26807-7 . 2023.

ZHAO, J.; LUO, Q.; DENG, H.; YAN, Y. Opportunities and challenges of sustainable agricultural development in China. Philosophical Transactions of the Royal Society B: *Biological Sciences*, Vol. 363, n. 1492, p. 893-904. https://doi.org/10.1098/rstb.2007.2190 . 2008.

ZHENG, Y.; ZHU, T.; JIA, W. Does Internet use promote the adoption of agricultural technology? Evidence from 1 449 farm households in 14 Chinese provinces. *Journal of Integrative Agriculture*, Vol. 21, n.. 1, p. 282-292. https://doi.org/10.1016/S2095-3119(21)63750-4 . 2022.

ZHU, Y.; ZHANG, Y.; PIAO, H. Does agricultural mechanization improve the green total factor productivity of China's planting industry?. *Energies*, Vol. 15, n. 3, 940. https://doi.org/10.3390/en15030940. 2022.