frontiers | Frontiers in Sustainable Food Systems

TYPE Hypothesis and Theory
PUBLISHED 08 January 2025
DOI 10.3389/fsufs.2024.1515207

OPEN ACCESS

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RECEIVED 22 October 2024
ACCEPTED 16 December 2024
PUBLISHED 08 January 2025

CITATION
Xu M, Shi L, Zhao J, Zhang Y, Lei T and Shen Y (2025) Achieving agricultural sustainability: analyzing the impact of digital financial inclusion on agricultural green total factor productivity.
Front. Sustain. Food Syst. 8:1515207.
doi: 10.3389/fsufs.2024.1515207

Achieving agricultural sustainability: analyzing the impact of digital financial inclusion on agricultural green total factor productivity

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Introduction: In order to achieve the sustainable development goal set by the United Nations,it is necessary to promote the green transformation and sustainable development of agriculture. In the context of the global economic digital revolution, examining the impact of digital financial inclusion (DFI) on agricultural green total factor productivity (AGTFP) provided a new perspective for DFI to promote agricultural transformation and upgrading.

Methods: Based on balanced panel data for 30 provinces in China from 2011 to 2022, the study used the slack-based measure (SBM) and global malmquist-luenberger (GML) index to measure AGTFP. Then the entropy method was used to measure the basic condition of digital logistics. Finally, causal relationship and potential mechanism of DFI on AGTFP were verified by means of bidirectional fixed effect and two-stage least square method.

Results: Our findings are as follows: firstly, DFI significantly increases AGTFP. This conclusion is still valid after a series of robustness tests and endogeneity control. Secondly, land transfer and digital logistics play positive mediating roles in the relationship between DFI and AGTFP. Thirdly, DFI has a higher impact on AGTFP in main grain-producing areas and the production-marketing balanced areas.

Discussion: This research provides not only theoretical and empirical support for optimizing China's digital inclusive financial service system and promoting the green development of agriculture but also an important reference for the agricultural development of developing countries.

KEYWORDS

digital financial inclusion, agricultural total factor productivity, land transfer, digital logistics, sustainable agriculture, agricultural carbon reduction

1 Introduction

As a major world agricultural producer, China inevitably produces a large number of pollutants during its agricultural production activities. According to the Second National Pollution Source Survey Report 2020, jointly released by China's environmental authorities, the agricultural pollution sources in China include the following: 10,671,300 tons of chemical oxygen demand; 216,200 tons of ammonia nitrogen; 144,900 tons of total nitrogen; and 212,000 tons of total phosphorus. It can be seen that China is facing serious agricultural pollution hazards, so ensuring the green development of agriculture has become a key issue (Lakhiar et al., 2024). In the midst of the digital transformation sweeping through the global economy, DFI, an innovative financial service paradigm, is progressively reshaping the production methods and resource allocation frameworks of traditional agriculture. As a basic industry of the national economy, agriculture can enhance economic resilience through the inter-sectoral input–output transmission mechanism and holds significant roles in national food security and the construction of ecological civilization. However, traditional agriculture encounters challenges such as costly and difficult-to-obtain financing and information asymmetry, which constrain the enhancement of agricultural production efficiency and the processes of modernization and transformation (Wang et al., 2024a); in this context, DFI, with its inclusive, convenient, and low-cost features, provides a new option for solving the plight of agricultural finance (Bao et al., 2024). DFI extends financial services to the rural grassroots through digital means, enabling small farmers and farming micro-enterprises to access economic resources more conveniently, thus supporting agricultural technological innovation, as well as green transformation and upgrading.

In recent years, as the state has placed significant value on agricultural moderation and green development, the study of AGTFP in agriculture has become a significant topic in assessing sustainable agricultural development. In 2016, the G20 High-level Principles for DFI, officially unveiled at the G20 Hangzhou Summit, comprehensively defined DFI as "encompassing all endeavors aimed at fostering financial inclusion via the utilization of digital financial services." Consequently, the advancement of DFI has escalated to a pivotal position within national and governmental strategies. In 2023, the State Council issued the "Implementation Opinions of the State Council on Promoting the High-Quality Development of Inclusive Finance," outlining the guiding principles, basic principles, and main objectives for advancing the high-quality development of inclusive finance over the following 5 years. The document emphasizes the need to promote the orderly development of DFI, enhance the level of inclusive financial technology, foster a healthy digital inclusive financial ecosystem, and improve the digital inclusive financial regulatory system (Behera and Sharma, 2019; Bao et al., 2024). The basic idea of total factor productivity (TFP), proposed in the scientific literature, has been widely applied in academic circles to measure the quality of economic growth or development (Solow, 1957; Milana and Ashta, 2021). TFP describes the growth degree of "desirable output" driven by innovation or management, such as technological progress and allocation efficiency improvement, excluding tangible factors, such as labor and capital. However, the "undesired output" caused by environmental pollution is not included in the economic growth performance measurement framework (Chang et al., 2023). AGTFP not only focuses on the improvement in agricultural production efficiency but also includes the undesired or "bad" output of pollution emissions into the growth accounting framework and emphasizes the sustainable use of resources and environmental friendliness. In addition, as opposed to traditional total factor productivity, which only measures the input–output efficiency of capital and labor, AGTFP further considers the negative externalities of environmental pollution and can better measure the real level of agricultural green development (Behera and Sharma, 2019). Current research focuses on the influences of technological innovation and policy support on AGTFP, while the role of digital financial inclusion has not been fully explored. While the literature has examined the influences of digital financial inclusion on economic growth, income distribution, and financial inclusion, the mechanism of its impact on the agricultural sector, especially on AGTFP, is not yet clear. Whether DFI, as a nascent financial modality capable of transcending traditional financial barriers and extending its reach to more rural and remote areas, can indeed make a significant contribution to the greening of agriculture remains a subject worthy of thorough investigation.

From the perspectives of DFI and AGTFP conceptual development, the concept of financial inclusion dates back to the 1970s; from the beginning of the 21st century, rapid advancements in big data, blockchain technology, artificial intelligence, and numerous other digital innovations have brought financial services and digital technology into closer alignment, thus giving rise to the emergence of DFI (Milana and Ashta, 2021). DFI not only inherits the core concept of financial inclusion, but also realizes the precision and personalization of services through technological innovation (Chang et al., 2023); it also refers to financial services provided through digital technology, aiming to improve financial accessibility (Guo et al., 2022), especially supporting rural and smallholder farmers (Ge et al., 2022). Studies have demonstrated that DFI can efficiently diminish the cost of financing and bolster the investment capabilities of farmers, thereby facilitating the enhancement of agricultural productivity (Hassan et al., 2022; He et al., 2022; Hashemizadeh et al., 2023). The concept of AGTFP was originally introduced by economists in the 1950s, marking the dawn of a shift toward a green and low-carbon approach to economic development (Li G. et al., 2022). In the context of current advancements in the digital and green economies, the academic community has offered significant insights into the exploration of the integration between DFI and AGTFP; the concept of big data and its application in agriculture has been explored, and the importance of data analysis methods was emphasized (Hua, 2024).

Regarding DFI and AGTFP measures, the research uncovered that the methodology employed to quantify DFI predominantly hinges on the DFI Index, which is meticulously compiled by the esteemed Digital Finance Research Center of Peking University (Li H. J. et al., 2022; Li et al., 2023; Li, 2023). The index encompasses multiple facets, typically incorporating key metrics pertaining to the scope of coverage, the extent of utilization, and the level of digital transformation; the DFI Index is formulated by amalgamating these three components, totaling 46 factors (Liu et al., 2021; Liu C. et al., 2023; Mao et al., 2023; Li et al., 2024; Mo et al., 2024). Additionally, a number of scholars employ the execution and utilization of digital financial inclusion plans and principles across 12 diverse regions as a metric for assessing the extent of digital financial inclusion (Sheraz et al., 2022; Shen and Hu, 2024; Shen et al., 2024; Shi et al., 2024). Certain academics have additionally devised controlled group experiments aimed at piloting digital financial inclusion policies, which serve as metrics for assessing digital financial inclusion (Wang X. et al., 2023; Wang et al., 2022, 2024b). Regarding the assessment of AGTFP, the emphasis lies primarily on empirically evaluating various agricultural indicators through the application of diverse models. Some scholars have devised a data envelopment analysis model, incorporating the Green Luenberger Productivity Indicator (GLPI), in order to quantify green total factor productivity within the agricultural sector (Qiu et al., 2022), while others have measured the inputs and outputs of agriculture utilizing the SBM-ML model to derive the AGTFP index (Wang, 2024), some employed the Super 24-SBM model to assess the Chinese AGTFP, taking carbon emissions into account (Qiu, 2023), and still other scholars employed the highly efficient MetaFrontier Malmquist model, also known as MinDS, to evaluate AGTFP (Zhan, 2022).

From the perspective of DFI's impact on enhancing AGTFP, a prevalent topic in current research endeavors, it has been conclusively demonstrated that DFI exerts a positive influence on augmenting AGTFP, based on existing scholarly investigations. Specifically, DFI fosters the sustainable growth of agricultural production by enhancing farmers' financial accessibility and capital utilization efficiency, thereby empowering them with greater financial autonomy and effectiveness (Xiong et al., 2022). The popularization of digital financial instruments enables farmers to better access credit, which facilitates the implementation of environmentally sustainable technologies, thereby enhancing the overall efficiency of agricultural production (Wang Y. et al., 2023). In addition, digital financial inclusion can improve agricultural resource allocation, reduce resource waste, and enhance the environmental friendliness of agricultural production (Ruan and Jiang, 2024); for example, the introduction of digital payment systems not only simplifies the transaction process, but also reduces transaction costs, enabling farmers to manage production resources more flexibly (Yiğiteli and Şanlı, 2024). At the same time, digital financial inclusion not only streamlines farmers' access to crucial market information, but also significantly bolsters their market competitiveness. Although numerous studies have conclusively demonstrated the favorable influence of DFI on green total factor productivity within the agricultural sector (Li et al., 2023; Shen et al., 2023), there is still a paucity of research on its specific mechanisms. Consequently, it is crucial for future research to intensify its focus on understanding how DFI impacts agricultural productivity through diverse channels, as well as to explore how it can safeguard farmers' economic interests while fostering sustainable agricultural development. In summary, despite the academic community's acknowledgment of the significant influence that DFI exerts on AGTFP, there remains a pressing need for intensified research into its underlying mechanisms of action.

Based on the panel data spanning from 2011 to 2022, encompassing 30 provinces across China, this research is intended to delve into the effects, underlying mechanisms, and regional disparities of DFI on AGTFP, employing rigorous empirical methodologies. First, this research theoretically analyzes how DFI directly enhances AGTFP by reducing transaction costs, increasing capital liquidity, enhancing the accessibility of financial services, etc. Second, this research explores LT and DL as intermediary variables and the indirect impacts of DFI on AGTFP through these paths. Finally, considering that the influence of DFI on AGTFP may be heterogeneous among different regions or producing areas, this research further analyzes the three following regions: main producing area, main selling area, and balanced production and marketing area. Based on these factors, the main marginal contributions and innovations of this research to the existing literature are mainly reflected in the following three aspects:

(1) This paper is intended to explore the impact of DFI development on the growth of AGTFP, expand the measurement range of AGTFP based on SBM-GML, verify the universality of DFI from the perspective of AGTFP, and provide a new theoretical basis, as well as empirical evidence.
(2) It is innovative to select two variables, LT and DL, as the mechanism variables through which to analyze DFI's effect on AGTFP, and further expand the existing theoretical frameworks and practical application results in the fields of agriculture and finance.
(3) According to the different effects of DFI on AGTFP under different regional conditions, the results of this study reveal possible heterogeneity under different agricultural production conditions and market environments in China, filling the research gap on DFI's promotion of AGTFP in different developmental regions.

2 Theoretical analysis and research hypotheses

2.1 Direct effects of DFI on AGTFP

The advancement of DFI has bolstered the accessibility and fluidity of agricultural funds through expanding financial service reach and reducing transaction costs, ultimately fostering an increase in green total factor productivity within the agricultural sector. Specifically, in terms of capital liquidity, DFI improves farmers' capital liquidity through modern financial technologies such as mobile payment and online lending, which enables farmers to access and deploy capital promptly to enhance the efficiency and productivity of agricultural inputs (Bu et al., 2024). Additionally, in terms of risk management, DFI harnesses the power of big data and artificial intelligence technologies to offer tailored agrarian insurance products that assist farmers in mitigating the detrimental effects of natural disasters and market volatility, thereby bolstering the stability and predictability of their agricultural production endeavors (Zhong et al., 2021). Finally, in terms of investment thresholds, DFI promotes technological innovation by simplifying lending procedures and reducing service fees, the intermediary costs for farmers to access external finance, and the economic and psychological thresholds for participation in modern agricultural markets. Accordingly, the following hypothesis was formulated:

> *H*1: DFI can promote AGTFP.

2.2 The role of land transfer

Land transfer (LT) plays an important role in promoting green agricultural development and has a significant impact on the promotion of AGTFP (Lu et al., 2020), revealing the extensive and profound influence of LT on promoting agricultural production efficiency, as well as improving land management structure and the whole agricultural development mode.

(1) Economies of scale and resource allocation effects: According to the theory of economies of scale, the long-term average cost decreases with increasing production scale. The concentration of land resources for large-scale agricultural production not only reduces the fixed costs of agricultural production by saving on lease costs but also reduces variable costs by allowing farmers to obtain more favorable bulk purchase prices, and has also facilitated a green transition in agriculture. By adopting more efficient irrigation systems and organic fertilizers, large-scale production reduces the use of

fertilizers and pesticides, which, in turn, reduces agricultural carbon emissions. In addition, further improvements in production efficiency and lower production costs through the promotion of mechanization, automation, and intelligent production, while reducing energy consumption and waste emissions, contribute to reducing carbon emissions from agriculture; this realization of economies of scale provides strong support for the promotion of AGTFP (Huimin and Jie, 2023). The theory of optimal allocation of resources holds that the market automatically adjusts the distribution of resources on both sides of supply and demand via the law of value through free competition and free choice of "Rational Economic Man," in order to realize the optimal allocation of social resources. The improvement of agricultural production efficiency depends on many factors, such as material capital, human capital, production systems, and technology. Through LT, the rational industrial plans and layouts could be constructed according to market demand and local resource advantages, including the introduction of research and development and the promotion of green agricultural technologies such as soil improvement, water management, and pest control, in order to enhance AGTFP (Wu and Zhang, 2024).

(2) Information diffusion and financial security: By providing low-cost financial services, DFI reduces transaction costs and information asymmetry for LT, thereby promoting efficient land allocation and more rational use. Firstly, DFI improves farmers' abilities to access relevant land market information and reduces both the difficulty and cost of farmers' access to information through digital platforms, enabling them to understand current market information more accurately and make more rational decisions, choose more environmentally friendly methods, and discover more efficient ways of growing. Secondly, DFI helps farmers to gain more capital input through tailor-made financial products such as land mortgage, which not only promotes agricultural production and management activities, but also enhances farmers' abilities to participate in the land circulation market, the funds from which are used to introduce green farming technologies, improve agricultural infrastructure, and promote green modes of production. Thirdly, Digital Pratt & Whitney Finance has obvious advantages over traditional financial instruments, with the application of new digital technology tools such as block chain and digital platforms in agriculture. On the one hand, it can maintain the transparency and legitimacy of financial transactions, thus providing assurance to farmers who use it; on the other hand, the appearance of digital finance reduces the risk of fraud and error for rural residents, thus effectively protecting the basic rights and interests of consumers. Through this method, the transfer of land resources becomes more efficient and secure, contributing to improve land use and production efficiency, thus contributing both directly and indirectly to AGTFP (Yang and Abate, 2024).

On the basis of the above analysis, the following hypothesis was proposed:

> *H2*: DFI can promote AGTFP through LT.

2.3 The role of digital logistics

In exploring the pathways to agricultural modernization and sustainable development, the power of digital logistics (DL) cannot be overlooked, as it has a unique advantage that profoundly influences the improvement of AGTFP, injecting new vitality into the transformation and upgrading of the agricultural economy. Mao et al. (2023) clearly pointed out that DL has become a key driving force for the growth of AGTFP due to its improvement of logistics services and operational efficiency (Pan, 2022). Behind this conclusion lies the profound impact of DL on agricultural production, supply chain management, and the entire agricultural ecosystem.

(1) DL, with its intelligent and information-driven features, has reconfigured the management paradigm of agricultural supply chains, directly facilitating the enhancement of market supply efficiency for agricultural products and the mitigation of environmental burdens. Through the integrated application of advanced technologies, such as the Internet of Things, big data, and cloud computing, DL has accomplished precise monitoring and efficient scheduling of agricultural products throughout the entire chain, from production to consumption (Sun et al., 2024). Thus, DL has not only significantly shortened the circulation time of agricultural products, reducing losses and waste resulting from information asymmetry and logistics inefficiencies, but also decreased carbon emissions and energy consumption in the logistics process by optimizing transportation routes and warehouse layouts, which aligns with the concept of green development and indirectly promotes the growth of AGTFP. As expounded in the production efficiency theory of neoclassical economics, technological progress and the optimization of resource allocation are key factors in enhancing production efficiency (Elbasi et al., 2024), and DL serves as a vivid manifestation of this theory. Additionally, DL improves the accuracy and availability of logistics data, providing a scientific basis for agricultural production decision making and enhancing the precision of agricultural production. Through in-depth mining and analysis of historical logistics data, agricultural producers can accurately grasp market demand trends, rationally adjust planting structures and production plans, and avoid resource waste caused by blind production. Simultaneously, precise logistics data also offer data support for agricultural product pricing and inventory management, further enhancing their overall efficiency and AGTFP.

(2) The vigorous development of DL is inseparable from the robust support of DFI, which offers flexible and diverse financial products and services, such as low-interest loans, supply chain finance, and digital payment solutions, effectively alleviating the financial constraints faced by agricultural producers and logistics service providers, thus enabling them to invest in efficient logistics technologies and equipment, such as automated sorting systems, intelligent warehouses, and cold chain logistics (He and Jiang, 2024). The application of these technologies not only boosts the efficiency and quality of logistics services but also further optimizes supply chain management and reduces logistics costs, directly contributing to the improvement of AGTFP. In this process, the theory of financial deepening is fully validated; that is, the popularization

and deepening of financial services can promote economic growth and improvement of production efficiency. Furthermore, DFI also enhances the transparency and flow speed of funds through integrated digital payment and financial management systems, reduces the operational costs of agricultural enterprises, and achieves cost reduction and efficiency enhancement in agricultural production. This optimization of the capital flow not only reduces the risks and costs of cash transactions, but also improves the efficiency and accuracy of financial management through electronic payments and bill management, providing more convenient and secure financial services for agricultural producers. Simultaneously, DFI utilizes big data and artificial intelligence technologies to precisely identify and assess risks in the logistics process, thereby providing effective risk management tools for agricultural producers and logistics service providers, ensuring the safe conduct of logistics activities, and further promoting the healthy development of DL (Lu et al., 2024).

Therefore, based on the above analysis, the following hypothesis is proposed:

> *H*3: DFI can contribute to AGTFP through DL.

3 Methods and data

3.1 Data sources

Since there is a certain lack of data in the national statistics of Xizang, Hong Kong, Macao, and Taiwan in China, the availability and continuity of data were taken into account; therefore, in order to evaluate the impacts of DFI on AGTFP in a more scientific, reasonable, and accurate manner, panel data from 30 provinces, autonomous regions, and municipalities, collected from 2011 to 2022, were selected for this research, excluding the data of Xizang, Hong Kong, Macao, and Taiwan. For the selected data, the Digital Financial Inclusion Index was derived from the Peking University Digital Financial Inclusion Index (2011–2021), and other variables were derived from the CSMAR and Wind databases, the China Research Data Service Platform (CNRDS), the China Statistical Yearbook, and the China Agricultural and Forestry Management Statistical Annual Report. A few missing values were supplemented via the linear interpolation method, and all variables were treated logarithmically to avoid heteroscedastic deviation caused by extreme values of data. The descriptive statistics of the empirical data are shown in Table 1.

3.2 Empirical model

3.2.1 Benchmark regression model

The chapter on the research hypothesis argues that DFI has a positive effect on AGTFP. To test this hypothesis, this study chose to adopt the fixed effect, the following equation is constructed in conjunction with the setting of the relevant variables:

$$AGTFP_{it} = \alpha_1 + \beta_1 DFI_{it} + \theta_1 Controls_{it} + \nu_i + \mu_t + \varepsilon_{it} \tag{1}$$

TABLE 1 Descriptive statistics.

Variable	N	Average	Standard error	Min	Max
AGTFP	360	0.051	0.0820	−0.059	0.602
DFI	360	5.338	0.666	2.909	6.133
LT	360	3.338	0.583	1.210	4.512
DL	360	−2.093	0.675	−3.816	−0.168
TAX	360	−2.532	0.311	−3.337	−1.670
IL	360	3.719	0.246	2.760	4.078
SC	360	−0.963	0.163	−1.717	−0.684
LL	360	2.023	0.106	1.713	2.182
R&D	360	−4.099	0.720	−6.055	−2.653

In Equation 1, $AGTFP_{it}$ is agricultural green total factor productivity, DFI_{it} is digital financial inclusion, $Controls_{it}$ the set of control variables, $\nu_i$is time-fixed effects, ε_{it} is random error term, the subscript i denotes the province, the subscript t is year; and $\mu_t$is the time-fixed effect.

3.2.2 Mediating effects model

According to the previous analysis, DFI can affect AGTFP both directly and also by promoting the degree of LT and DL. This research extended the basic Model (1) into Model (2) in order to study the mediating effects of the degrees of LT and DL in the relationship between DFI and AGTFP. Due to the serious endogeneity of the traditional three-stage mediating effect model, the two-stage mediating effect model was used in this study, following the methods of the published literature (Shen, 2024; Shen and Zhang, 2024). The specific form of the model is as follows:

$$MED_{it} = \alpha_1 + \beta_1 DFI_{it} + \theta_1 Controls_{it} + \nu_i + \mu_t + \varepsilon_{it} \tag{2}$$

In Equation 2, MED_{it} is the mediating variable, β_1 is the regression coefficient of DFI, and the remaining variables are defined as in Equation 1. In Equation 2, the focus of this study is to check whether the regression coefficient of the DFI is as expected, and whether it passes the significance test, according to the basic principle of the two-stage intermediary effect model. If its regression coefficient is significantly negative, then it can be considered that DFI can achieve this goal through mediating variables when affecting AGTFP.

3.3 Definition of variable

3.3.1 Explanatory variable

Digital financial inclusion (DFI). It refers to the system of providing inclusive financial services to a wide range of consumers and small and micro enterprises through the means of advanced digital technology. To portray the development of DFI in each region, the China DFI Index, jointly compiled by the Digital Finance Research Center of Peking University and Ant Group, was chosen. The index was compiled using Ant Group's nationwide transaction account big data, which contain transaction information from hundreds of millions of users, thus ensuring their breadth and depth (Zhang and Ren, 2022). The index effectively reflects the popularity and quality levels of digital financial services by comprehensively assessing the coverage, usage, and quality of digital finance in each region.

3.3.2 Explained variable

Agricultural green total factor productivity (AGTFP) is an important indicator that comprehensively measures the efficiency of agricultural production and environmental impacts, reflecting the efficiency of agricultural activities in utilizing resources, as well as their environmental friendliness. AGTFP is currently characterized by the data envelopment and indicator system construction methods, as well as stochastic frontier analysis (Zhao et al., 2022; Zhu et al., 2022). This research employed the non-radial and non-angular SBM directional distance function, which incorporates non-consensual outputs, alongside the global Malmquist–Luenberger (SBM-GML) productivity index, to gage AGTFP across various provinces (autonomous regions and municipalities directly under the central government; Zhang L. et al., 2023), which can not only improve the accuracy of AGTFP measurement, but also effectively reflect the relationships between environmental and economic objectives in different regions, as well as demonstrate the dynamic change process of AGTFP in the time series. In the measurement process, the consensual output is expressed as the total output value of agriculture (in the narrow sense of agriculture, i.e., cultivation) at constant prices; the non-consensual output is expressed as the emissions of agricultural surface pollutants (including agricultural fertilizers, pesticides, agricultural films, and agricultural solid waste); and input variables encompass the cultivated land area, the workforce employed in agricultural activities, the aggregate power of agricultural machinery, the adjusted application rates of agricultural fertilizers, and the volume of water utilized for agricultural purposes.

AGTFP is an important index with which to comprehensively measure agricultural production efficiency and environmental impact, reflecting the efficiency of resource utilization and the environmental friendliness of agricultural activities. At present, agricultural AGTFP mainly adopts the data envelopment and index system construction methods, as well as the stochastic frontier analysis method. In order to better measure AGTFP, this research adopted non-radial and non-angular SBM directional distance functions containing non-consensus outputs, two indexes of input and output, respectively, combined with the Slacks Based Measure-Global Malmquist Luenberger (SBM-GML) productivity index. The MAXDEA software version 8.1 was used to accurately measure AGTFP in 30 provinces (autonomous regions and municipalities directly under the Central Government) in China. The specific measurement formula is as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i \tag{3}$$

In Equation 3, E is the total agricultural carbon emission, E_i is the carbon emission of i carbon source, and δ_i is the carbon emission of carbon source i. AGTFP can not only effectively reflect the relationship between environmental goals and economic goals in different regions, but also better show the dynamic change process of AGTFP in a time series. Specific measurement indicators are shown in Table 2.

TABLE 2 AGTFP index system.

Category	Indicators
Desirable output	Total agricultural output at constant price
Undesired output	Agricultural fertilizer emissions
	Pesticide emissions
	Agricultural film emissions
	Solid waste emissions from farmland
Input variables	Crop sown area
	Number of laborers employed in agriculture
	Total power of agricultural machinery
	Agricultural fertilizer conversion application amount
	Agricultural water consumption

3.3.3 Mediating variables

Land Transfer (LT). In China, under the policy guidance of building a strong agricultural country, guaranteeing national food security, and the external impetus of urbanization, the tendency of farmers to "leave farming" and "turn their backs on farming" has increasingly become obvious, and the demand for LT has become more and more urgent. In May 2017, the General Office of the Communist Party of China's Central Committee promulgated the "Opinions on Accelerating the Development of a Policy Framework for Cultivating New Agricultural Management Entities," while the General Office of the State Council issued the "Opinions on Accelerating the Construction of a Policy System and Nurturing Four Core Agricultural Enterprises." Within this overarching policy backdrop, the facilitation of LT holds immense potential to bolster agricultural productivity, a pivotal aspect of agricultural policies globally. Regarding the extent of LT, this research utilized the agricultural land transfer ratio, defined as the proportion of family-contracted farmland that has been transferred, relative to the total operational family-contracted farmland area, as a proxy variable (Huang et al., 2022); this ratio serves as an efficient gage of agricultural land transfer levels and has gained widespread adoption in cross-provincial research endeavors.

Digital logistics (DL). As a crucial component within the contemporary economic landscape, the degree of development in DL directly impacts the operational efficiency of regional economies and the overall responsiveness of the market. This study measures DL from both input and output dimensions. DL input selects the fixed asset investment in the logistics industry, the proportion of transportation in financial expenditure, and the number of employees in the information-based logistics industry as its measurement indicators; meanwhile, DL output is quantified by total express volume, total freight volume, cargo turnover, and value added of the transportation, storage, and postal industries (Zhang L. H. et al., 2023; Zhang Y. et al., 2023). At the same time, the entropy value method was used to standardize and reduce the dimensionality of various indicators of DL, to obtain a comprehensive index of DL. The DL index system and its references are shown in Table 3.

3.3.4 Control variables

Combined with the practices outlined in the existing literature, we selected the five following indicators as control variables in this study. TAX level (TAX), social consumption level (SC), Labor level (LL), industrialization level (IL) and R&D intensity (R&D). From a

TABLE 3 DL indicator system.

Dimension	Norm	Unit
Inputs	Investment in fixed assets in the logistics industry	USD billions
	Fiscal expenditure on transportation/ total fiscal expenditure	USD billions
	Number of employees in the information-based logistics industry	Person
Outputs	Total express volume	Million pieces
	Total freight volume	Tons
	Cargo turnover	Billion tons/km
	Value added of transportation, storage and postal services	USD billions

TABLE 4 Measured control variables.

Variable name	Measurement	Bibliography
Tax burden level	Tax revenue/GDP	Ullah et al., 2024
Social consumption level	Total retail sales of consumer goods/GDP	Wu et al., 2024
Labor force level	Regional employment/ Provincial population	Roy and Dubey, 2023
Industrialization level	Industrial value added/GDP	Liang et al., 2023
R&D intensity	Internal expenditure on R&D/ GDP	He and Wang, 2021

practical point of view, the tax burden level is an important manifestation of the economic distribution relationship reflected by the national tax. The higher the local tax burden level, the higher the local income level, which will directly affect the agricultural development level. The social consumption level reflects the development level of productive forces. The higher the level of productive forces, the higher the agricultural productivity will be. The labor force level determines the comprehensive quality level of the labor force, as well as their ability to master digital finance, which will have direct impacts on agricultural production efficiency and output level. The industrialization level reflects the actual level of productivity and production relations, and the higher the level, the higher the agricultural production capacity. Research and development intensity is an important measure of digital technology investment, representing the agricultural technological level; the higher the level of agricultural technology, the higher the efficiency of agricultural production. To summarize, the above variables are inextricably related to agricultural and financial development, so it is scientific and reasonable to consider them when empirically testing the relationship between DFI and AGTFP. Their specific measurement methods and references are shown in Table 4.

4 Survey result

4.1 Benchmark regression results

Through correlation coefficient calculation, most of the variables were found to be significant at the 1% level, and the results were satisfactory. Before using baseline regression, a variance inflation factor test was also carried out on the participating regress variables, for which the average variance inflation factor (VIF) was 1.49, far less than the critical value of 10, which proves that there is no serious multicollinearity problem between variables. The results of the correlation coefficient test and multicollinearity show that the econometric model constructed in this study passes the test and the results obtained by substituting data are reasonable.

In this study, STATA 18.0 software[1] was used to select a fixed effect model for multiple regression analysis. The advantage of the fixed effect (FE) model is that it can be used to accurately and effectively evaluate the influence between variables. Therefore, this research firstly evaluated the direct influence of DFI on AGTFP, as shown in Model (1) in Table 5, and then added control variables for another regression, as shown in Model (2) in Table 5. It is evident that DFI exerts a pronounced and positive influence on AGTFP, regardless of whether control variables are introduced or not; specifically, the coefficients of 0.038 and 0.033, respectively, underscore this significance, both attaining a 1% level of statistical significance. Consequently, the advancement of DFI is conducive to enhancing AGTFP. Based on the findings from the analysis of control variables, TAX exhibits a prominent negative influence within the model, featuring a coefficient of-0.071, suggesting that a rise in tax burden potentially hinders the advancement of AGTFP. Conversely, the coefficient of R&D amounts is 0.066, which is statistically significant at the 5% level, demonstrating that increased investment in Research and Development (R&D) can contribute positively to the development of AGTFP. IL, SC, and LL are insignificant, and the possible reasons for this include that the imbalance of the development of the industry may mask its potential positive impact on AGTFP; high consumption may not be fully transformed into green and efficient production activities, thus failing to significantly enhance AGTFP; and the effect of the labor force level on AGTFP may be confounded by other unobserved variables.

4.2 Robustness tests

This research employed three distinct methodologies for conducting rigorous robustness testing. First, to avoid the problem of heteroskedasticity and within-group correlation, clustered standard errors were used, thus allowing us to adjust the standard errors by taking into account the within-group correlation in the data, leading to a more robust estimation. Second, the two-stage least squares method (2SLS) was utilized to test for endogeneity by using the explanatory variables, lagged one period as a whole, as an instrumental variable. Finally, before and after indentation of 1% was used to avoid the effect of extreme values in the data.

Based on exhaustive robustness tests, the regression results presented in Table 6 consistently emphasize the significantly positive coefficient of DFI's influence on AGTFP, which is in perfect harmony with the discoveries of prior empirical studies, thus underscoring the robustness of the study's findings across diverse model specifications and control variables and showcasing a high degree of reliability. Specifically, in Model (5), the coefficient of DFI stands at 0.029 and is

1 Accessible website: https://www.stata.com/

TABLE 5 Regression results.

Variable	(1) AGTFP	(2) AGTFP	(3) LT	(4) DL
DFI	0.038***	0.033***	0.347***	0.119***
	(0.007)	(0.010)	(0.037)	(0.027)
TAX		−0.071**	0.146	0.122
		(0.033)	(0.205)	(0.153)
IL		0.080	−0.433**	−0.393**
		(0.058)	(0.206)	(0.174)
SC		−0.038	−0.020	0.090
		(0.067)	(0.208)	(0.126)
LL		−1.214	−1.805	4.015
		(1.263)	(2.082)	(2.456)
R&D		0.066**	−0.396*	0.375***
		(0.032)	(0.200)	(0.124)
Constant	−0.153***	2.090	5.473	−7.455
	(0.038)	(2.476)	(5.060)	(5.083)
Time-fixed effect	Yes	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes	Yes

***, **, and * indicate significance at the 1, 5, and 10% levels, respectively, with robust standard errors in parentheses.

TABLE 6 Result of robustness test.

Variable	(5) AGTFP	(6) AGTFP	(7) AGTFP
L. AGTFP		0.684***	
		(0.082)	
DFI	0.029***	0.019**	0.029***
	(0.009)	(0.008)	(0.009)
TAX	−0.063**	−0.009	−0.063**
	(0.029)	(0.024)	(0.029)
IL	0.047	0.065	0.047
	(0.047)	(0.065)	(0.047)
SC	−0.014	−0.052	−0.014
	(0.062)	(0.057)	(0.062)
LL	−0.991	−0.992	−0.991
	(1.168)	(0.803)	(1.168)
R&D	0.060*	0.057**	0.060*
	(0.029)	(0.026)	(0.029)
Constant	1.797	1.844	1.797
	(2.288)	(1.569)	(2.288)
Time-fixed effect	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes

***, **, and * indicate significance at the 1, 5, and 10% levels, respectively, with robust standard errors in parentheses.

statistically significant at the 1% level, clearly demonstrating that DFI exerts a significant and positive influence on AGTFP. In Model (6), the coefficient of DFI is 0.019; despite the fact that this coefficient falls below the level observed in Model (5), this discrepancy could potentially stem from a decrease in the sample size. Within Model (7), the coefficient of DFI stands at 0.029, attaining statistical significance at the 1% threshold, thereby reinforcing the substantial positive influence of DFI on AGTFP, a result emphasizing that the positive effect of DFI is consistent across different model settings and robustness tests.

4.3 Tests for mediating effects

Because the traditional three-step method of mediating effects is suitable for psychological research, the test of mediating effects in economics may not be reliable, and there are some problems such as endoplasmic bias and unclear identification of some channels; therefore, this research adopted method proposed by Proksch et al. (2024) to examine the underlying mechanism by closely observing the influence of core independent variables on intermediary variables. The impacts of LT and DL on AGTFP have been explained in the theoretical mechanism section, and the mechanism test steps are shown in columns (3) and (4) of Table 5.

In Model (3), the DFI coefficient is 0.347, which is statistically significant at the 1% level, a finding which highlights the important role of DFI in advancing the degree of LT, thus confirming hypothesis H2. A possible reason for the positive impact of DFI on land is that digital finance provides more information and resources, thus providing more efficiency and flexibility to land resource allocation; for example, by improving the efficiency of LT and optimizing the allocation of land resources through digital technology, farmers, as the main body of agricultural production and management, can transfer land with low utilization rates to a management body with the ability and willingness to carry out efficient agricultural production, so as to further improve the utilization and output rates of land resources, thus helping to improve agricultural production efficiency and provide basic support for sustainable agricultural development.

In Model (4), the DFI coefficient was 0.119, which was also statistically significant at the 1% level. The results show that the development of DFI plays an important role in promoting the development of DL, thus verifying hypothesis H3. A possible reason for the positive impact of DFI on DI is that the digital financial platform integrates big data and blockchain technology, which can provide financing support for farmers, lower the threshold of farmers' access to financial services, optimize supply chain management, and promote information sharing. In addition, with the development of DFI, DL capital investment and output efficiency both increases. For example, the digital financial platform can reduce the transaction costs of farmers due to information asymmetry, and farmers can use the DL platform to purchase, produce, and sell agricultural products; promote the production passion of agricultural enterprises and farmers; and promote the improvement of comprehensive agricultural benefits.

4.4 Heterogeneity analysis

Considering the special industrial characteristics of agriculture, this research divided 30 provinces in China into main grain-producing areas, main grain-marketing areas, and balanced production and marketing areas to explore the heterogeneity of DFI affecting AGTFP in different regions. The division results are as follows: the primary grain-producing regions encompass 13 provinces, including Heilongjiang, Jilin, and Liaoning, among others, regions that usually have superior geographic, soil, and climate conditions, which not only ensure self-sufficiency, but can also transfer large quantities of commodity grains; the main grain-marketing areas include Beijing, Tianjin, Shanghai, and seven other provinces that are relatively economically developed, but have large populations and little land, with large gaps in grain production and demand, and the need to transfer large quantities of grain in to meet supply; the production and marketing balanced area includes 10 provinces, such as Shanxi, Ningxia, and Qinghai, where food production and consumption are relatively balanced and do not require large transfers in or out.

The findings are presented in Table 7, wherein Model (8) reveals the regression outcomes specific to the primary food-producing region. Notably, the coefficient of DFI fails to attain significance, potentially suggesting that, despite the region's advantageous circumstances for food production, the direct influence of digital financial inclusion on enhancing AGTFP remains constrained, possibly due to the fact that financial services in the region are already more mature, or because the rates of technology uptake and transformation are close to saturation. Model (9) presents the regression outcomes for the primary grain-marketing region, revealing a DFI coefficient of 0.042, which signifies a substantial positive influence at the 1% significance level, underscoring the efficacy of DFI in bolstering AGTFP within provinces that exhibit a harmonious balance between grain production and marketing. Model (10) presents the regression outcomes for balanced production and marketing regions, with a DFI coefficient of 0.043, demonstrating a statistically significant positive impact at the 5% level. In general, there exists a notable disparity in the influence that varying levels of economic development and industrial structures across distinct regions exert on both DFI and AGTFP. In terms of the enhancement effect of DFI on AGTFP, the effect of DFI is most significant in the main grain-marketing area, followed by the balanced production and marketing area, while the effect is relatively weak in the main grain production area. The economic status and distribution of resources in the primary grain-marketing region and the balanced production and marketing zone are comparatively equitable. The primary function of DFI in these areas is evident in optimizing resource allocation, augmenting the accessibility of financial services, and bolstering the assimilation and implementation of agricultural technology, thereby fostering the enhancement of AGTFP. The role of DFI in improving AGTFP in the main food-producing areas is not as significant as expected, probably because these areas have superior natural conditions and more mature agricultural infrastructure, and their traditional financial services are already more developed; therefore, the marginal impact of DFI is relatively lower.

TABLE 7 Heterogeneity analysis model results.

Variable	(8) Main grain production area	(9) Main grain-marketing area	(10) Production and marketing balanced area
DFI	0.017	0.042***	0.043**
	(0.020)	(0.010)	(0.016)
TAX	−0.101	0.077	−0.004
	(0.067)	(0.095)	(0.048)
IL	0.089	0.087	0.036
	(0.138)	(0.067)	(0.104)
SC	−0.031	0.060	−0.269**
	(0.100)	(0.088)	(0.115)
LL	−3.232	−0.295	0.735
	(2.759)	(0.789)	(0.630)
RD	0.041	0.054	0.149**
	(0.063)	(0.090)	(0.049)
Constant	6.210	0.514	−1.374
	(5.182)	(1.830)	(1.469)
N	156	84	120
Time-fixed effect	Yes	Yes	Yes
Individual-fixed effect	Yes	Yes	Yes

***, **, and * indicate significance at the 1, 5, and 10% levels, respectively, with robust standard errors in parentheses.

5 Discussion and policy implications

5.1 Discussion

This study explores the influence of Chinese DFI on AGTFP, and the conclusion shows that DFI has a significant promoting effect on AGTFP, which verifies the hypothesis H1 in this paper. This finding is consistent with the results of the previously published literature (Liu D. et al., 2023; Shen et al, 2023; Jin and Zhong, 2024). In fact, the green development of agriculture cannot be separated from the support of financial funds, as the support of digital technology and inclusive funds will not only reduce the cost of agricultural production, but also stimulate the passion of rural enterprises and the rural labor force to develop the agricultural industry, so as to improve the efficiency of agricultural production and achieve rapid development of the agricultural industry. At the same time, with the rapid development of digital economy and digital finance, DFI has achieved substantial development. In addition, the study showed that LT and DL played a mediating role in the influence of DFI on AGTFP, confirming the hypothesis H2 and H3. Significantly contribute to the improvement of AGTFP, thus suggesting that DFI can indirectly enhance the efficiency and effectiveness of agricultural production by optimizing land resource allocation and improving logistics efficiency, findings which are consistent with those of Xie (2023). In essence, LT and DL play important roles in promoting the green development of agriculture. Specifically, the growth of land use efficiency will promote the improvement of agricultural production efficiency, while the application of DL will stimulate the enthusiasm for agricultural production and drive agricultural development.

10.3389/fsufs.2024.1515207

5.2 Policy implications

Based on the three aforementioned empirical conclusions, this research proposes the following three policy recommendations for China and developing countries as references:

First, in order to strengthen the design and implementation of regional financial policies, it is necessary to formulate targeted financial policies and support measures according to the actual needs and infrastructural conditions of different regions. In the main grain-marketing areas and regions with balanced production and marketing, the depth and breadth of financial services can be promoted by increasing financial technological investment in order to stimulate the potential of AGTFP in these regions; for example, the introduction policy of financial technology can be optimized, the taxes and fees of financial technology can be reduced, the construction and use of agricultural digital platforms can be increased, and the application of digital finance according can be popularized according to local conditions in these regions. In major grain-producing areas, the popularization of basic financial services should be considered in order to improve farmers' acceptance and efficiency of existing financial products. For example, the digital transformation of traditional financial institutions will lower the threshold of farmers' access to financial services, so that more farmers can enjoy convenient services brought by digital finance, thus improving agricultural production efficiency.

Second, optimize LT allocation and DL efficiency systems. Promote the transparency and standardization of the land transfer market and use digital technology to improve the information symmetry of LT and reduce transaction costs, which would strengthen the construction and upgrading of rural logistics infrastructure; utilize cloud computing, big data, and other technologies to improve the efficiency of logistics management; shorten the supply chain; and reduce operating costs. These proposed measures will, in turn, help to realize the efficient flow of agricultural products from field to table and improve the greening of the entire agricultural production chain.

Third, increase research and development on financial technological innovation. Set up a specialized agricultural fintech innovation fund to support the research and development of new financial products and services, for example, smart credit, precision insurance, and blockchain-based supply chain financial solutions. Focus on innovative technologies that can solve practical problems in agricultural production and optimize agricultural insurance products through data analysis while using industrial finance as a carrier, accelerating the integration and development of DFI and the transformation of modern agriculture, innovating the investment and financing model of agricultural credit support, improving the investment and financing mechanism in the agricultural sector led by the government with the diversified participation of the society, and promoting the process of deepening agricultural capital.

5.3 Research limitations and future prospects

Future research endeavors can be directed toward the two following pivotal dimensions: Firstly, the enhancement of sample data refinement in necessary; while the provincial-level sample data employed in this study offer a comprehensive macro-analytical perspective, future investigations ought to augment the granularity of the sample data to delve deeper into the nuanced impacts of DFI on AGTFP across diverse geographical regions, extending the scope to encompass prefecture-level cities and potentially even counties, which would enable us to identify with greater precision the diverse impacts across various geographic and economic settings. Secondly, a thorough assessment of policy effects is crucial; despite utilizing a fixed effects model to assess the connection between DFI and AGTFP, the examination of policy impacts remains incomplete. Future research endeavors ought to integrate a more comprehensive evaluation framework through which to explore the long-term outcomes and potential implications of DFI on AGTFP.

6 Conclusion

Based on a detailed analysis of panel data from 30 provinces in China (excluding Xizang, Hong Kong, Macao, and Taiwan) from 2011 to 2022, this research deeply discusses the Impact of DFI on AGTFP, and draws the following three core conclusions:

(1) The benchmark regression outcomes reveal a substantial and positive impact of DFI on AGTFP, a finding that persists even after incorporating control variables. At the same time, robustness tests confirm the reliability of these findings, with various model specifications and adjustments to control variables failing to significantly alter the conclusion that digital financial inclusion has a positive effect on AGTFP. This underscores the pivotal role that the expansion of DFI plays in enhancing the efficiency of agricultural production.
(2) The mediation effect test further reveals the specific mechanism by which DFI affects AGTFP, in which LT and DL, as important mediating variables, significantly contribute to the improvement of AGTFP. This suggests that DFI can indirectly enhance the efficiency and effectiveness of agricultural production by optimizing land resource allocation and improving logistics efficiency.
(3) The heterogeneity analysis results reveal that DFI exhibits heterogeneity across diverse grain-producing regions. Specifically, DFI markedly elevates AGTFP in the primary grain marketing region and the equilibrium zone of production and marketing, whereas its impact remains insignificant in the primary grain production area. China's main grain-producing areas have better agricultural production conditions, higher comprehensive quality of rural labor, lower application cost, and higher application depth of DFI, which can better promote the growth of AGTFP.

To summarize, the actual contribution of this research is mainly reflected in that, taking China as an experimental sample, this research not only discuss the influence of DFI on AGTFP from the theoretical level but also verify how DFI affects AGTFP from the empirical level, thus helping to enrich the research between DFI and AGTFP. On the one hand, it can provide ideas for sustainable agricultural development in China in the future; on the other hand, it can also provide practical experience for other developing countries to promote agricultural development and provide important ideas for realizing the green and sustainable development of global agriculture.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: data derived from public domain resources. The data presented in this study are available in China Statistical Yearbook (https://data.stats.gov.cn/easyquery.htm?cn=E0103) and Express Professional Superior data (https://www.epsnet.com.cn/index.html#/Index).

Author contributions

MX: Data curation, Methodology, Software, Writing – original draft. LS: Investigation, Methodology, Validation, Writing – original draft. JZ: Data curation, Formal analysis, Software, Writing – original draft. YZ: Data curation, Formal analysis, Methodology, Software, Writing – original draft. TL: Methodology, Supervision, Software, Formal analysis, Writing – review & editing. YS: Conceptualization, Formal analysis, Funding acquisition, Project administration, Software, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the National Social Science Foundation of China (grant number: 22BH153); the Research Innovation Project of Southwest University of Political Science and Law (grant number: 2024XZXS-078), the program of Chongqing Municipal Education Commission (grant number: 24SKJD010), the program of Sichuan Police Law Enforcement Research Center (grant number: JCZFQN202402), the Chongqing Graduate Research and Innovation Project of Chongqing Municipal Education Commission (grant number: CYB240183), and the program of Chongqing Municipal Education Commission (grant number: KJQN202400318).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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