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Research on the Impact of Digital Green Finance on Agricultural Green Total Factor Productivity: Evidence from China

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Abstract: Green development has become one of the important concepts leading China's economic developments, and it is extremely meaningful to boost the continuous growth of agricultural green total factor productivity (AGTFP) to achieve the construction of a powerful agricultural country. Using China's provincial data from 2011 to 2020, this manuscript calculates AGTFP through the SBM–GML model, and the digital green finance (DGF) through a comprehensive indicator system. The double fixed-effect model, quantile model and spatial Durbin model are used for in-depth study of the benchmark influence, the nonlinear effect and spatial spillover effect of DGF on AGTFP. The main research conclusions of the article are as follows: (1) DGF is significantly conducive to the improvement of AGTFP. Along with the continuous growth of AGTFP, the promoting effect of DGF has gradually increased. (2) In terms of impact path, green finance can properly promote the growth of AGTFP, while the role of the degree of digitization is not very significant. Meanwhile, the main channel for DGF to promote AGTFP is through green technology efficiency. (3) The impact of DGF on AGTFP varies spatially, while the role is more effective in regions with a higher degree of economic development and well-developed modernization. (4) There is a spatial spillover effect of DGF's impact on AGTFP, which means that DGF can simultaneously promote the growth of AGTFP in local regions and neighboring regions.

Keywords: digital green finance; green finance; agricultural green total factor productivity; green technology efficiency; spatial Durbin model

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1. Introduction

Green development is a fundamental requirement for the high-quality development of agriculture in China, which is also extremely vital in accelerating the realization of building a powerful agricultural country. China is a big agricultural country; China's total agricultural carbon emissions account for about 30% of the total agricultural carbon emissions in Asia. In 2020, China announced the goal of peaking carbon emissions by 2030 and carbon neutrality by 2060. Stimulating low-carbon agriculture has become more meaningful for sustainable agriculture. The realization of the "dual carbon" goal will be more difficult without the deep involvement of agriculture, which makes the green transformation of agricultural production methods more urgent [1]. In the report of the 20th National Congress, China further emphasized the need to accelerate the green economic cycle, to adhere to the main national policies of resource conservation and environmental protection, and to accelerate the transformation of the agricultural production and development pattern. China proposed in the Central Financial Work Conference in October 2023 that in order to build a powerful agricultural country, we must do a good job in the financial development of the five articles, which once again highlights the importance of the persistent progress of green finance and DGF. Therefore, promoting agriculture towards greening and digitalization is the core requirement of sustainable agriculture, and rooting

the idea of green development in the agricultural industry chain is the essence of realizing modern and sustainable agriculture [2].

Against the current background of the continuous development of a low-carbon economy, green finance has become a very useful means to motivate the sustainable development of the regional economy and environment. The primary objective of green finance is to allocate capital to facilitate green projects and industries, aiding in the dual goals of economic growth and environmental protection [3]. Green finance is an effective tool to lead China's low-carbon development and plays a crucial role in boosting green agriculture [4]. Existing research shows that green finance can lead the flow of capital resources to a reasonable and efficient place, and improve the efficiency of resource allocation [5,6]. It can also reduce the credit financing of enterprises in heavily polluting industries, optimize the efficiency of resource allocation between industries [7], enable funds to enter energy-saving, environmentally protective and other green projects, and then enhance the green technology innovation and the production efficiency of green industry enterprises [8], thus effectively promoting industrial green productivity growth [9]. However, there are dramatic differences in the financial resource development levels among different regions in China, especially in the application of agriculture, with a serious financial inhibition effect [10]. Therefore, it is very necessary to investigate the mechanisms and constraints of green finance on high-quality agricultural development to realize the "dual carbon" strategic goal [11,12].

With the rapid development of electronic information technology, the deep integration of information technology represented by the Internet, big data, cloud computing and traditional financial tools have greatly given rise to digital finance [13]. Compared with traditional financial services, digital finance has higher efficiency and wider coverage to stimulate economic and social development [14]. Digital finance realizes financial services across time and space through the Internet platform. Digital finance can greatly raise the efficiency of traditional financial services, and provides users with a wider range of more personalized financial products and services [15]. Meanwhile, through big data analysis and intelligent risk control systems, it can reduce the risk, and effectively mitigates all the costs to both sides of the transaction in the transaction process [16]. Existing research has shown that digital finance has become a crucial part of regional economics, which can sharply increase the number of loans from financial institutions and residents' consumption, alleviate the financing constraints of enterprises and promote sustainable economic improvement [17]. And, as an important engine to achieving carbon neutrality, it can promote a more rational industrial structure, achieve the suppression effect of carbon emissions through technological innovation and energy efficiency improvement [18], effectively reduce industrial pollution emissions and achieve a significant increase in industrial productivity [19].

In 2018, the United Nations Environment Programme (UNEP) proposed the concept of DGF for the first time. DGF effectively combines the advantages of both green finance and digital finance, and can quickly extend the service boundary to the countryside [20]. From a macro perspective, DGF can rely on big data on the basis of the original green financial services, provide a more convenient transaction method, effectively cut the cost of agricultural producers and financial institutions during financial services, and lower the threshold of financial accessibility [21,22]. From a macro perspective, DGF can effectively promote industrial restructuring [23], which has a great impact on the enhancement of technical efficiency [24,25], and then enhance the total factor productivity of the industry [26]. However, the current research related to DGF affecting AGTFP has not constructed an appropriate analytical framework, and the empirical research on the impact mechanism between the two is also apparently rare.

AGTFP refers to a vital driving factor in the change of agricultural economic development methods under the constraints of environmental protection and emission reduction, and is also a crucial indicator for assessing the targets of long-term sustainable development of regional agriculture [27]. AGTFP indeed can well reflect the comprehensive level of natural resource utilization efficiency and environmental impact in agricultural activities [28], and is extremely important for boosting high-quality economic development and realizing

agricultural modernization [29,30]. It has been found that the development of financial instruments provides a mechanism for financial support and optimization of resource allocation, which is vital for the sustained and stable growth of AGTFP [31]. Guo J. et al. (2022) measured China's GTFP through the GML model, and concluded that both digital finance and green finance can be conductive to GTFP [32]. Li G. et al. (2023) analyzed the theoretical influences of green finance on AGTFP. The study was based on China's provincial panel data, and the conclusions also supported the boosting effect of green finance on AGTFP [33].

Using China's provincial panel data from 2011 to 2020, this paper empirically explores whether DGF can affect AGTFP, and delves into the impact paths and spatial spillover effects. Compared with current research, the first contribution of the research is to prove the promotional effect of DGF on AGTFP, which enriches the literature about the influencing factors of AGTFP. At the same time, the paper explores the impact mechanism in multiple dimensions, which deepens the awareness of the internal relationship between the two. In addition, the paper also explores the spatial spillover effect of DGF's impact on AGTFP, which supplements empirical evidence for promoting coordinated development of digital green finance. From the practical perspective, it provides a certain reference basis for China to realize sustainable development and continue to promote high-quality agricultural development.

The rest of the paper is organized as follows. Section 2 reviews the relevant theories and formulates the research hypotheses. Section 3 describes the research design. Section 4 discusses empirical results and analysis. Section 5 discusses the research findings. Section 6 draws research conclusions and makes policy recommendations. Section 7 discusses the limitations and further research directions.

2. Theoretical Framework and Research Hypothesis

2.1. Theoretical Framework of DGF on AGTFP

In the context of setting the "dual carbon" target and accomplishing sustainable green development of agriculture, it is particularly vital to conduct in-depth research on the impact of DGF on AGTFP. Then, can DGF well stimulate the stable increase in AGTFP? What is the impact mechanism? Is there spatial heterogeneity among regions? Does DGF's impact on AGTFP have a spatial spillover effect? Considering the above issues, we have proposed the theoretical framework shown in Figure 1.

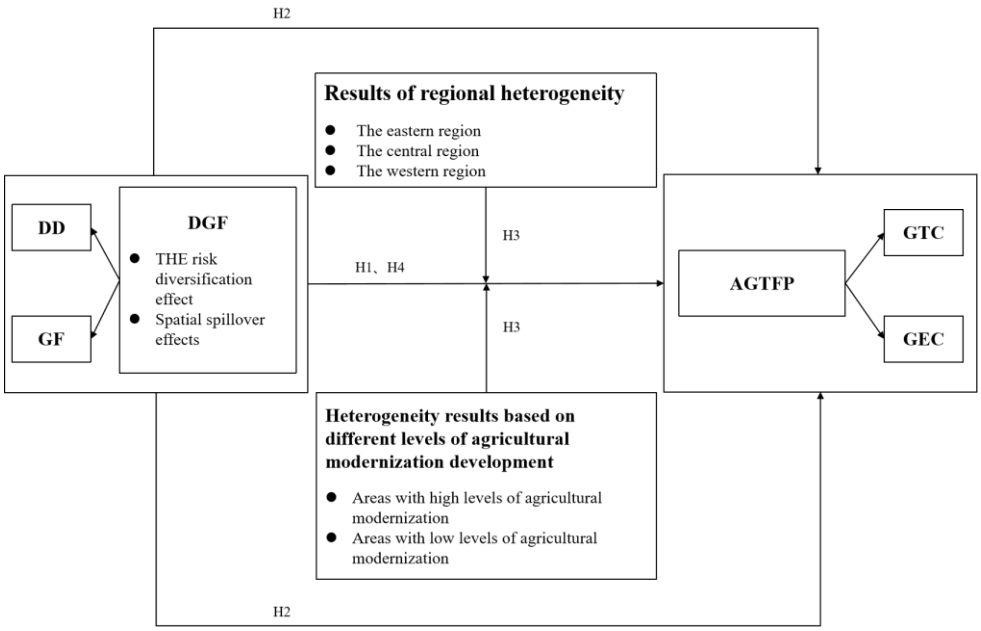

Figure 1. Theoretical framework of the impact of DGF on AGTFP.

2.2. The Direct Effect of DGF on AGTFP

Agriculture, as the foundation of the country, is highly relevant to green finance and digital development simultaneously [34]. On one hand, agriculture has a weak nature in that the production process is easily affected by the environment and climate, and it should become one of the key areas of green financial support [35,36]. On the other hand, accompanied by the integration of digital technology and traditional finance, digital finance has made it possible to rapidly increase the speed of the productive sector in obtaining financial support. Agriculture is a fundamental industry that ensures national stability, and should become a key object of support [37,38]. The proposal of the "dual carbon" goal heralds a new stage of China's green development, comprehensively promotes rural revitalization and speeds up the modernization of agriculture and rural areas, always shouldering the responsibility and mission of promoting harmony between humans and nature. In order to fundamentally solve the problem of extensive agricultural production methods in rural areas, and then comprehensively promote green development, the establishment of a green ecological system in the countryside urgently requires the support of green finance [39].

Green finance can not only provide financial security for agricultural green technological innovation and promotion of agricultural green technology, but also promote the modernization of agriculture and the countryside. Green finance is also conducive to guiding agricultural producers and managers to form green production and living styles, and thinking highly of the ecological industry and rural green development [40]. Digital finance expands the service boundary of green finance, which can make green finance work faster, effectively addressing the weakness of traditional green finance services [41]. Based on this, this paper brings forward the following hypothesis.

Hypothesis 1. *DGF can directly enhance AGTFP.*

2.3. The Impact Mechanism of DGF on AGTFP

Low-carbon agriculture is a necessary path to achieving agricultural modernization, and green finance can undoubtedly facilitate green development of agriculture [42], which not only enables agricultural producers to get more loans for the purchase of advanced equipment and technologies and the implementation of green production methods, but also provides agricultural producers with a risk diversification and economic compensation mechanism, and provides more convenient and flexible financial support [43–45]. The introduction of these green financial products provides the necessary capital and risk management tools for the improvement of AGTFP, and through financial instruments and DGF platforms, agricultural producers can more easily access financial services such as loans and financing for the enhancement of green agricultural production efficiency. Meanwhile, the financial support can be conductive to the wide application of green technology in agriculture, which in turn improves AGTFP [46].

Existing research has proven that green finance can achieve green economic growth and raise the efficiency of resource utilization, facilitating the coordinated development of the environment and economy [47]. Green finance can also guide the capital flowing to high-tech industries, enhance the adoption and application of green production technology, accelerate the optimization and adjustment of the industrial structure [48] and focus the favorable production resources in the production sector with a higher input–output rate, so as to increase the level of productivity of the industry [49]. Accordingly, the following hypothesis is raised.

Hypothesis 2. *DGF can promote AGTFP through green finance, or promote AGTFP through increasing the efficiency of green technologies.*

2.4. Spatial Heterogeneity of DGF on AGTFP

The ecological resources, policy objectives, geographic environment and economic development level differ significantly among provinces in China [50]. The different economic development level in each region leads to an obvious regional heterogeneity among factor endowments. Empirical research has found that there exist considerable regional differences in China's digital financial development due to the influences of economic development, science and technology, income level and other factors [51]. Places with better levels of economic development also hold a higher modernization level and a more complete network system, and tend to attract a concentration of capital, technology and talent more easily. Accordingly, in areas with higher levels of digital financial development, the integration of financial instruments and digitalization is also more comprehensive, which can give rise to financial services with broader coverage and wider scope of application, and boost the efficiency of financial activities effectively [52]. On the contrary, in regions where the development of digital finance is relatively backward, the financing environment, financial services, and financial allocation efficiency provided by the market will be greatly reduced, which will adversely affect the promotion of DGF on AGTFP. Thus, the following hypothesis is put forward.

Hypothesis 3. *There is spatial heterogeneity in the impact of DGF on AGTFP.*

2.5. Spatial Spillover Effects of DGF on AGTFP

Combining the above assumptions, the relationship between DGF and AGTFP is then analyzed from a spatial perspective. Green finance is a financial instrument that supports and facilitates environmental protection and low-carbon economic development through the introduction of environmental, social and governance factors [53], and has a significant spatial transmission effect on high-quality economic development, which means that a change in green finance in a local region can also influence the economic development of the neighboring provinces [54,55]. And digital finance, under the spatial influence of the original traditional finance, compresses the spatial and temporal distance through efficient information dissemination, which again strengthens the spatial spillover effect of financial instruments [56]. Previous research has shown that regional green finance not only boosts the local area's high-quality development, but also has a stimulative spillover effect on its neighboring regions [57]. Through the construction of three spatial weighting matrices using spatial econometric modeling, related empirical results suggest that green finance is conductive to both local and neighboring regions' GTFP [58]. According to above analysis, this paper raises the following hypothesis.

Hypothesis 4. *DGF's impact on AGTFP has a spatial spillover effect.*

3. Research Design

3.1. Methods

3.1.1. Panel Data Model

In an effort to investigate the direct impact of DGF on AGTFP, this study establishes a panel fixed-effects model as follows:

$$AGTFP_{it} = \alpha_0 + \alpha_1 DGF_{it} + \sum \alpha_2 X_{it} + \varepsilon_{it} \quad (1)$$

In Equation (1), i and t represent the province and the year, respectively. AGTFP represents the explained variable. The core explanatory variable is DGF. X represents a set of control variables that may influence AGTFP. This paper mainly focuses on the coefficient α_1, which represents the direct impact of DGF on AGTFP. ε_{it} is a random perturbation term.

3.1.2. Quantile Model

Referring to Dong R et al. (2023) and Xu G et al. (2022) [59,60], this paper selects the quantile model to research in depth the nonlinear relationships between DGF and AGTFP. Quantile regression is characterized by relaxing the assumptions of normal distribution and homoskedasticity of ordinary OLS regression, and the regression coefficients can be obtained for any quantile points. Therefore, for the explanatory variables whose conditional distributions are not symmetric, quantile regression can portray the relationship between the explained variables and the explanatory variables more comprehensively. Meanwhile, this model may give more attention to the tail characteristics of the data. In addition, quantile regression also has the characteristic of being less susceptible to extreme values. The expression is:

$$AGTFP_{q,it} = \alpha_{q,0} + \alpha_{q,1} DGF_{q,it} + \sum \alpha_{q,2} X_{q,it} + \varepsilon_{q,it} \quad (2)$$

In Equation (2), q represents the number of quartile points, $\alpha_{q,1}$ represents the efficiency of the impact of DGF on AGTFP under different quartile points, and other variables and symbols mean the same as those described above indicated.

3.1.3. Spatial Econometric Model

Drawing on the research of Wang H et al. (2021) and Qin et al. (2023) [10,61], this article constructs a spatial econometric model to prove the existence of the spatial spillover effect of DGF's impact on AGTFP.

Firstly, Moran's test is adopted to identify the existence of spatial autocorrelation between DGF and AGTFP. Secondly, with the help of the LM test, LR test, Wald test and Hausmann test, the investigation is carried out to find out which spatial econometric model is the most suitable, followed by empirical analysis.

The spatial lag model (SAR) model is set up as follows:

$$AGTFP_{it} = \alpha + \rho \sum_{j=1}^{N} w_{ij} AGTFP_{jt} + \beta DGF_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

where DGF_{it} and $AGTFP_{it}$ represent DGF and AGTFP in year t of area i, respectively. α is a constant term. ρ is the spatial autoregressive coefficient, and β is the estimated coefficient of DGF. X_{it} represents the $k \times 1$-dimensional control variable set, and γ represents the $1 \times k$-dimensional coefficient vector. w_{ij} represents the elements of column j of row i in the spatial weight matrix; μ_i and δ_t represent spatial and temporal fixed effects; ε_{it} is a random error term.

The Spatial Error Model (SEM) model is set as follows:

$$\begin{aligned} AGTFP_{it} &= \alpha + \beta DGF_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \\ \varepsilon_{it} &= \lambda \sum_{j=1}^{N} w_{ij} \varepsilon_{it} + \sigma_{it} \end{aligned} \quad (4)$$

where λ is the spatial error coefficient, and the other variables and symbols possess the same meanings as described above.

The Spatial Durbin Model (SDM) is set as follows:

$$\begin{aligned} AGTFP_{it} = \quad & \alpha + \rho \sum_{j=1}^{N} w_{ij} AGTFP_{jt} + \beta DGF_{it} + \varphi \sum_{j=1}^{N} w_{ij} DGF_{it} + \gamma X_{it} \\ & + \theta \sum_{j=1}^{N} w_{ij} X_{it} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (5)$$

where φ is the impact of the spatial lag value of DGF on the AGTFP; θ is the effect of the spatial lag value of the control variable on the AGTFP; and the other variables and symbols have the same meanings as described above.

3.2. Measurement of Main Variables

3.2.1. Measurement of DGF

DGF, as an emerging force in the financial system, is receiving more and more attention and promotion. Empowering green financial instruments through digital means not only contributes to green finance's further progress, but also to the realization of environmental sustainability. DGF is characterized by high efficiency, transparency and traceability. Through the utilization of digital technology, it can also effectively reduce the costs of green finance. Currently, traditional financial institutions are gradually adopting digital technologies to support the financing needs of environmentally friendly projects. For the sake of promoting the integrated development of DGF, the forms of financial instruments need to be more diversified, and the digital infrastructure needs to be improved. Therefore, China's financial regulatory authorities such as the China Banking and Insurance Regulatory Commission (CBIRC) and the People's Bank of China (PBOC) need to improve the relevant regulations of DGF. Large commercial banks provide more digital green finance supply. Digital technology enterprises can provide the necessary technical supports. The participation of these departments helps to promote the rapid progress of digital green finance.

Drawing on the existing literature, this paper constructs the DGF evaluation index system under scientific and reasonable conditions, as shown in Table 1. The degree of digitization is an important indicator which is widely used to measure a region's digital development. Drawing on the practices of Guo F (2020) and other scholars [62,63], we choose the second-level indicator "digitalization degree" in the Peking University Digital Inclusive Finance Index as the proxy variable for evaluating the level of digital development in this study. Regarding green finance, this paper primarily refers to Ma J (2021) and "Guiding Opinions on Building a Green Financial System", issued by the People's Bank of China. Green credit, green securities, green insurance and green investment are selected as the secondary indicators of green finance. The specific indexes are calculated after deflating and quantifying the continuous variables of China's relevant data from 2011 to 2020 [8,64,65].

Table 1. Evaluation index system of DGF development level.

Primary Indicator	Secondary Indicator	Metric Weights	Indicator Description
Degree of digitalization (41.41%)	Mobile	20.58%	Proportion of mobile payments
			Percentage of mobile payment amount
	Affordable	10.27%	Average loan interest rate of small and micro-operators
			Average personal loan interest rate
	Credit transformation	3.93%	Proportion of the number of Huabei payments
			Proportion of the payment amount of Huabei
			Proportion of the number of sesame credit-free deposits
			Proportion of sesame credit-free deposit amount
	Facilitation	6.63%	Proportion of the number of QR code payments made by users
			The proportion of the amount paid by the user's QR code
Green finance (58.59%)	Green credit	29.29%	Proportion of interest expenses in high-energy-consuming industries
			Green credit balances
	Green securities	14.65%	Proportion of market value of environmental protection enterprises
			Proportion of market value of high-energy-consuming industries
	Green insurance	8.79%	Ratio of agricultural insurance scale
			Agricultural insurance loss ratio
	Green investment	5.86%	Proportion of investment in environmental pollution control
			Proportion of public expenditure on energy conservation and environmental protection

In terms of setting weights for primary indicators, this paper adopts a combination of subjective and objective methods, drawing on Li X (2014) [66]. The subjective method is the expert scoring method, while the objective method is the entropy method. The average of subjective and objective weights is the comprehensive weight. A weight of 58.59% is given to Green finance and a weight of 41.41% is given to the degree of digitization. The weight setting of the second-level indicator of Digitalization degree refers to the "Peking University Digital Inclusive Finance Index" published by the Digital Finance Research Center of Peking University. The weight of the secondary indicators of green finance is based on the research of Lee C (2022) and Qin et al. [9,61] and measured by the objective entropy method. The third column of Table 1 shows the weight of each secondary indicator in DGF.

3.2.2. Measurement of AGTFP

Regarding the selection of AGTFP measurement indexes, the evaluation system of AGTFP was constructed with reference to the existing literature [67], which includes three major categories of variables, namely, input variables, desirable output variables and undesirable output variables (Table 2).

Table 2. Evaluation index system of AGTFP.

Variable Type	Variable	Indicator Description
Input variables	Labor input	Number of people employed in agriculture
	Land input	Total sown area
	Energy inputs	Total power of agricultural machinery Water inputs
	Agricultural inputs	Reduced amount of chemical fertilizer application Pesticide application rate The amount of agricultural film used
Desired output variables	Gross Domestic Product	Gross agricultural output
Undesired output variables	Carbon emissions	Carbon emissions from agricultural production

The agricultural production behaviors always include desired and undesired outputs. Due to the simultaneous radial and non-radial relationships between variables, the traditional DEA method cannot be realized, and there may also be the existence of multiple decision-making units with efficiency values of 1, resulting in the inability to compare between decision-making units. Therefore, this paper applies the super-efficient SBM model including non-desired outputs proposed by Fu W et al. (2022) [67]. The non-radial non-angle super-efficient SBM model containing non-expected outputs can be expressed as:

$$\min \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{l0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}}\right) + \sum_{b=1}^{s_2}\frac{s_l^b}{b_{l0}}}$$

$$\text{s.t.}\begin{cases} x_{i0} \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j - s_i^x, (i = 1, \cdots, m) \\ y_{k0} \geq \sum_{j=1,\neq 0}^{n}\lambda_j y_j + s_k^y, (k = 1, \cdots, s_1) \\ b_{l0} \geq \sum_{j=1,\neq 0}^{n}\lambda_j b_j - s_l^b, (l = 1, \cdots, s_2) \\ 1 - \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}} + \sum_{b=1}^{s_2}\frac{s_l^b}{b_{l0}}\right) > 0 \\ \sum_{j=1,\neq 0}^{n}\lambda_j = 1, s_i^x, s_k^y, s_l^b, \lambda_j \geq 0, (j = 1, \cdots, n) \end{cases} \quad (6)$$

In the first step, it is assumed that each area is a decision-making unit (DMU), and each DMU contains inputs, desired outputs and non-desired outputs. In the above equation, *p* is the efficiency value of each DMU; x, y and b are the inputs, desired outputs and non-desired outputs, respectively; m, s_1 and s_2 are the quantities of inputs, desired outputs and non-desired outputs, respectively; s_i^x, s_k^y and s_l^b are the slack variables of inputs, desired outputs and non-desired outputs, respectively; and λ is the intensity variable, which denotes the specific weights that correspond to each DMU in the calculation process. When the efficiency value is less than 1, it means that the DMU is ineffective; on the contrary, when the efficiency value is greater than 1, it means that the DMU is effective.

In the second step, this paper draws on the experience of Yang et al. (2022) [68] to further decompose the GML index into a green technical efficiency index (GEC) and a green technical progress index (GTC) with the following formula:

$$\begin{aligned} GML &= GEC \times GTC \\ GEC &= \frac{E^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{E^{t}(x^{t},y^{t},b^{t})} \\ GTC &= \frac{E^{G}(x^{t+1},y^{t+1},b^{t+1})}{E^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \frac{E^{t}(x^{t},y^{t},b^{t})}{E^{G}(x^{t},y^{t},b^{t})} \end{aligned} \tag{7}$$

In the above equation, E^G and E^t represent the global frontier and the efficiency value when the frontier is period t. The GML index represents the rate of change of AGTFP; the GEC index reflects the proximity of the actual production of agriculture to the maximum yield, which reflects the catching-up speed of the technological laggards; and the GTC index represents the progress speed of the green technology frontier, which means the dynamic change of the frontier of production possibilities expanding outward. If GML, GEC and GTC are all greater than 1, it indicates that there has been an increase in current AGTFP, green technological efficiency and green technology.

In the actual calculation, since GML, GEC and GTC are year-on-year values, which are not conducive to the calculation of subsequent empirical tests, the efficiency value of AGTFP in the initial year of 2010 is set to 1 by referring to Z Yin et al. (2021) [69], and the subsequent years are derived by multiplying cumulatively by logarithms of the GML index. GEC and GTC are derived by the same calculation.

3.2.3. Control Variables

Considering that AGTFP may be affected by many factors, this paper refers to the present literature to select control variables.

The first control variable is urbanization level (UL). The development of urbanization can drive the development of local employment and promote the non-farm transfer of the rural population. At the same time, the increase in urban construction land will also affect the land available for agricultural production. In this study, we refer to Liu Y et al. (2021) and Gao Q et al. (2022) to adopt the ratio of non-farm population to the total population to represent the urbanization level of each region [11,70].

The second is agricultural machinery density (MD). On one hand, a higher density of agricultural machinery implies an increase in greenhouse gas emissions, which are undesired outputs. On the other hand, the use of agricultural machinery also enhances the efficiency of agricultural production, which increases the gross value of agricultural output in turn. Therefore, the effect of machinery density on AGTFP is uncertain. Referring to Gao Q et al. (2021) and Fang L et al. (2021), we use the ratio of total farm machinery power to sown area to represent agricultural machinery density [70,71].

The third is disaster-affected area (DA). Science natural disasters significantly affect agricultural production, this paper uses the logarithm of the disaster-affected area of agricultural production in each region to measure DA, referring to Wang F et al. (2022) [67]. The fourth is level of rural human capital (HUM). This study draws on Zhou X (2023) et al. and Fang L et al. (2021) and uses the logarithm of the average schooling years of rural

residents to express HUM [37,71]. The fifth is the government's fiscal support (FS). We use the logarithm of provincial fiscal expenditures on agricultural, forestry and water affairs with reference to Guo J et al. (2022) [32].

3.3. Data Source and Descriptive Statistics

This paper collects and sorts out the panel data of 30 provinces (except Tibet) in China from 2011 to 2020, among which the green credit data come from the China Industrial Statistical Yearbook and the bank green credit data released by the China Banking and Insurance Regulatory Commission, the green securities data come from the Choice financial terminal, the green insurance data are obtained from the China Insurance Statistical Yearbook, and the green investment data are derived from the China Environmental Statistical Yearbook and the China Financial Statistical Yearbook. The input–output data related to agricultural production are derived from the Chinese Population Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Yearbook, China Animal Husbandry Yearbook, China Environmental Statistics Yearbook and provincial statistical yearbooks. In order to eliminate the impact of inflation and price fluctuations, all economic variables are deflated by the corresponding price index based on 2011. We use the linear interpolation method to supplement missing data for individual variables. To avoid interference from abnormal data, this paper presents descriptive statistics for all variables using stata17.0 software, which shows that there are no obvious outliers in Table 3. The VIF values of all explanatory variables are far below the critical value of 10, which indicates that the model has no multicollinearity issues.

Table 3. Results of descriptive statistics for variables.

Variable	Sample Size	Mean	Standard Deviation	Min	Max	VIF
AGTFP	300	0.411	0.343	0.01	1.902	— —
DGF	300	−0.688	0.312	−1.995	−0.0471	2.40
UL	300	0.59	0.122	0.35	0.896	3.02
MD	300	0.648	0.239	0.112	1.335	1.12
HUM	300	2.045	0.0778	1.766	2.275	1.72
DA	300	5.168	1.637	0	7.888	2.08
FS	300	6.521	0.706	4.519	7.902	1.84

Note: we only need to calculate the VIF values of the explanatory variables, so we did not list the VIF value of the dependent variable AGTFP.

4. Empirical Results and Analysis

4.1. Baseline Effect Analysis

4.1.1. Baseline Regression Results

In this paper, we use stata17.0 software to conduct a Hausman test, and use panel data to determine the use of fixed effects. After controlling the individual effect and time effect, we finally construct a two-way fixed-effects model to initially evaluate the relationship between DGF and AGTFP, and the regression results are shown in Table 4. Column (1) reports the regression results of the random effects model of DGF on AGTFP. Column (2) reports the results of the two-way fixed-effects model of DGF on AGTFP. It can be seen that DGF significantly increases AGTFP with or without controlling for province and time. Columns (3) to (5) of Table 4 utilize the quantile model by selecting three quantiles of 0.1, 0.5 and 0.9 for regression analysis. It is evident that the correlation of the regression coefficients for DGF is significantly positive for all three quantiles at 1% level. In addition, the regression coefficients of DGF on AGTFP gradually increase with the increase in the loci, indicating that the promotional effect of DGF on AGTFP gradually increases. Hypothesis 1 is validated.

Table 4. Baseline regression results of DGF's impact on AGTFP.

	(1) AGTFP	(2) AGTFP	(3) AGTFP (0.1)	(4) AGTFP (0.5)	(5) AGTFP (0.9)
DGF	0.152 ***	0.200 ***	0.127 ***	0.266 ***	0.348 ***
	[0.054]	(0.043)	(0.041)	(0.052)	(0.056)
UL	0.382 *	−3.432 ***	0.0213	1.284 **	1.920
	[0.197]	(0.435)	(0.090)	(0.633)	(1.343)
MD	0.0363	−0.0788	−0.145	0.229 *	−0.0229
	[0.065]	(0.066)	(0.092)	(0.137)	(0.073)
HUM	−0.0856	−0.0666	−0.0156	−0.315	−0.749
	[0.256]	(0.300)	(0.215)	(0.734)	(0.841)
DA	−0.111 ***	−0.0528 ***	−0.0774 ***	−0.0503 **	−0.115 ***
	[0.011]	(0.009)	(0.007)	(0.020)	(0.039)
FS	0.355 ***	0.177 ***	0.309 ***	0.455 **	0.370 ***
	[0.022]	(0.057)	(0.028)	(0.214)	(0.111)
_cons	−1.296 **	1.519 **			
	[0.538]	(0.730)			
Province fixed	NO	YES	YES	YES	YES
Year fixed	NO	YES	YES	YES	YES
N	300	300	300	300	300
adj. R^2		0.9004			

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively, and the standard errors in parentheses are the same as in the table below.

4.1.2. Impact Mechanism Analysis

Table 5 presents the regression results of the impact of digitization degree (column 1) and green finance (column 2) on AGTFP. The development of the degree of digitization has injected new energy into agricultural green production, but the development of digitization has placed new demands on the knowledge level and practical skills of agricultural practitioners, and for some agricultural producers, although agricultural production can be promoted through the introduction of advanced green production technology, it may lead to a decline in the efficiency of the production process due to the limitations of their knowledge reserves and ability to use technology. However, such an impact will gradually improve over time. Green finance offers financial support and risk management tools for the development and application of green technologies in agriculture. It also provides new types of financial products, such as green credit and green insurance, to provide risk diversification and economic compensation mechanisms for agricultural producers. The introduction of these green financial products has provided agricultural production with the necessary financial resources and risk management tools, and has provided an effective guarantee for the promotion of AGTFP.

Table 6 shows the regression results of DGF on the green technology progress index and green technology efficiency. DGF has a significant promotion effect on the improvement of green technology efficiency, but there is an inhibition effect on green technology progress. Theoretically, DGF's development is effectively conducive to green technological progress, but the actual application results may be affected by the decision-making behavior and motivation of agricultural producers, who may be more inclined to increase the final output value and achieve a rapid increase in income by increasing the input of resource factors or optimizing the allocation of all resource factors after obtaining the help of DGF. This bias may result in agricultural producers investing less in green technological advances, thereby slowing the development of green technologies.

Table 5. Regression results of degree of digitization and green finance on AGTFP.

	(1) AGTFP	(2) AGTFP
DD	0.0466	
	(0.039)	
GF		0.285 ***
		(0.062)
UL	−3.483 ***	−3.364 ***
	(0.469)	(0.437)
MD	−0.0997	−0.0882
	(0.069)	(0.066)
HUM	0.0838	−0.0854
	(0.311)	(0.301)
DA	−0.0501 ***	−0.0531 ***
	(0.009)	(0.009)
FS	0.208 ***	0.191 ***
	(0.059)	(0.057)
_cons	0.672	1.530 **
	(0.800)	(0.732)
Province fixed	YES	YES
Year fixed	YES	YES
N	300	300
adj. R^2	0.8926	0.9001

Note: ***, ** represent the significance levels of 1%, 5% respectively.

Table 6. Regression results of DGF on green technology progress index and green technology efficiency.

	(1) GTC	(2) GEC
DGF	−0.103	0.303 ***
	(0.063)	(0.072)
UL	0.837	−4.269 ***
	(0.639)	(0.726)
MD	−0.0140	−0.0658
	(0.097)	(0.111)
HUM	1.047 **	−1.113 **
	(0.441)	(0.501)
DA	−0.0273 **	−0.0256 *
	(0.013)	(0.015)
FS	0.0417	0.135
	(0.084)	(0.095)
_cons	−2.754 **	4.272 ***
	(1.074)	(1.219)
Province fixed	YES	YES
Year fixed	YES	YES
N	300	300
adj. R^2	0.8539	0.1901

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively.

According to Tables 6 and 7, it can be seen that DGF can provide security for agricultural production and effectively stimulate the growth of AGTFP, while the role of DGF is not very significant. Meanwhile, DGF can promote the growth of AGTFP by improving the efficiency of green technology. Hypothesis 2 is confirmed.

Table 7. Results of regional heterogeneity.

	(1) AGTFP (The Eastern Region)	(2) AGTFP (The Central Region)	(3) AGTFP (The Western Region)
DGF	0.262 ***	0.105 ***	0.149 **
	[0.086]	[0.037]	[0.066]
UL	−3.721 ***	5.465 ***	4.278 ***
	[0.885]	[0.664]	[0.982]
MD	−0.0824	−0.0260	−0.282 *
	[0.117]	[0.039]	[0.167]
HUM	−0.538	−0.140	0.350
	[0.456]	[0.294]	[0.362]
DA	−0.0388 **	0.00129	−0.0205
	[0.016]	[0.008]	[0.018]
FS	0.387 ***	0.206 ***	−0.113
	[0.104]	[0.067]	[0.115]
_cons	2.102	−3.685 ***	−1.379
	[1.343]	[0.894]	[1.174]
Province fixed	YES	YES	YES
Year fixed	YES	YES	YES
N	110	90	100
adj. R^2	0.9342	0.9807	0.9292

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively.

4.2. Heterogeneity Analysis

Since there are large differences in ecological resources, policy objectives, geography and economic level among regions in China, this paper divides China's 30 provinces into three groups based on their location: eastern, central, and western. Columns (1) to (3) in Table 7 express the results of DGF on AGTFP in the three regions, respectively. The results show that DGF significantly contributes to the growth of AGTFP in the three regions. The eastern region makes the largest contribution, followed by the central region and western region. A possible reason for this is that the eastern region is relatively the most economically developed, with more rapid technological development and financial development, and the integration of the two is also more complete, making the promotion of AGTFP more obvious. This is also in agreement with the benchmark regression.

Agricultural modernization is a key way to achieve steady agricultural development and increase agricultural productivity, and the difference in the degree of agricultural modernization between provinces may make differences in the effect of DGF on AGTFP. Therefore, this paper divides the 30 provinces in the country into two parts for regression according to the degree of agricultural modernization. Columns (1) and (2) in Table 8 express the results of the regions with high and low agricultural modernization, respectively. The results show that DGF can effectively enhance AGTFP in both regions with high and low agricultural modernization, and that the enhancement effect is more significant in regions with high agricultural modernization. Regions with a high degree of agricultural modernization are usually better able to adapt to the requirements of DGF and achieve a green transition and sustainable development in agriculture, while regions with a low degree of agricultural modernization may be limited by the level of technology and management, and the application of financial services and inputs is relatively small, so the enhancement of agricultural productivity is affected to a certain extent. The test results are in accordance with the above results, again verifying the validity of the conclusions. Hypothesis 3 is validated.

Table 8. Heterogeneity results based on different levels of agricultural modernization [1].

	(1) AGTFP (Areas with High Levels of Agricultural Modernization)	(2) AGTFP (Areas with Low Levels of Agricultural Modernization)
DGF	0.344 ***	0.0981 **
	[0.098]	[0.046]
UL	−4.623 ***	1.373
	[1.196]	[0.865]
MD	−0.269	−0.00810
	[0.187]	[0.052]
HUM	−0.757	−0.0299
	[0.510]	[0.320]
DA	−0.0739 ***	−0.0221 **
	[0.021]	[0.010]
FS	0.320 **	−0.0422
	[0.135]	[0.082]
_cons	3.955 **	0.196
	[1.536]	[0.976]
Province fixed	YES	YES
Year fixed	YES	YES
N	100	200
adj. R^2	0.9136	0.9424

Note: ***, ** represent the significance levels of 1%, 5% respectively. [1] Areas with high levels of agricultural modernization include Beijing, Shanghai, Jiangsu, Tianjin, Heilongjiang, Liaoning, Shandong, Zhejiang, Guangdong and Jilin; Areas with low levels of agricultural modernization include Shaanxi, Guangxi, Hainan, Ningxia, Shanxi, Yunnan, Qinghai, Guizhou, Gansu, Fujian, Hubei, Henan, Xinjiang, Jiangxi, Hunan, Anhui, Hebei, Sichuan, Inner Mongolia and Chongqing.

4.3. Spatial Spillover Effect Analysis

4.3.1. Spatial Autocorrelation Analysis

Before conducting spatial econometric analysis, the spatial correlation of the relevant variables needs to be investigated. This paper introduces Moran's I to test the spatial autocorrelation of DGF and AGTFP. Tables 9 and 10 report the global Moran indices of DGF and AGTF, respectively. Under two different spatial weight matrices, the global Moran's I indexes of digital DGF and AGTFP pass the test for 2011–2020, and most of them passed the 1% significance level test. This indicates that both DGF and AGTFP have positive and strong spatial autocorrelation under both geographic distance weight matrix (W1) and economic distance weight matrix (W2). According to the test results, the spatial econometric model can be used for empirical analysis.

Table 9. Global Moran index of DGF, 2011–2020.

Year	W1			W2		
	Moran's I	Z	*p*	Moran's I	Z	*p*
2011	0.079	3.329	0.000	0.474	3.298	0.000
2012	0.064	2.814	0.002	0.437	2.957	0.002
2013	0.055	2.579	0.005	0.430	2.955	0.002
2014	0.057	2.632	0.040	0.293	2.080	0.019
2015	0.056	2.576	0.005	0.386	2.644	0.004
2016	0.080	3.202	0.001	0.429	2.840	0.002
2017	0.064	2.738	0.003	0.383	2.556	0.005
2018	0.116	4.235	0.000	0.515	3.400	0.000
2019	0.095	3.658	0.000	0.473	3.150	0.001
2020	0.098	3.748	0.000	0.504	3.345	0.000

Table 10. Global Moran index of AGTFP index from 2011 to 2020.

Year	W1			W2		
	Moran's I	Z	*p*	Moran's I	Z	*p*
2011	0.054	2.623	0.004	0.370	2.621	0.004
2012	0.060	2.729	0.003	0.481	3.275	0.001
2013	0.053	2.581	0.005	0.457	3.195	0.001
2014	0.042	2.264	0.012	0.365	2.591	0.005
2015	0.064	2.927	0.002	0.484	3.411	0.000
2016	0.058	2.759	0.003	0.424	3.017	0.001
2017	0.059	2.913	0.002	0.450	3.308	0.000
2018	0.059	2.902	0.002	0.440	3.258	0.001
2019	0.045	2.461	0.007	0.411	3.049	0.001
2020	0.030	1.893	0.029	0.328	2.351	0.009

4.3.2. Selection of Spatial Econometric Models

In this research, the spatial spillover effects of DGF and AGTFP were tested using Stata 17.0 software. Under the economic distance weight matrix (W2), LM-Lag and Robust LM-Lag tests were used, and the results showed *p*-values of 0.040 and 0.003, respectively, which passed the significance level tests of 5% and 1%. In addition, LM-Error and Robust LM-Error tests were also used, and the *p*-values were 0, passing the 1% significance level test. This indicates that the spatial lag and spatial error models fit relatively well under the economic distance weight matrix (W2). Secondly, the Spatial Durbin Model (SDM) was used to test whether it could be transformed into the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM). Under the economic distance weight matrix, LR-SAR and LR-SEM tests were used, and the results showed *p*-values of 0.011 and 0, respectively, which passed the 5% and 1% significance level tests. In addition, Wald-SAR and Wald-SEM tests also passed the 1% significance level test. Therefore, the SDM was chosen as the final model for this research. Finally, the Hausman test is used to determine the applicability of fixed-effects models. The results suggest that the Hausman test passed the 1% significance test and rejected the original hypothesis; therefore, the fixed-effects model is more applicable to this research. In summary, this paper chooses to establish an SDM with two-way fixed effects for empirical research (Table 11).

Table 11. LM, LR, Wald and Hausman test results.

The Type of Inspection	Statistics	*p*-Value
LM-Lag	4.207	0.040
Robust LM-Lag	8.631	0.003
LM-Error	38.446	0.000
Robust LM-Error	42.870	0.000
LR-SAR	16.480	0.011
LR-SEM	26.620	0.000
Wald-SAR	16.770	0.010
Wald-SEM	27.560	0.000
Hausman	23.930	0.000

4.3.3. Spatial Regression Results Analysis

Columns (1) to (3) in Table 12 report the spatial regression results of SAR, SEM and SDM, respectively. All three models yielded the result that DGF can significantly promote the growth of AGTFP.

Table 12. Regression results of the spatial econometric model.

	(1) AGTFP (SAR)	(2) AGTFP (SEM)	(3) AGTFP (SDM)
DGF	0.172 ***	0.174 ***	0.150 ***
	(0.038)	(0.039)	(0.038)
UL	−3.042 ***	−3.211 ***	−2.237 ***
	(0.390)	(0.429)	(0.490)
MD	−0.0215	−0.0104	0.0255
	(0.059)	(0.065)	(0.061)
HUM	−0.00481	−0.0422	0.167
	(0.264)	(0.265)	(0.263)
DA	−0.0471 ***	−0.0499 ***	−0.0412 ***
	(0.008)	(0.008)	(0.008)
FS	0.144 ***	0.153 ***	0.146 ***
	(0.050)	(0.052)	(0.053)
W× DGF			0.0898 *
			(0.054)
W × UL			−2.070 **
			(0.804)
W × MD			−0.168 **
			(0.066)
W × HUM			−0.0165
			(0.393)
W × DA			−0.0166
			(0.012)
W × FS			0.0413
			(0.090)
rho	0.269 ***		0.225 ***
	(0.056)		(0.060)
lambda		0.217 ***	
		(0.065)	
Province fixed	YES	YES	YES
Year fixed	YES	YES	YES
N	300	300	300
sigma2_e	0.00747 ***	0.00781 ***	0.00713 ***
	(0.001)	(0.001)	(0.001)
Log-L	304.5509	299.4805	312.7888

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively.

The urbanization level (UL) has a remarkable negative impact on AGTFP, probably due to the fact that the rural–urban migration of the rural population in the process of urbanization leads to a reduction in the agricultural factors of production, which in turn reduces the efficiency of agricultural production. Machinery density (MD) has a non-significant effect on AGTFP. The probable reason may be that machinery inputs can promote an increase in agricultural output, but it also increases the emission of non-desired outputs, resulting in its non-significant effect on AGTFP. The effect of rural human capital (HUM) on AGTFP is not significant. The enhancement of rural human capital can promote the acceptance of advanced technology and equipment by agricultural producers on the one hand, but on the other hand, it may also lead to the transfer of rural labor to the non-farming sector, which reduces the resource allocation efficiency of agricultural production. The affected area (DA) has a notable negative effect on AGTFP, indicating that when the land is affected by natural disasters, it will significantly inhibit the enhancement of AGTFP. The impact of fiscal support (FS) on AGTFP is significantly positive, suggesting that the financial support provided by the government in the agricultural production process can effectively promote the development of agriculture and improve AGTFP. In summary, DGF and FS have a significant promotion effect on AGTFP, while UL, MD, HUM, DA and other factors limit or inhibit the improvement of AGTFP.

Table 13 reports the direct effect in column (1), the indirect effect in column (2) and the total effect in column (3), respectively. We can see that both the direct and total effects of DGF are significantly positive, which indicates that DGF has a significant contribution to AGTFP in local provinces. In addition, DGF has a significant positive indirect effect on AGTFP in neighboring provinces, which implies that DGF has a significant spatial spillover effect, i.e., the development of DGF in one region can promote the improvement of AGTFP in neighboring regions through the transfer of technology, experience and talents. Regarding the control variables, an increase in urbanization level may attract rural workers from local and neighboring regions, leading to a reduction in the allocation efficiency of agricultural production factors. Machinery density has a positive but insignificant effect on AGTFP in the region, and a significantly negative effect on neighboring regions, probably because more agricultural machinery is invested in the current agricultural production process and the pollution from production processes spreads to neighboring areas, thus inhibiting, to a certain extent, the increase in AGTFP. Rural human capital is not significant for AGTFP in this region and neighboring regions, but shows a positive trend, indicating that improving rural human capital still has positive significance. The affected area has a significant negative effect on AGTFP in both the region and neighboring regions, inhibiting its development. Financial support plays a greater role in promoting AGTFP in the region. Overall, these results show that DGF has a remarkable positive influence on AGTFP, and is able to promote the development of neighboring regions through the radiation effect while promoting the development of the region. Hypothesis 4 is confirmed.

Table 13. Decomposition results of spatial effects.

	(1) AGTFP (Direct Effects)	(2) AGTFP (Indirect Effects)	(3) AGTFP (Total Effect)
DGF	0.162 ***	0.147 **	0.310 ***
	(0.040)	(0.067)	(0.085)
UL	−2.491 ***	−3.095 ***	−5.587 ***
	(0.445)	(0.906)	(0.878)
MD	0.0174	−0.189 **	−0.171 *
	(0.058)	(0.075)	(0.095)
HUM	0.162	0.0351	0.197
	(0.265)	(0.476)	(0.610)
DA	−0.0434 ***	−0.0311 **	−0.0745 ***
	(0.008)	(0.013)	(0.015)
FS	0.154 ***	0.0965	0.251 *
	(0.053)	(0.111)	(0.134)
Province fixed	YES	YES	YES
Year fixed	YES	YES	YES

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively.

4.4. Robustness Test

To verify the robustness of the conclusions, this study conducts robustness tests on the benchmark model and the spatial econometric model. In the case of the benchmark model, the robustness test is conducted in two ways. Firstly, we perform a bilateral tail reduction of 5% of the sample, and the regression result in Table 14 column (1) is still positive. Secondly, considering the possible lag in the impact of DGF on AGTFP, a first-order lag is applied to DGF. As shown in Table 14 column (2), the regression coefficient of DGF is also notable positive at the 1% level. The regression results of both methods show that DGF significantly promoted the effect of improving AGTFP, supporting the previous conclusion.

In terms of spatial econometric modeling, this study adopts the following three methods for robustness testing. Columns (1) to (3) in Table 15 express the robustness test results by using the main independent variable of one lag period, performing bilateral tail reduction of 5% of the sample, and replacing the neighbor weight matrix.

Table 14. Results of benchmark regression robustness test.

	(1) AGTFP (Tail Reduction)	(2) AGTFP (One Lag Period)
DGF	0.175 ***	
	[0.051]	
L.DGF		0.150 ***
		[0.053]
UL	−3.361 ***	−3.259 ***
	[0.448]	[0.508]
MD	−0.0796	−0.0239
	[0.067]	[0.071]
HUM	−0.00857	0.000333
	[0.305]	[0.314]
DA	−0.0528 ***	−0.0509 ***
	[0.009]	[0.009]
FS	0.191 ***	0.154 **
	[0.058]	[0.060]
_cons	1.245 *	1.386 *
	[0.738]	[0.782]
Province fixed	YES	YES
Year fixed	YES	YES
N	300	270
adj. R^2	0.8966	0.8868

Note: ***, ** and * represent the significance levels of 1%, 5% and 10% respectively.

Table 15. Robustness test results.

	(1) AGTFP (One Lag Period)	(2) AGTFP (Tail Reduction)	(3) AGTFP (Replace the Adjacency Weight Matrix)
L.DGF	0.121 ***		
	(0.046)		
DGF		0.119 ***	0.179 ***
		(0.045)	(0.038)
UL	−2.032 ***	−2.178 ***	−2.836 ***
	(0.557)	(0.498)	(0.444)
MD	0.0639	0.0341	−0.0465
	(0.065)	(0.062)	(0.059)
HUM	0.311	0.242	0.115
	(0.275)	(0.266)	(0.264)
DA	−0.0397 ***	−0.0403 ***	−0.0465 ***
	(0.009)	(0.008)	(0.008)
FS	0.114 **	0.164 ***	0.146 ***
	(0.056)	(0.053)	(0.051)
rho	0.174 ***	0.238 ***	0.256 ***
	(0.065)	(0.059)	(0.067)
sigma2_e	0.00690 ***	0.00730 ***	0.00724 ***
	(0.001)	(0.001)	(0.001)
Province fixed	YES	YES	YES
Year fixed	YES	YES	YES
N	270	300	300
LOG-L	287.1557	308.8637	311.2108

Note: ***, ** represent the significance levels of 1%, 5% respectively.

The results reveal that the regression coefficient of the first-order lagged term of DGF is significantly positive at the 1% level. In addition, the regression coefficients of DGF after shrinking and the regression coefficients of DGF after replacing the weight matrix are also significantly positive at the 1% level. This suggests that the results of the research in this

study not only have a certain degree of reliability, but also can still draw similar conclusions when different situations and assumptions are considered. It further supports that DGF has a significant effect on AGTFP and proves the reliability of the research findings.

5. Discussion

Against the backdrop of the digital age, digital finance has received increasing attention. In line with Zeng Z et al. (2019), we believe that digital finance is closely related to the rural revitalization strategy, and the rapid development of the agricultural economy cannot be achieved without the support of digital finance [72]. Unlike Lan, J et al. and L Qin et al. [7,9,26], this paper introduces digitization techniques in analyzing the impact of green finance on AGTFP. We conclude that digital green finance has a significant promotion effect on AGTFP, and along with the continuous improvement of AGTFP, the promotion effect of digital green finance becomes more significant.

At the country level, the impact of DGF on AGTFP is significant. This trend remains significant after dividing the country into eastern, central and western regions. The most pronounced effect is in the eastern region, followed by the central region, while the western region benefits less. Similar to the findings of G LI et al. (2023) [33], in the eastern region, where DGF is more widely and intensively applied because of economic development and high technology level, its effect on the yield increase of AGTFP is particularly significant. Yu, HJ et al. (2023) also conclude that digital economic development will have different effects on different regions [73], which also validates the conclusions we have drawn.

In terms of the path of influence, the degree of digitization does not have a significant effect, while green finance is the primary driver of AGTFP. The role of degree of digitization is not obvious, which is probably because the degree of integration between digitalization and green finance is not high enough. The conclusions of J Guo et al. (2022) confirm our viewpoints to a certain extent [32]. He concludes through empirical tests that green finance can promote the development of green industry by promoting industrial restructuring. But due to the different levels of economic development between regions, some areas of digital infrastructure have not reached a fully developed level, so the role of promoting the green development of industry is not obvious. Yu Z et al. (2022) also argued that the growth of the digital economy might instead increase carbon emissions when the development of digital economy is at a low level [74]. It further validates our conclusion.

DGF has a negative impact on the advancement of green technologies in agriculture. On the one hand, agricultural producers in China have a weak sense of sustainable development and other issues. On the other hand, at present, the modernization level of agricultural production in China is not high, and advanced production methods have not yet been popularized, which results in a certain impediment to the promotion of DGF on the progress of agricultural green technology. This is similar to the research of Huang Y et al. (2022) and Yu HY et al. (2024) [8,75]. They empirically found that the effect of green finance on green technological progress was not a linear relationship, and was susceptible to other factors, thus weakening the impact on green technological innovation to a certain extent.

In terms of spatial spillover effects, whether in the SAR model, SEM model or SDM model, we can conclude that the improvement in the development level of DGF can notably enhance the AGTFP of the local and neighboring regions. Similar to the conclusion drawn by Yan, L. et al. (2023) and Wang, B et al. (2023) [49,55], green finance has a remarkable spatial spillover effect, which is conductive to AGTFP in neighboring regions along with the local region.

6. Conclusions and Policy Implications

6.1. Conclusions

Based on the panel data of 30 provinces in China from 2011 to 2020, this paper empirically analyzes the impact of DGF on AGTFP and its mechanism of action by using a quantile model and spatial econometric model on the basis of measuring the DGF and AGTFP. The specific conclusions are as follows: (1) DGF has a direct promotional effect

on AGTFP, and the promotional effect of DGF on AGTFP gradually increases with the continuous improvement of AGTFP. (2) From the perspective of the impact path, green finance can provide security for agricultural production and effectively promote the growth of AGTFP, while the role of degree of digitization is not very significant. A possible reason is that DGF is still in the development stage, and the advantages of digitization have not been fully utilized. Improvement in digital infrastructure and digital literacy is an important aspect to stimulate the role of digitization in the future. At the same time, DGF can promote the growth of AGTFP by improving the efficiency of green technology. (3) There is spatial heterogeneity in the impact of DGF on AGTFP, which is specifically manifested in a more significant role in regions with a high degree of economic development and perfect modernization. (4) There is a significant spatial spillover effect of DGF on AGTFP, which can promote the development of neighboring regions through radiation while promoting the development of the region.

6.2. Policy Implications

Based on the above findings, this study makes the following recommendations. Firstly, strengthen the awareness education and technical training of agricultural producers, enhance their knowledge and understanding of green technologies, and guide them to adopt and apply green technologies more actively. Secondly, strengthen the development and promotion of DGF. Given that DGF has a direct role in promoting AGTFP, the government should increase its support for DGF, such as providing policy support, optimizing the financial environment and promoting the innovation and application of financial technology to stimulate and support the development of DGF in the agricultural sector.

Thirdly, promote regional coordinated growth and enhance the overall development level of DGF. Since there is a spatial spillover effect of DGF on AGTFP, the connection and interregional cooperation should be strengthened to continuously popularize and enrich the development of the DGF. Fourthly, support for scientific and technological innovation should be increased by providing financial and resource support to green agricultural science and technology enterprises, to encourage the research, development and application of agricultural green production technologies, establish digital agricultural ecosystems, and promote the collection, sharing and application of agricultural data to provide more accurate and reliable data support for DGF. Big data, cloud computing and other technologies should be used to promote agricultural informatization, increase the agricultural production efficiency, decrease production costs and achieve green agricultural development.

7. Limitations

There are also some shortcomings in this study. First, this study selects provincial panel data. Due to data collection limitations, the sample size of this study is not sufficient, which may have an impact on analyzing the role of DGF on AGTFP. Future research can extend the sample selection and expand the sample size to make the conclusions more informative. Second, the indicator selection of DGF still needs further improvement. If data can be obtained, more indicators that directly reflect the level of rural digitization can be selected. Future research can continue to go deeper to establish a rural digital green finance indicator system to more accurately explore the impact.

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