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Digital Financial Inclusion, Land Transfer, and Agricultural Green Total Factor Productivity

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Abstract: Improving agricultural green total factor productivity is important for achieving high-quality economic development and the SDGs. Digital inclusive finance, which combines the advantages of digital technology and inclusive finance, represents a new scheme that can ease credit constraints and information ambiguity in agricultural production. First, this study focused on agro-ecological functions; we incorporated total agricultural carbon sequestration and emissions extraction into the evaluation system and used the mixed-direction-distance function to calculate agricultural green total factor productivity. Then, based on panel data from 31 provinces in China collected from 2011 to 2021, we used the two-way fixed effect model, the interactive fixed effect, and the plausibly exogenous variable method to test the impact of digital financial inclusion on agricultural green total factor productivity, and its mechanism of action. The panel-corrected standard error and fixed effect Driscoll–Kraay methods were used to account for the unobserved heterogeneity and cross-section dependence in the panel data. The results showed that digital financial inclusion can significantly improve agricultural green total factor productivity. This conclusion remained valid following robustness tests using the spatial econometric model and the method of changing explanatory variables. Digital financial inclusion can improve agricultural green total factor productivity by facilitating the transfer of agricultural land. Sound digital infrastructure and strict green credit policies enhance the role of digital inclusive finance in promoting the green development of agriculture. These conclusions could help the financial sector to formulate flexible, accurate, reasonable, and appropriate financial policies and products that would support agriculture, and enhance the role of digital inclusive finance in promoting sustainable agricultural development.

Keywords: digital financial inclusion; agricultural green total factor productivity; agriculture carbon emission; land transfer; total carbon sink; carbon neutrality; green finance

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1. Introduction

The sustainable development of agriculture and food systems is central to the Sustainable Development Agenda proposed by the United Nations in 2015, dominating eight of the seventeen SDGs [1]. On the one hand, agriculture has distinct industrial characteristics that are influenced by climate change and should be paid attention to and studied. The current carbon sink capacity is not enough to offset the greenhouse gases produced via production processes, which poses a serious threat to global food security, human health, and sustainable economic and social development [2]. Carbon emissions caused by human activities are a significant cause of global climate change, and agriculture is the main contributor to global carbon emissions, accounting for 30% of the world's total [3,4]. According to the UN Food and Agriculture Organization (FAO), carbon emissions from the global agri-food system increased by 16% between 1990 and 2019, reaching 17 billion tons of carbon dioxide equivalent (CO_2-eq) in 2019, and thus accounting for 31% of global anthropogenic carbon emissions. This proportion is rising. On the other hand, the global food system—dominated by food production and consumption—has also become an essential factor contributing to ecological and environmental problems, such as land degradation, freshwater resource depletion, atmospheric nitrogen deposition, water eutrophication, and soil acidification [5–8]. For example, disorderly and improper land use behaviors have led to rural land pollution, water pollution, and air pollution. Operations relying on large amounts of pesticide and fertilizer input have caused severe agricultural non-point source pollution. Research data show that the utilization rate of fertilizers and pesticides in China is less than 1/3, the recovery rate of mulching film is less than 2/3, the effective treatment rate of livestock and poultry manure is less than 50%, and the rates of straw burning and water eutrophication are severe [9]. According to the Second Bulletin of the National Survey of Pollution Sources released in 2020, the chemical oxygen demand, total nitrogen, and total phosphorus emissions of water pollution from agricultural sources in China for this year reached 10.6713 million tons, 1.4149 million tons, and 212,000 tons, respectively, accounting for 49.77%, 46.52%, and 67.22% of the national total.

In this critical period of high-quality economic development, economic development must shift from its past reliance on resource growth to improving total factor productivity (TFP). Due to the rapid development of conventional agriculture in China over the past 40 years, the agricultural production environment has been hugely damaged, mostly reflected in the quality of cultivated land and soil, which has led to serious agricultural product safety problems. The excessive application of chemical fertilizers and pesticides and the unreasonable disposal of livestock manure have overwhelmed natural ecosystems' purification and recovery capacities, which has had a significant impact on the agricultural environment. Green development prioritizes the environment and resources as the main elements of economic progress, green and low carbon acts as its main principle, and the sustainable development of the economy, environment, and society acts as its goal. As the foundation of the national economy, the positioning and function of green development in agriculture are particularly important, and are essential for protecting people's health and the virtuous cycle of the ecosystem, the atmospheric environmental system, and the economic and social systems. China's agricultural development has relied on excessive resource consumption for a long time, and the rural ecological environment is now sending distress signals. Therefore, agricultural development has now reached an important period in which it must change from the model of "sacrificing the environment for economic growth" [10]. It is necessary to significantly improve AGTFP, alleviate the negative effects of environmental pollution, and achieve sustainable economic development.

The AGTFP system also aims to identify and prioritize key technologies that can help increase agricultural productivity and efficiency, reduce environmental impacts, and improve the quality and safety of agricultural products. It also aims to promote the adoption of new technologies by farmers and facilitate cooperation between researchers, extension workers, and other stakeholders in the agricultural sector. Improving AGTFP, especially its technological development component, is the main driving force for the substantive development of Chinese agriculture. The goal of "double carbon" represents a new direction for agricultural development, aimed at "climate-smart agriculture" (CSA) through the use of sustainable agricultural technologies, such as conservation agriculture, agroforestry, and crop diversification, in order. This is designed to achieve a reduction in greenhouse gas emissions from agriculture and food systems, enhance the flexibility to adapt to climate change, and ensure the sustainable improvement of agricultural productivity. In this context, the Chinese government has identified not only agriculture but also rural areas and farmers as a top priority in its efforts to achieve rural revitalization and modernization. The Strategic Plan for Rural Revitalization (2018–2022), initiated by the CPC Central Committee and The State Council, stresses the importance of "continuously improving agricultural innovation, competitiveness and total factor productivity." Introducing modern agricultural machinery and equipment, accelerating strategic scientific and technological innovation, changing the quantitative growth mode whereby agriculture depends on factor input, and promoting AGTFP are essential for upgrading agricultural production. Changing the quantitative growth mode of agriculture (which currently relies on factor inputs), improving farmland soil quality and carbon sequestration capacity, and significantly improving the degree of green production and resource utilization efficiency are not only important factors for achieving the "double carbon" goal but are also important ways to achieve high-quality agricultural development. In this context, the key strategy for achieving the established goals is to improve the Agricultural Technology Foresight and Priority-setting (AGTFP) system, which guides the development of China's agricultural technology.

With the rapid developments seen in this era of scientific and technological revolution, digital technologies, such as big data, cloud computing, and block-chain, are being integrated across borders, and have been applied in various fields of the economy and society. This approach has spawned new economic forms, including the platform economy and crowdsourcing economy, and the digital economy is undergoing unprecedented and rapid development. The service form of the financial industry has also undergone a fundamental change, and digital trends are becoming increasingly prominent in financial services. Traditional finance pays more attention to the market environment and economic benefits, and thus cannot address the financing challenges of agricultural production. Digital financial inclusion (DFI), as a financial form matching the digital economy, combines the ideas of inclusive finance with convenient and efficient application. It thus expands the breadth and depth of financial services, opens up the "last mile" of financial services to agriculture and rural areas, realizes unity in terms of efficiency and fairness, and provides a new plan for promoting the AGTFP [11–13]. The effects of DFI are mainly "stock optimization" and "incremental supplement," and it thus not only supplements the traditional financial service system but also profoundly changes and reshapes enterprises' production and business activities. In 2020, the Rural Revitalization Bureau and five other departments jointly issued the Key Points of Digital Rural Development in 2022, which proposed the continuous promotion of the development of DFI in rural areas, the research into and development of financial products suitable for the needs of agricultural operators, and the expansion of mobile payment convenience services to rural areas. In 2021, the State Council issued the Peak Carbon Dioxide Emissions Action Plan for 2030, which emphasized the central role of finance in reducing peak carbon dioxide emissions. According to the McKinsey Global Institute, China is becoming a world digital leader, especially in the area of digital finance. Given the importance of DFI in eliminating information asymmetry, easing farmers' financing constraints, and promoting the adoption of green technologies, this study focuses on analyzing the impact of DFI on AGTFP, and the mechanism of this action, in order to provide empirical evidence and a theoretical basis to help relevant market players to respond in a timely way.

2. Literature Review

Driven by financial resources and digital technology, the issue of how to actualize the full potential of DFI in relation to AGTFP and adapt finance to better serve agriculture and rural areas has become an area of intense focus amongst the government and scholars in recent years. According to the existing literature, research related to the subject of this paper can be roughly divided into the following aspects.

The first aspect concerns the method of measuring and indexing the construction of AGTFP. Most scholars use the random frontier method, data envelopment analysis, the Solow residual method, or the algebraic index method to calculate and analyze AGTFP in different regions. Among them, the use of the modified-radial-distance function and the mixed-distance function, derived from the data envelopment analysis method, has become the most common method [14,15]. Huang et al. and Geng et al., respectively, used the directional-distance function and the mixed-distance function to measure the AGTFP in China and describe its temporal and spatial evolution and convergence [15,16]. Both showed that the AGTFP was increasing year by year, and there were obvious regional differences. At the same time, they also pointed out that the improvement of technical efficiency plays a key role in promoting the green transformation of agricultural development. Apart from the differences in measurement methods, the evaluation index systems constructed were also slightly different. Most studies build an accounting system based on the carbon emissions generated by the agricultural films, the pesticides, and the agricultural machinery used in agricultural production and operation [17–19]. A few scholars found that the unreasonable use of pesticides and fertilizers, and the improper disposal of agricultural livestock and poultry manure, will cause pollution to the soil, air, and agricultural products. For example, Huang and Hu addressed solid pollutants, chemical fertilizer pollutants, livestock and poultry, and other pollution sources, and calculated agricultural non-point source pollution, using this as the unexpected output when constructing the AGTFP [14,20].

The second area of focus is exploring the effects on AGTFP from different perspectives. For example, Sun et al. investigated the nonlinear effect of environmental regulation on AGTFP, and pointed out that there is a threshold effect of environmental regulation on AGTFP; that is, when the threshold interval of environmental regulation intensity is reached, its negative effect on AGTFP gradually increases [21]. Liu et al. pointed out that urban expansion can significantly inhibit AGTFP in a given region, but because of the presence of spatial and geographical correlation, urban sprawl is conducive to the improvement of AGTFP in neighboring cities [22]. Ge et al. proposed that registered residence urbanization and permanent urbanization can improve AGTFP by optimizing factor allocation, capital expansion, and technological spillover [23]. Hong et al. pointed out that both the import and export of agricultural products can promote the improvement of AGTFP, and rural finance is an important mediating channel [24]. Yu et al. explored whether China's pilot carbon emissions trading policy will promote the improvement of AGTFP. The results show that the pilot policy exerts strong environmental-regulatory and technological innovation effects to improve AGTFP [25]. There are also studies on crop insurance [26–28], agricultural fiscal expenditure [29], agricultural services [30], economic agglomeration [31], green technology [32], and digital agriculture [33] that cannot be ignored in promoting the improvement of AGTFP.

Thirdly, research has focused on the mechanisms and paths by which innovation in DFI affects green total factor productivity (GTFP). As the lifeblood of the economy, finance is vital for promoting the green development of agriculture. Internationally speaking, fintech effectively promoted inclusive finance development and financial services in rural areas. Through essential financial services, such as micro-loans, transfer remittances, payments, and settlements, fintech has improved the lifestyle, ecological environment, health, and incomes of rural residents, and contributed to the development of agriculture and rural areas. From the perspective of domestic practice, fintech not only promotes the development of inclusive finance but also plays an essential role in the modernization of the agricultural industry, the facilitation of rural public services, and the construction of a rural credit system [33]. DFI integrates traditional finance and emerging finance. With the continuous innovation and development of digital technology, DFI is advancing further still. For example, the "Internet finance + agricultural value chain" model connects digital technology with rural financial markets, providing a financing service with controllable risks for "agriculture, rural areas, and farmers". By supporting the construction of agricultural infrastructure, the development of featured agricultural products, the expansion of small and micro enterprises in rural areas, and education and medical care in rural areas, digital financial inclusion will inevitably promote the modernization and clean development of the agricultural industry chain [34]. Most scholars believe that DFI will affect AGTFP by relaxing financing constraints [35], strengthening environmental governance [36], promoting regional entrepreneurship [37], correcting factor mismatch [38], and boosting consumption [39]. Guo et al. and Li et al. showed that green finance can improve AGTFP by guiding funds toward green and environmentally friendly agricultural projects and limiting the negative externalities of highly polluting enterprises through social supervision [40,41].

To sum up, many valuable studies have been undertaken on DFI and AGTFP, yielding ideas and empirical insights that will help this paper to explore the mechanism of influence of DFI on AGTFP. However, there are still some flaws in the existing literature, such as:

1. The evaluation index system, established in the existing literature for measuring AGTFP, only considers the undesired output of agricultural carbon emissions, ignoring the dual attributes of agricultural production, namely, carbon source and carbon sink. Ignoring the total ecological value of agriculture will make its evaluation inaccurate;
2. The existing literature mainly uses the directional-distance function when evaluating China's overall agricultural green total factor productivity. This method needs to be improved in order to deal with a situation in which the evaluation system contains both the expected and the unexpected output;
3. The existing literature analyzes the impact of digital financial inclusion on agricultural green total factor productivity by mainly using geographical location to divide samples according to regional resource endowment and economic development. This method attaches too much importance to economic development and needs to incorporate institutional, technological, and policy factors. In addition, the existing literature has yet to reveal the role and action of land transfer (LT) in DFI's effect on AGTFP.

Therefore, the potential innovations of this paper are as follows: (1) We focus on the ecological function of agriculture, and bring the total carbon sink and carbon emissions of planting into the evaluation system of AGTFP, using the mixed-direction-distance function to calculate them. (2) In assessing the mechanism of DFI's influence on AGTFP, this paper innovatively introduces the intermediary variable of agricultural land transfer and then expands the perspectives and content of research on digital finance in relation to its support for green agricultural development. Improving agricultural production efficiency and activating the surplus rural labor force by facilitating the orderly circulation of rural land has become a meaningful way to promote agricultural economic development. (3) Different from the method of heterogeneity analysis applied to sample division that is based on simple geographical location, this paper divides samples according to the perfection of digital infrastructure and the intensity of environmental regulation and it analyzes the heterogeneous influence of DFI on AGTFP. (4) This approach allowed us to indirectly evaluate the effectiveness of the green financial reform pilot zone and the national big data comprehensive experimental zone in relation to the green development of agriculture. Our conclusions will help administrative departments, enterprise managers, and financial institutions in taking the relevant measures that will make up for the defects discussed.

3. Theoretical Analysis and Research Hypothesis

3.1. Direct Impact of DFI on AGTFP

The low and disparate demands for agricultural funds, and the difficulty of collecting credit information, make it difficult for the agricultural sector to obtain support from traditional financial institutions. DFI, which is based on digital technology, can significantly improve the fund-matching efficiency, and thus the availability, of financial services in the agricultural sector at low cost, thus promoting the improvement of AGTFP.

First, DFI, developed in tandem with internet and mobile communication technologies, can expand the coverage of rural financial services, build a credit database of agricultural and rural lending groups, help financial institutions identify potential capital demanders, and eliminate financial exclusion in incredibly remote rural areas [42]. Lowering the agricultural loan threshold allows more farmers to obtain productive credit support, and the refined and diversified development of insurance businesses will reduce the risks associated with agricultural production. In the digital age, the presence of relatively straightforward digital financial products and services means farmers are not required to develop specific financial knowledge. The convenience and low thresholds of digital finance enable farmers to quickly exploit financial services, such as digital payments, financial management, and credit, while improving their financial literacy. This can encourage small farmers, large growers, and agricultural enterprises to expand their application of imported agricultural machinery, improved varieties, and new agricultural technology and equipment, and thus realize the intensification, modernization, and industrialization of agricultural production [43,44]. Furthermore, the development of insurance products can help to mitigate the risks associated with agricultural production, such as crop failures or natural disasters. By diversifying and refining insurance products, farmers can obtain more tailored coverage that meets their specific needs and circumstances. This can increase their resilience to unexpected events and provide a safety net in the case of losses. Together, these measures can contribute to the sustainable development of the agricultural sector, promote rural economic growth, and improve the welfare of farmers.

Secondly, DFI can use massive amounts of information, carry out multidimensional data analyses, and mine information, such as counterparties' ability and willingness to complete the agreement, thus reducing information asymmetry. It is a valuable tool that can be used to promote the development of green finance. More precisely, DFI has the advantages of scene, channel, data, and technology, and can thus effectively monitor and measure the environmental benefits brought about by the green behavior of enterprises and reduce the costs of information disclosure. Because of its targeted marketing function and naturally green nature, DFI can accurately (but conditionally) provide sufficient funds for green business activities related to planting, breeding, animal husbandry, and rural tourism. This helps high-quality production factors flow into environmental protection projects, such as green agriculture and guiding the green transformation of traditional agriculture while reducing the moral and adverse selection problems caused by information asymmetry [45–47]. For example, the use of a comprehensive platform of green finance in Quzhou City, China, has helped established a carbon account system, covering carbon accounts in six fields: industry, agriculture, energy, construction, transportation, and individuals. These comprehensively and systematically record the carbon emission data of major economic entities and support the online practice of carbon account finance by generating online carbon credit reports. In terms of digital literacy, digital financial inclusion can also guide the public to improve its environmental understanding and form green and low-carbon living habits, and can encourage them to adopt low-carbon consumption, thus proving the green attributes of digital finance [48].

Third, DFI, which operates on the internet, promotes collaboration among financial sub-industries, by establishing partnerships and sharing financial resources between financial technology companies, banks, and microfinance institutions, for instance. This enables the entire financial ecosystem to establish greater collaboration and more effective resource utilization, ultimately benefiting businesses and consumers. At the same time, digital platforms can provide greater data access regarding, and greater insight into, consumer behavior preferences, which is not only conducive to shaping business models and promoting the development of new formats but can also accelerate the innovation of financial products and services, enabling them to meet the needs of enterprises and consumers as they change in real-time. In addition, with the rapid development of information technology as the foundation of digital finance, new media, such as mobile payments, online lending, and mobile banking, have been widely used in rural areas, and are continuously developing green and environmental-protection functions. Through online platforms, these are transformed into actual green business activities that directly promote agriculture's green development and agricultural carbon fixation and efficiency.

Finally, due to its easy-to-use and low-cost characteristics, DFI can provide financial support for agricultural enterprises, improve the possibility of agricultural green technological innovation, and effectively alleviate the "long tail" dilemma in the rural financial market [49,50]. Development finance institutions (DFIs) could address this issue by providing easily accessible and low-cost financing options for rural communities, including farmers and agricultural businesses. This could help to encourage the adoption of green technologies in agriculture, such as sustainable farming practices or renewable energy systems. DFIs could also provide technical assistance and support to rural communities, helping to build capacity and promote the development of local knowledge and skills. This could help to improve the effectiveness and sustainability of green agricultural technology innovation. With the financial guarantee of green agricultural production, efficient, low-carbon, and green agricultural business models have been widely developed. Digital technology promotes the intelligent and precise management of agricultural production. In facility cultivation and field planting, intelligent agricultural management systems, such as biological breeding technology, soil detection technology, farmland remote sensing monitoring technology, soil testing formulae, and other intelligent agricultural management systems, are used in various ways. They enhance the interconnection of agricultural production; help farmers in the management of sowing, water-saving irrigation, fertilizing, spreading, harvesting operations, and other activities; reduce resource and energy consumption; and reduce production costs. Agricultural machinery is gradually replacing the conventional labor force and using biochemical technology; the environmental deterioration caused by land cultivation overload and high-intensity fertilizer and pesticide application can be alleviated, directly reducing agricultural carbon emissions and promoting green agricultural development [51]. Based on this, we put forward research Hypothesis 1:

Hypothesis 1 (H1). *Because DFI plays a vital role in alleviating financing constraints and improving green technology adoption in agricultural production, DFI will significantly improve AGTFP.*

3.2. Heterogeneous Impact of DFI on AGTFP

The key to the improvement of AGTFP lies in the optimization of factor allocation, the innovation of agricultural technology, and the improvement of human capital [52]. Due to differences in digital infrastructure construction and economic endowment, the effects of DFI may be heterogeneous in different environments [53,54]. As an essential means to resolve the problem of small-scale, extensive, and decentralized agricultural production, improving the construction of digital infrastructure is an important method for establishing the philosophy of "planting with brains, growing with wisdom and selling with traceability", and represents a historic opportunity to realize the green development of agriculture [55].

For example, information collection and transmission and data processing capabilities are significantly enhanced in regions with better digital infrastructure. Digital technology can help provide real-time feedback via agricultural production data; help farmers improve crop production and management processes; achieve accurate fertilizer, pesticide, and water implementation; and provide practical solutions to improve production patterns and reduce agricultural carbon emissions [56,57]. The development of digital platforms breaks the information barrier existing in traditional rural areas, and can thus improve the efficiency of agricultural product trade and promote the development of rural commodity markets. In areas where internet technology is more popular, the network of big data promotes the rapid transfer of agricultural surplus labor to urban non-agricultural sectors, directly alleviating the "over-densification" of agricultural labor and contributing to land transfer. The presence of new agricultural subjects will reduce the degree of land fragmentation, expand the scale of operation, and intensify agricultural production through land circulation [58,59]. Therefore, we propose research Hypothesis 2:

Hypothesis 2 (H2). *The internet, blockchain, big data analysis, and other digital technologies are the basis of the promotion and application of DFI. Therefore, in areas with good digital infrastructure, DFI contributes more significantly to promoting AGTFP.*

Furthermore, according to the "compliance cost" effect, strict and compliant environmental regulations will increase the pollution control cost and market participants' green technology research and development funds. Strict external regulatory forces have a specific crowding-out effect on productive investment [60,61]. According to the theory of environmental economics, the root cause of environmental deterioration is the confusion of property rights and the lack of a market; thus, environmental regulation measures such as environmental tax and carbon trading marketization are relied on to solve the problem. At this time, environmental regulation becomes a vital measure to coordinate agricultural production and environmental protection. In areas with higher environmental regulation intensity, agricultural producers need to pay more attention to the problems of low-factor utilization rates, excessive pollution emissions, and high resource mismatch rates in production and management. In order to avoid punitive administrative measures and high fines, producers will have to alleviate or offset the rigid constraints placed on energy use by environmental regulation policies by carrying out green technological innovation and increasing the use of energy-saving production factors. Through new green financial instruments, such as green credit, green bonds, and green insurance, DFI prioritizes the direction of limited inclusive funds towards agricultural enterprises with good environmental ratings or small farmers contributing less to environmental pollution, so as to bridge the funding gap and enable agricultural industry transformation and green technology innovation. This can guide farmers to transform their production methods, improve the added value of agricultural products, and reduce non-pollutant output, ultimately improving AGTFP [62,63]. With the increase in attention paid by the government to environmental protection, environmental-related financial subsidies are becoming more comprehensive, and pricing strategies, such as carbon emission indicators and pollution rights, in the current market are more mature. Under such strict administrative control, the green attributes of DFI are further highlighted. This helps agricultural producers to realize the clean transformation of traditional agricultural models through information transmission, technical support, and environmentally limited capital supply. Therefore, we propose research Hypothesis 3:

Hypothesis 3 (H3). *Environmental regulation is an important factor affecting the adoption of agricultural green technology. Therefore, in areas with more stringent environmental regulations, DFI is more significant in promoting AGTFP.*

To sum up, this study believes that digital financial inclusion can reduce the financing constraints of agricultural production and improve farmers' digital literacy and financial literacy so that they can adopt a cleaner production model to improve agricultural green total factor productivity. In addition, the marketization degree of the land market, the construction degree of digital infrastructure, and the implementation policies of the government on environmental regulation are also important factors that affect the improvement of AGTFP in DFI.

3.3. Channel Mechanism of LT

Under increasingly tight resource and environmental constraints, the key to improving AGTFP is to overcome issues related to small-scale farmers' fragmented scale management. LT is the direct transfer of land management rights between different subjects; transferring farmers' land management rights to other farmers or organizations is an economic behavior that helps ensure unchanged land contracting rights. LT thus affects agricultural factor allocation, technology adoption, and production efficiency to some extent [64]. LT enables agricultural production to reorientate from "survival ethics" towards "profit maximization," effectively solves the problems of land abandonment and arable land fragmentation caused by the household contract responsibility system, and increases the possibility of land contiguity management and large-scale planting and breeding. This can reduce the cost of agricultural production and form a scale effect in land management, but it also helps to improve the coordination efficiency of different production factors and maximize the factor combination productivity. The large-scale production mode integrates advanced agricultural machinery and equipment, agricultural technology, and management means to curb agricultural non-point source pollution while improving agricultural production efficiency, thus promoting low-carbon and green development [65]. Secondly, LT rearranges land property rights among subjects with different behavioral tendencies and business decision preferences, which is conducive to enabling different market participants to take part in labor division activities and thus generate greater labor division efficiency, according to their factor endowment conditions and comparative advantages [66]. For example, farmers with non-agricultural comparative advantages can improve the degree of matching between surplus land and other production factors by transferring their surplus land to improve agricultural production efficiency. The high efficiency induced by resource integration is especially prominent in regions with greater degrees of land fragmentation. The farmland transfer policy has promoted a labor force transfer amongst farmers with low productivity, increased the scarcity of labor factors necessary to the operation process, increased the costs of agricultural labor, and promoted the directing of agricultural production towards the capital [67]. Farmers will increase their investment in and introduction of mechanical agriculture technology to achieve the goal of low-carbon agricultural development. Finally, LT represents a contract between land transfer and labor transfer. In remote rural areas, information exchange related to land transfer is blocked, and the transaction cost is high, which significantly restricts the marketization of the rural LT system [68]. As a facilitator of information transmission, DFI alleviates information asymmetry between land supply and demand entities, dramatically reduces the economic costs of collecting and transmitting information for all parties involved in the transaction, and promotes the transferal and contracting of rural land. This process can expand the technological frontier of agricultural production, reduce the waste of agricultural resources, avoid the resource waste and low-efficiency caused by decentralized planting, and in this way promote the improvement of AGTFP. Therefore, we propose research Hypothesis 4:

Hypothesis 4 (H4). *LT is an important factor in promoting agricultural scale and modernization. Therefore, DFI can improve AGTFP by promoting LT.*

4. Study Design and Data Sources

4.1. Definitions of Variables

4.1.1. Explained Variable

Agricultural green total factor productivity (AGTFP) can not only be used to measure the utilization efficiency of agricultural inputs but can also reveal the comprehensive efficiency of green agricultural development, which reflects the basic situation of agricultural modernization. The agricultural production process is subject to the strict conditions of joint production, i.e., the input factors in the production process produce different outputs, in terms of types, quantities, etc., under given conditions, which are diverse but can be generally divided into expected outputs (agricultural products or carbon sinks) and undesired outputs (carbon emissions). In this paper, the defined goal of the planting industry is the establishment of a green total factor productivity rating system.

Input variables—This study takes the province as an independent decision-making unit. The input factors are defined based on the theory of agricultural production factors, and the consumption of land, water, labor, and other intermediate materials is selected as the input variable, reflecting the necessary material conditions for agricultural production and development. Labor input is measured by the number of employees engaged in agriculture, forestry, animal husbandry, and fishery at the end of the year. Agricultural land input can be divided into cultivated and sown areas. In order to better reflect the actual land use situation, this study uses the sowing area to represent the amount of land input. Agricultural machinery is the total mechanical power used in agriculture, forestry, animal husbandry, and fishery production. This study uses the total mechanical power to express the amount of mechanical input. The applied quantity of chemical fertilizers includes agricultural nitrogen fertilizer, phosphorus fertilizer, potassium fertilizer, and compound fertilizer used. The quantity of pure fertilizer applied is the main focus of this study. Under normal circumstances, the effective irrigated area should be equal to the sum of the irrigated field and the irrigated land area that has been equipped with irrigation equipment and can carry out normal irrigation. This study considers the effective irrigation area to represent the water resource. This paper labels agricultural plastic films and pesticides as the capital investments.

Expected output variable: The first expected output is measured by the gross output value of agriculture, forestry, animal husbandry, and fishery, and is calculated using the price index of the gross output value of agriculture, forestry, animal husbandry, and fishery (2010 = 100) to eliminate the influence of price changes. In an ecological carbon sink system, agriculture acts as a carbon sink. Agricultural carbon sinks measure the second expected output. According to the research of Chen [69], this paper defines an agricultural carbon sink as an entity involved in the process of absorbing carbon dioxide from the atmosphere, thus reducing the concentration of greenhouse gases in the atmosphere through agricultural production methods, such as crop planting. Agricultural carbon absorption is measured based on the economic output, carbon absorption rate, and economic coefficient of the main crops planted in the country. The calculation formula of agricultural carbon absorption is $CS = \sum_{m=1}^{n} CS_m = \sum_{m=1}^{n} cs_m \times Y_m \times (1-Q)/HI_m$. While CS_m is the carbon absorption of a specific crop, n is the number of crop species, cs_m is the carbon that the m class crops absorb to synthesize a unit of organic matter through photosynthesis, Y_m is the actual output of agricultural cash crops, Q is the water content of the fruit when the crop is mature, and HI_m is the accounting coefficient of the economic output value of cash crops. The agricultural carbon sink addressed in this paper mainly comprises crops with wide planting areas, large product yields, and high economic output values. According to a summary of the existing literature [70–74], the relevant parameters of crop categories and their corresponding carbon absorption rates are shown in Table 1.

Table 1. Parameters of economic coefficient, water content, and carbon absorption of crops.

Crop Variety	Economic Coefficient	Water Content	Carbon Absorption Rate	Crop Variety	Economic Coefficient	Water Content	Carbon Absorption Rate
Rice	0.45	0.12	0.41	Rapeseed	0.25	0.10	0.45
Wheat	0.40	0.12	0.49	Sugarcane	0.50	0.50	0.45
Corn	0.40	0.13	0.47	Cotton	0.10	0.08	0.45
Beans	0.34	0.13	0.45	Melon	0.70	0.90	0.45
Potato	0.70	0.70	0.42	Vegetable	0.60	0.90	0.45
Peanut	0.43	0.10	0.45				

Unexpected output: Agricultural carbon emissions—Agricultural carbon emissions are key global greenhouse gases [75]. Compared with other sectors, the carbon emission sources in the agricultural sector are very complicated. Considering the agricultural and industrial structure, statistical factors, and data comparability among various provinces in China, this paper focuses on the carbon emissions related to agricultural land use, that is, the carbon emissions caused by the human use of agricultural land for production activities. The differences between farming systems in China are shown in Table 2.

Table 2. Difference of human landscapes.

Farming System	Northern Region	Southern Region
Crop ripening	One crop a year or three crops every two years	Two or three crops a year
Cultivated land type	Dry-land farming	Paddy field
Grain crops	Wheat	Rice
Oil crops	Peanut	Oil seed rape
Sugar crop	Beet	Sugarcane
Economic crops	Cotton, millet, soybeans, etc.	Cotton

The unexpected output is expressed by the total agricultural carbon emissions converted from six pollution sources: chemical fertilizer, pesticide, plastic film, diesel oil, plowing, and irrigation (unit: 10,000 tons). The calculation method uses the carbon emission coefficient published by the IPCC to calculate the carbon emissions generated by agricultural production activities. This method estimates the corresponding carbon emissions according to the correlation coefficient and combines the macroeconomic data of various regions [76]. The calculation process of agricultural carbon emissions is $E = \sum E_j = \sum T_j \times \rho_j$, where E is the total agricultural carbon emission, E_j is the carbon emission of the j-th carbon source, and ρ_j is the carbon emission coefficient of the j-th carbon source. With reference to the existing literature [77–80], the carbon emission coefficients of each carbon source can be determined, as shown in Table 3.

Table 3. Carbon emission coefficient of production factors.

Carbon Source	Pesticide	Fertilizers	Diesel	Agricultural Film	Irrigate	Plough Fields
Carbon coefficient	4.934 kg/kg	0.896 kg/kg	0.592 kg/kg	5.18 kg/kg	266.48 kg/hm^2	312.6 kg/hm^2

4.1.2. Core Explanatory Variable

Digital financial inclusion (DFI)—The DFI, created by Peking University's Digital Finance Research Center, is based on Ant Financial's massive base of real transaction data. The index has been widely used in the empirical analysis of digital finance [81,82]. Therefore, this paper uses this index to measure the development level of digital finance. Based on the statistical sampling period, we use data from the Peking University Digital Financial Inclusion Index (4th Edition) as a proxy indicator. Starting from the first-level dimensions of coverage breadth, use depth, and digital support service, the index uses 24 specific indicators to examine financial development, including the number of Alipay accounts per 10,000 people, the proportion of Alipay hardbound users, and the average number of bank cards bound to each Alipay account, which together reflect the convenience and universality of the development of DFI [83].

4.1.3. Channel Variables

Land transfer (LT)—This paper measures the total area of household-contracted farmland transfers. This index includes leased (subcontracted) areas, transferred areas, swapped areas, shared cooperation areas, and other land transfer areas.

4.1.4. Control Variable

Since many macro and micro factors affect agricultural green total factor productivity, to minimize the error of model causal inference caused by missing important variables, this paper selects six control variables according to the research perspectives of the existing literature [21,26,27,84]. The level of economic development is measured using real GDP per capita. The total fiscal expenditure on agriculture, forestry, and water conservancy affairs measures fiscal support for agriculture. Rural e-commerce is measured using rural postal delivery route miles (km). The income gap is measured by the ratio of urban residents' per capita disposable income to rural residents (rural =1). The industrial structure is measured by the ratio of the added value of the tertiary industry to that of the secondary industry. Technological innovation is measured by the number of invention patent applications accepted (items) in each province or city.

4.2. Model Setting

4.2.1. EBM-GML Index Method

This paper uses the data envelopment analysis (DEA) method to measure AGTFP. However, in the traditional DEA model, in the calculation of production efficiency, because the input calculation proportion and angle selection are often different, errors easily arise in the results. Although the Slacks-based Measure (SBM) solves the relaxation problem of input or output variables that are not considered in the traditional DEA model to a certain extent, where there is an undesirable output, resource consumption and environmental pollution are usually radial relations calculated concerning a fixed function proportion in real life. Meanwhile, the traditional factors of production (such as labor and capital) and output are not non-radial relations calculated via a fixed function proportion. Neither the DEA model nor the SBM model can simultaneously deal with the radial and non-radial distance functions. In view of this, the Epsilon-Based Measure (EBM), which combines radial and non-radial distance functions, is used to measure agricultural production efficiency. The linear programming form is:

$$\vec{D}_0\left(x, y^d, y^u; g\right) = \max \beta w^T \tag{1}$$

The constraint conditions are:

$$s.t. \begin{cases} X^R\sigma \leq x^R + \beta_{x^R} \times diag(g_{x^R}) \\ X^{NR}\sigma \leq x^{NR} + \beta_{x^{NR}} \times diag(g_{x^{NR}}) \\ Y^{Rd}\sigma \geq y^{NR} + \beta_{y^{Rd}} \times diag\left(g_{y^{Rd}}\right) \\ Y^{NRd}\sigma \geq y^{NRd} + \beta_{y^{NRd}} \times diag\left(g_{y^{NRd}}\right) \\ Y^{Ru}\sigma = y^{Ru} + \beta_{y^{Ru}} \times diag\left(g_{y^{Ru}}\right) \\ Y^{NRu}\sigma = y^{NRu} + \beta_{y^{NRu}} \times diga\left(g_{y^{NRu}}\right) \\ \beta = \beta \cdot \mathrm{sgn}(|g|)^T \geq 0 \end{cases} \tag{2}$$

In Equations (1) and (2), w represents the standardized weight vector and σ represents the weights of the X input and Y output.

Agricultural production has the characteristics of continuity and a long time span, and agricultural production technology is constantly changing and developing. The expansion of the scale of agricultural operations caused by land transfer and the improvement of enterprise management efficiency will drive the development and promotion of agricultural production technology. In order to better describe the dynamic evolution of agricultural production efficiency, this paper introduces the Global Malmquist–Luenberger (GML) index. The GML index, based on a global production technology set, can deal with multiple inputs and multiple outputs, and at the same time, it can avoid a situation in which linear programming has no solution. The continuous production front avoids the inward deviation of the production front, avoiding not only technical retrogression but also the passive improvement of production efficiency. Global benchmark (G) encapsulates all current benchmarks (C) into a single global production possibility set to be used as a common reference set. The equation is:

$$GML_{t,t+1} = (x_t, y_t, b_t, x_{t+1}, y_{t+1}, b_{t+1}) = \left(1 + D_G^T(x_t, y_t, b_t)\right) / \left(1 + D_G^T(x_{t+1}, y_{t+1}, b_{t+1})\right) \tag{3}$$

In Equation (3), $D_G^T(x, y, b) = \max\{\beta | (y + \beta y, b - \beta b) \in P_G(x)\}$, $P_G = P_C^1 \cup P_C^2 \cup \cdots \cup P_c^t$ is obtained according to the global benchmark production possibility set, and β is the directional distance function value.

4.2.2. Econometrics Model

In order to verify the direct impact of DFI on AGTFP, combined with research Hypothesis 1, this paper constructs the following panel econometric model:

$$AGTFP_{it} = a_0 + a_1 DFI_{it} + a_2 Control_{it} + \nu_t + \lambda_i + \varepsilon_{it} \tag{4}$$

In Equation (4), a_0 represents a constant term, a_1 and a_2 represent regression coefficients to be fitted and calculated, subscripts i and t represent individuals and time, respectively, *Control* represents a series of control variables, λ_i represents the individual fixed effect, v_t represents the time fixed effect, and ε_{it} represents a random disturbance term that obeys a white noise process.

In order to test the channel of DFI to improve AGTFP, combined with research Hypothesis 3, this paper used the intermediary effect model to fit the calculation. Considering the inherent endogenous defects of the traditional three-stage mediating effect model, and according to the operational suggestion of mediating the effect analysis put forward by Jiang [85], this paper only investigates the influence of DFI on mechanism variables in the empirical part. Bai introduced the interactive effect of individuals and time into the linear panel model to reflect the differences in common factors among individuals [86]. Compared with the traditional panel fixed effect model, the interactive fixed effect model fully considers the multidimensional shocks in the real world and the heterogeneity of different individuals' responses to these shocks, which can better reflect economic reality [87–89]. In order to better deal with the endogenous problem of the intermediary effect test equation, this paper uses an interactive fixed effect model to fit and calculate the regression coefficient and significance of the channel variables. Therefore, based on model 4, this paper establishes the following intermediary effect model:

$$LT_{it} = c_0 + c_1 DFI_{it} + c_2 Control_{it} + \lambda_i + \nu_t + \delta'_i F_t + \varepsilon_{it} \tag{5}$$

In Equation (5), c_0 represents a constant term, and c_1 and c_2 represent regression coefficients to be fitted and calculated. Additionally, F_t is the common factor, δ_i is the factor load, and $\delta'_i F_t$ is the interactive fixed effect. The meanings of the other symbols are consistent with Equation (4).

4.3. Data Sources and Description

Following the principles of data availability and the consistency of statistical caliber, this paper selects panel data from 31 provinces in the Chinese mainland collected from 2011 to 2021 as statistical samples. The primary data sources of this study are the China Statistical Yearbook, China Rural Statistical Yearbook, China Rural Management Statistical Yearbook, and the statistical bureaus of various provinces and cities. This paper's economic variables that are involved in monetary measurement are smoothed based on 2011. Very few missing data are filled in by linear interpolation. In order to alleviate the heteroscedasticity problem, all variables are logarithmic. In order to reduce the influence of outliers, the paper also performs a 1% tail reduction on both ends. As the AGTFP calculated by the EBM-GML index method is the ratio of the period from t to t + 1, in order to prevent the first period data from all being 1, the paper sets the time span of the statistical sample for calculating AGTFP as 2010–2021. The descriptive statistical analysis of each variable is shown in Table 4.

Table 4. Descriptive statistics of the variables.

Variable	Code	Mean	Standard Error	Min	Max
Agricultural green total factor productivity	AGTFP	0.3294	0.2883	−0.3713	1.2602
Digital financial inclusion	DFI	5.2760	0.6743	2.9360	6.0683
Land transfer	LT	16.2218	1.2899	12.0111	19.1255
Financial support for agriculture	FSA	6.1629	0.5835	4.6599	7.1612
Rural e-commerce	REC	11.4615	0.8637	8.8203	12.5888
Income gap	IP	0.9516	0.1577	0.6152	1.3584
Industrial structure	IS	0.2146	0.3763	−0.4492	1.5880
Level of economic development	LED	10.8575	0.4449	9.8830	11.8415
Technological innovation	TI	9.4752	1.5720	4.6151	12.2225

5. Empirical Results

5.1. Baseline Regression

The *p*-values of the Hausmann test and the likelihood ratio test reject the null hypothesis at the 1% level, indicating that the fixed effect model is the most suitable for the sample data; therefore, this paper used the fixed effect (FE) as the benchmark regression model. One of the limitations of using panel data is the possible presence of heteroscedasticity, cross-sectional dependence, or both. This can generate incorrect inferences. In order to eliminate heteroscedasticity, cross-section correlation, and autocorrelation in the panel data, a fixed effects model with Driscoll–Kraay standard errors is used to assess the influence of DFI on AGTFP. The Driscoll–Kraay standard errors are "heteroskedasticity- and autocorrelation-consistent and are robust to general forms of cross-sectional and temporal dependence" [90,91].

As can be seen from Table 5, the results of the mixed ordinary least square method without control of the individual effect and time effect show that the regression coefficients of DFI on AGTFP are 0.1896 and 0.1295, respectively, and pass the significance test at the 1% level. The results of the two-way fixed effect (TWFE) model show that the regression coefficients of DFI are 0.1950 and 0.1219, respectively, and both pass the significance test at the 1% level. The above four results indicate that DFI can improve AGTFP. In addition, H1 is confirmed. It can also be found that when there are control variables, the regression coefficient of DFI is minor, indicating that ignoring external factors will exaggerate the effect of DFI, and it is thus reasonable to consider the missing variables.

Table 5. Benchmark regression results.

Variable	POLS	POLS	TWFE	TWFE
DFI	0.1896 *** (10.96)	0.1295 *** (4.96)	0.1950 *** (3.46)	0.1219 ** (2.93)
LED		−0.1220 ** (−1.97)		−0.3443 * (−2.04)
FSA		0.2987 *** (5.06)		0.2486 *** (9.51)
REC		−0.0106 (−0.62)		0.0807 ** (2.82)
TI		−0.1762 *** (−5.33)		0.0471 * (2.08)
IP		−0.1233 (−0.99)		−0.4690 * (−2.14)
IS		0.0010 (0.02)		0.0572 * (0.49)
Individual effect	No	No	Yes	Yes
Time effect	No	No	Yes	Yes
R-Square	0.1955	0.3113	0.6724	0.7023
F test			33.56 ***	30.56 ***
Hausman test				20.04 ***

Note: ***, **, and * are significant at the levels of 1%, 5%, and 10%, respectively. The *t*-statistic is reported in parentheses.

DFI services that can be accessed through mobile terminals not only reduce the time costs and transportation costs but can also use big data technology to create more credit products that meet the different needs of different agricultural operators, improve the accuracy of financial services, and enhance the financing willingness of agricultural producers. When farmers' financing is facilitated, they can improve agricultural efficiency and achieve economies of scale by transforming their traditional agricultural production mode into intensive and modern production modes. In addition, in the context of green consumption becoming dominant and the government gradually strengthening regulations on the agricultural environment, the financing provided by digital financial products or agricultural producers and operators not only focuses on the material and financial conditions of agricultural production but also emphasizes the cleanliness of the output. For example, China Construction Bank launched "Yunongtong" digital inclusive financial products, emphasizing the investment targets' green properties. In order to obtain the support of DFI, agricultural production and operation entities will have to pay attention to green investment in their own production and operation activities. For example, an ecological orientation of digital insurance in crop planting can help prevent pollution in agricultural production, reducing carbon emissions and non-point source pollution, and thus promoting green agricultural production. In order to obtain continuous credit funds, farmers will have to introduce new agricultural production technologies, varieties, and ideas, and pay more attention to the coupling and coordination between agricultural production and environmental protection. They will have to do so while also improving agricultural production efficiency, so as to protect the ecological resources of mountains, rivers, lakes, and grasses; these green and low-carbon production modes will improve AGTFP.

5.2. Robustness Test

The results of the benchmark regression show that DFI can significantly improve AGTFP. In order to verify the robustness of this conclusion, this paper uses three methods. First, the interactive fixed effect model replaces the two-way fixed effect model, which fully considers the multi-dimensional shocks that occur in the real world and the heterogeneity of different individuals' responses to these shocks. The second is to replace the proxy variable of DFI. DFI relies on digital technology to break the constraints of geographical space, optimize the rational allocation of rural financial market elements, develop the financial service model, alleviate the problem of information asymmetry, and make the transaction process more standardized and convenient. This reduces the supply and use costs of financial services for farmers, which enables the coverage of more "long tail groups" and alleviates the problems of insufficient financial demand and financial exclusion in rural areas. Therefore, we replace the DFI total index with the coverage index. Based on the diagnostic test of the adjacency weight matrix, this paper uses a spatial autoregression model (SAR) with fixed space and time to calculate the spatial spillover effect.

According to the robustness test results shown in Table 6, the fitting results of the three methods all show that the regression coefficients of DFI to AGTFP are 0.1023, 0.0611, and 0.1187, respectively, and they all pass the significance test. Although the significance of DFI is reduced in the first and third methods, it can still play a significant positive role within an acceptable range. These results show that the benchmark regression results are robust and reliable, and H1 is thus strongly confirmed.

Table 6. Results of robustness test and endogenous test.

Variable	Robustness			Endogeneity	
	Interactive Fixation Effect	**Coverage Breadth**	**SAR**	**GS2SLSAR**	**LTZ**
DFI	0.1023 **	0.0611 ***	0.1187 *	0.0748 **	0.5235 **
	(2.58)	(5.96)	(1.93)	(2.40)	(1.96)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively. The spatial autoregressive model reports the total effect.

5.3. Endogeneity

Although this paper tries to control for other economic characteristics that affect the AGTFP as much as possible, and thus prevent the omission of important variables, the model's settings must still consider the endogenous problems of measurement errors and two-way causality. For example, the high overall AGTFP in a region will make the production mode of relevant producers more reasonable and the resource allocation more effective, which means that the external environment will "force" relevant entities to actively raise and use funds in order to realize intensive management and improve resource utilization efficiency, which will promote the development of DFI. In order to eliminate the deep-seated endogenous relationship between these and carry out the most appropriate methods of causal inference in econometrics, this paper uses the instrumental variable method to overcome endogenous problems.

Distance is influenced by economic behavior but not by economic development [92]. Since the DFI data here are calculated based on the transaction big data of Ant Financial Services, which is headquartered in Hangzhou City, Zhejiang Province, the distance from the provincial capital city to Hangzhou City is chosen as the tool variable. Generally speaking, the greenness degree of agricultural production will not change as a result of the geographical distance between cities. The distance between the provincial capital and Hangzhou will not affect the AGTFP through DFI. At the same time, although the main means of operating DFI is via the internet, its popularization and application will still be influenced by spatial and geographical factors. Increasing the distance from Hangzhou will thus make it more difficult to popularize this tool [93]. Therefore, geographical distance satisfies the principles of relevance and exclusivity. Everything is inextricably linked from the perspective of economics, and so finding an instrumental variable with strict exclusiveness is challenging. In this paper, the idea of plausibly exogenous instrumental variables proposed by Conley et al. [94] was used for reference; the strict exclusivity requirement of instrumental variables is relaxed, and point estimation is performed using the method of local to zero (LTZ). In addition, the generalized spatial panel autoregressive 2SLS (GSAR2SLS) model is also used to verify the robustness of the endogenous test conclusion. The spatial spillover effect and the endogenous problem of economic variables can be controlled simultaneously using the form of interaction between endogenous variables and spatial high-order lag terms as tool variables, and estimating spatial panel data based on two-stage least squares (2SLS) [95,96].

According to Table 6, the DFI regression coefficients are 0.0748 and 0.5235, respectively, and both models have passed the significance test at the 5% level. The conclusion that DFI can significantly improve AGTFP thus still holds, providing sufficient evidence for confirming research Hypothesis 1.

6. Path Mechanism and Heterogeneity Test

6.1. Mediating Effect

In order to verify the intermediate mechanism of DFI regarding its effect on the improvement of AGTFP, combined with the intermediary effect equation, the results in Table 7 were calculated.

Table 7. Results of mechanism test and heterogeneity test.

Variable	LT	Pilot Zone for Green Finance Reform		National Big Data Comprehensive Pilot Zone	
		Pilot City	Non-Pilot City	Pilot City	Non-pilot City
DFI	0.2461 *** (3.00)	0.3301 ** (3.09)	0.0324 (0.55)	0.1721 ** (2.27)	0.0717 (1.61)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes
R-Square		0.8772	0.6993	0.8290	0.7576

Note: *** and ** are significant at the 1% and 5% levels, respectively. The *t*-statistic is reported in parentheses.

As seen from Table 7, the regression coefficient of DFI to LT is 0.2461, and this passes the significance test at the 1% level. The results show that DFI can improve AGTFP by promoting the agricultural LT channel mechanism, and research Hypothesis 3 is thus verified. In the context of modern digital agriculture, the directional focus of rural LT in China has changed from ordinary farmers to a new type of agricultural operators, such as family farms, rural professional cooperative organizations, leading agricultural enterprises, and rural collective economic organizations. The scale and area of LT are now larger, and the capital requirements are higher. Traditional financial institutions are reluctant to provide financial services in rural areas due to the natural weakness of agricultural production, the seasonal dispersion of farmers' capital requirements, and the difficulty encountered in assessing and quantifying the information characteristics of the pledge.

As a new form of business combining modern digital technology and traditional inclusive finance, DFI provides a new scheme to alleviate farmers' credit constraints and information asymmetry in LT. By utilizing emerging information technologies, such as big data, cloud computing, and artificial intelligence, DFI can expand the scope and accessibility of financial services, and give full play to its role in improving the efficiency and broadening the scope of information dissemination. With the support of information technology, financial institutions can obtain customer information and credit information more efficiently and accurately, which will alleviate the information imbalance between land supply and demand subjects, dramatically reduce the economic costs levied on land transaction parties in collecting and transmitting information, and get rid of the restrictions imposed by "free rent" and the "acquaintance society" on rural areas. This will help to gradually realize the marketization of rural LT and facilitate the transfer of agricultural land when a contract of agricultural land transfer is established [97]. DFI still impacts LT in terms of digital securities and digital insurance [98]. The securitization transfer of agricultural land, which relies on digital technology, promotes the market-oriented pricing of land factors, helps guide social capital into rural areas, and provides more profit space for rural factor markets. Digital agricultural insurance can better facilitate the risk-compensation mechanism, and it guarantees the acceleration of rural LT and the revitalization of land and other factor resources. Finally, digital inclusive finance provides farmers with a new channel for timely, accurate, and comprehensive access to financial knowledge, which can improve their financial literacy, enhance their ability to collect and analyze market information, tap entrepreneurial opportunities, and implement family decisions that are more in line with their own interests [99]. Farmers can rely on the DFI model to obtain appropriate regional farmland and expand the leasing scale to thus achieve large-scale production.

6.2. Heterogeneity Test

6.2.1. Digital Infrastructure

In order to implement The State Council's Program of Action to Promote the Development of Big Data, the National Development and Reform Commission launched comprehensive big data pilot policies in eight regions, including Guangdong, Shanghai, and Beijing, in 2016. The pilot zones have a better foundation of digital facilities, and more developed and mature digital financial systems and product supply chains. This paper uses the pilot policy as a grouping criterion to verify whether different levels of digital facilities lead to bias in DFI practices.

As seen in Table 7, the regression coefficient of DFI in the national big data comprehensive pilot cities is 0.3301, and this passes the 5% significance test, while the coefficient in the non-pilot cities is 0.0324, and this does not pass the significance test. The results indicate that DFI significantly promotes AGTFP in regions with better digital infrastructure (more obvious green orientation of credit funds), which aligns with expectations. Hypothesis 3 is verified. The reason for this phenomenon lies in the fact that DFI can effectively bridge the "digital divide", making it more accessible to those who have had difficulty accessing the internet in the past, and the marginal effect of digital technology and inclusive finance on agricultural production and operation is made more substantial. In regions with relatively complete and developed digital infrastructure, internet technology is more popular, and the impacts of DFI on residents will be felt sooner; further, such impacts on farmers' production and operation will thus be more mature. With the implementation of the strategies of Broadband China and digital countryside, the digital infrastructure in agricultural and rural areas has continuously improved, and the information collection, transmission, and processing capabilities of all links in the chain of agricultural production have significantly enhanced, improving farmers' decision-making efficiency, optimizing factor input, and helping them to adopt green technology to improve AGTFP. For example, digital technology shows advantages in terms of information processing, reducing the costs of information access on both sides of the transaction, and improving the efficiency of product transactions [100]. At the same time, digital networks will help broaden farmers' horizons and social networks; facilitate the transfer of rural labor to the non-agricultural sector; accelerate increases in the scale, efficiency, and intensity of agricultural operations; and enhance the efficiency of green technologies.

6.2.2. Environmental Regulation

With limited endogenous financing and China's financial structure dominated by indirect financing, bank credit has become an essential source of funds for enterprises' innovative activities [101]. Since 2017, the China Municipal Government has successively implemented pilot green financial policies in ten regions, including Zhejiang, Guangxi, Guizhou, and Xinjiang. The purpose is to broaden the financing channels of green funds, establish a sound mechanism for the disclosure of corporate environmental responsibility information, actively guide social capital towards green project investment, and finally realize the green transformation of traditional industries and the sustainable development of the economy and society [102]. Green finance, based on the Green Industry Guidance Catalogue, brings the pollution behaviors of market players under the remit of credit management. Therefore, green finance can be regarded as an environmental regulation mechanism that uses credit management and environmental information ratings to encourage enterprises to focus on front-end prevention and control, rather than end-stage emission reduction [103]. Therefore, it is reasonable to believe that environmental regulation in the pilot zone is now stronger, and the green orientation of the credit funds is more obvious.

As seen from Table 7, the regression coefficient of DFI in the pilot cities of the green finance pilot zone is 0.3301, and this passes the significance test at 5%; in the non-pilot cities, the regression coefficient is 0.0324, which does not pass the significance test. The results show that DFI significantly promotes AGTFP in regions with higher environmental regulation intensity, which aligns with expectations. Research Hypothesis 4 is verified. Green finance is a new financial strategy that takes financial institutions as the main body and encourages market players to conduct clean and low-carbon production through various channels to realize pollution control and environment-friendly production. Through a series of green finance standard systems and incentive policies, the pilot zone directly provides financial support to green and low-carbon projects, using digital technology and the basic concept of inclusive finance to provide green financial products; this helps in establishing constantly innovating financial service systems and setting up special financial funds. In addition, the digital governance mode of DFI and green finance jointly promote the remodeling of a low-carbon civilization, which can enhance the low-carbon cultivation of farmers; promote the modernization of rural digital governance and the new form of green civilization; and promote the green and low-carbon transformations of the green countryside, green agriculture, and small and micro enterprises [104]. For example, Zhejiang Anji County Rural Commercial Bank has launched several innovative and unique green credit products, such as the "Liangshan Agriculture and Forestry Loan" and the "Liangshan White Tea Loan", which effectively reduced the financing burden of tea farmers in Anji County, and they also constructed the "Anji Model" of green development, which will help towards developing a new form of civilization.

7. Conclusions and Policy Implications

7.1. Conclusions

As a new form of finance featuring the deep integration and innovation of modern digital technology and more traditional inclusive finance, DFI contributes towards comprehensively promoting rural revitalization and realizing sustainable agricultural development. Agriculture and rural areas are sources of greenhouse gas emissions and are essential contributors to carbon sequestration.

In this paper, from the perspective of the planting industry, narrowly defined carbon emissions in agricultural production and the total carbon sink of agricultural planting were included in the evaluation system, and the EBM-GML index method was then used to calculate the AGTFP. This paper systematically assessed the direct impact and indirect mechanisms of DFI's effects on AGTFP at the theoretical level. Then, based on panel data from 31 provinces in mainland China, from 2011 to 2021, the relationship between the two was empirically tested using econometrics methods, such as the TWFE model, the plausibly exogenous instrumental variable method, and the interactive fixed effect model. This study used the fixed effects panel regression estimator with Driscoll–Kraay standard errors to estimate the proposed model's main hypothesis. Consistent with the conclusions of existing articles [24,105,106], the results of this study suggested that DFI can significantly improve AGTFP. This conclusion remained valid after changing the explanatory variables, changing the econometric model, and solving the endogeneity problem.

Mechanism studies show that DFI can improve the information transparency of the rural land transaction market, ease financial constraints in market transactions, help to gradually realize the marketization of rural LT, and facilitate the transfer of agricultural land when a contract of rural land transfer is established. Promoting agricultural LT has become a vital mechanism by which DFI improves AGTFP. The heterogeneity results showed that DFI had a more significant promotional effect on AGTFP in the pilot cities of green finance reform and national big data comprehensive experimentation; that is, the developmental degrees of digital infrastructure and government departments' environmental control were essential factors enabling DFI to promote sustainable agricultural development. The paper argues that DFI is an effective means by which countries can transform agricultural production, improve production efficiency, and realize low-carbon agriculture.

7.2. Policy Enlightenment

In order to give full play to the role of inclusive finance in promoting the green development of agriculture, it is necessary to solve the common problems faced by inclusive digital finance and pay attention to top-level design. Local government departments should guide and support commercial and financial institutions to actively participate in agricultural production and the supply of financial products in the circulation market through policies that help establish the large-scale and industrialized development of agricultural production. The following policy implications can be inferred from the research conclusions:

1. The administrative departments should give full play to the abilities and activities of all parties, and strengthen the mechanisms of cooperation and co-governance in pollution control. The agricultural non-point source is scattered in nature, and industrial development in agricultural regions is lacking, thus diversified cooperation among departments, regions, governments, and farmers is required. In order to give full play to the guiding role of the government and attract intermediate agricultural organizations and farmers to fulfill their responsibilities, the introduction of a professional technical management system and the strengthening of the social supervision mechanism can facilitate the communication of government endowments to the market, and improve the effectiveness of agricultural pollution control. At the same time, by means of production taxes, environmental taxes/subsidies, government funding, and emission rights trading, the driving force motivating responsible subjects at all levels to participate in the control of non-point source agricultural pollution can be enhanced. In addition, a mechanism for the co-control and management of non-point source agricultural pollution in which the government, agricultural intermediary organizations, and farmers coordinate and cooperate with multiple subjects can be established. Government departments should guide market players in the research and development of low-emission, low-residue, and intelligent new green fertilizers and pesticides; strengthen the innovation of mechanized, intelligent, and precise fertilization and application technologies; and give full play to the role

of big data and artificial intelligence technology in the prevention and control of agricultural pollution;

2. Technological innovation is a prerequisite for success in the collaborative management of agricultural pollution and carbon reduction. The government should establish and improve the “agricultural big data” platform, support and encourage commercial financial institutions to develop and improve the digital financial inclusion credit data analysis technology, innovate the supply model of agricultural digital financial inclusion products, and expand the credit scale. At the same time, they should attach greater importance to the construction of DFI systems and improve the inclusiveness, coverage, and accuracy of financial services. The government should increase the degree of digital support in rural areas; constantly improve DFI systems and infrastructure construction; and ensure the accurate delivery of financial products by optimizing digital functions, such as personal payment, micro-credit, and internet insurance. This can be executed by encouraging internet companies, such as JD Finance, Ant Financial, and Duxiaoman, to enter into the rural market, and by developing and designing digital financial products and services that benefit farmers according to their local conditions. This will help to protect the rights of economic entities, such as very poor individuals, farmers, and small- and medium-sized enterprises, in obtaining financial services. Banks and other financial institutions should rely on 5G, intelligent terminals, and other technologies to support county- and regional-level subjects in independently obtaining financial services through various channels, and solve the problems in the network layout in rural and remote areas. They should also give full play to the information-related advantages of emerging financial businesses. Financial institutions not only need to make good use of digital technology to strengthen their role in collecting information from rural “credit white households”, but should also help farmers to better understand market information and thus help with the green development of agriculture. Local administrative departments and financial institutions can join forces to introduce standardized county data, formulate general rules for county loans, and improve their ability to identify customers and extend credit. Local governments should cooperate with commercial financial institutions to popularize knowledge related to digital agricultural finance through various channels, such as online media publicity and grassroots farmers’ professional training, to improve farmers’ awareness and operational abilities in relation to inclusive digital finance;
3. We should accelerate the innovation of the LT mode and mechanisms, and attach importance to regional differences during circulation. After the implementation of reforms in land confirmation and agricultural rights separation, we should actively explore and refine the three rights separation reforms, and introduce supporting policies to encourage land transfer and achieve large-scale management. While helping farmers and collective economic organizations to transfer contracted land in the traditional way, we should also build a platform providing information and services related to transfers; encourage farmers to transfer land through new modes, such as principal agent, cooperative shareholding, land trusts, and mortgaging; and clarify the rights and responsibilities of both parties involved in a land transfer. At the same time, local governments should formulate LT price systems based on the actual agricultural conditions in the region to ensure a basic balance between supply and demand, and they should implement a reasonable transfer price. In order to deal with the problem of arable land fragmentation, the government should encourage villagers to merge and exchange plots within their communities, and promote the consolidation of small scattered plots into large plots to achieve large-scale management and improve the allocation efficiency of various production factors;
4. Administrative departments should promote the construction of “green+” financial service coordination systems between green finance and inclusive finance, technology and finance, and rural finance and supply chain finance. They should also adapt the environmental and social risk management concept, the pricing mechanism, and the

value discovery function of green finance to other financial systems, thus promoting the development of financial businesses, such as those involved in green securities, green funds, and green insurance. At the same time, we should pay attention to the heterogeneity of different financial ecosystems in the process of integration, and construct a negative list mechanism for green inclusive finance. Banks should increase their input in financial infrastructure at the rural grassroots level and set up more "green financial service offices" organized by rural credit cooperatives and other institutions to provide agricultural business entities with green financial education and other services. The financial sector must explore the establishment of a green finance evaluation system that is in line with the development of green agricultural projects influenced by local conditions, encourage banks to increase the proportion and weight of green finance in their evaluations, and promote the innovation of green financial products and services.

7.3. Limitation

This study analyzed the promotional effect of DFI on AGTFP in rural areas of China, providing strong evidence for the benefits of giving financial support to green agricultural development. However, some limitations are worth noting:

(1) This study only considered the undesirable output of agricultural carbon emissions when evaluating AGTFP, ignoring agricultural non-point source pollution. In future studies, it would be beneficial to use a single analysis method to calculate the total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) of agricultural non-point source pollutants, and include them in the calculation of green total factor productivity. In addition, this paper mainly takes chivalrous planting as its statistical sample. The data on forestry, fishery, and animal husbandry, under the broader definition of agriculture, should also be included in the evaluation system.

(2) This is an empirical study that was undertaken at the level of statistics and econometrics, and the research conclusions do not provide detailed operation schemes. In future studies, it would be helpful to use the case analysis method to deeply analyze the specific experiences of financial institutions that are using DFI products to promote green and clean agricultural production, based on specific cases.

(3) It would be beneficial to use digital financial inclusion in agricultural policy systems to perform policy evaluations, such as using DID, RDD, and other methods to make up for the deficiencies in the study of causal inference.

(4) Clarifying the total amount of agricultural carbon emissions and carbon sinks is a prerequisite for relevant research. However, compared with industrial carbon sources, agricultural carbon sources are more diverse and complex, and many calculation methods may make the calculation results quite different. Although the IPCC coefficient method we used is widely used, it needs to fully reflect the whole picture of carbon emissions in the production process of agricultural systems. Compared with agricultural carbon emissions, agricultural carbon sinks are mainly calculated based on different carbon sinks. Due to the different characteristics of different carbon sinks, the measurement methods are challenging to unify. A significant error often exists between the carbon sink data, obtained by different methods, and the actual value. Establishing a more scientific assessment system or using digital technology to monitor natural carbon sinks would be beneficial.

(5) It would be useful to refine the statistical sample to the level of micro-data.

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