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The Impact of the Digital Economy on High-Quality Development of Agriculture: A China Case Study

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Abstract: With the progress of information technology, digital technology has rapidly penetrated into all sectors of the national economy and is accelerating the reconstruction of the economic development model, which has become a new engine to drive economic growth and lead industrial development. Based on the panel data of China's provinces from 2013 to 2020, this paper empirically tested the effect and mechanism of digital economic development on high-quality agricultural development by constructing an evaluation index system for high-quality agricultural development with economic, social, and ecological benefits. The results show that the development of the digital economy has promoted the high-quality development of agriculture, and the promotion effect in the eastern region is stronger than that in the central and western regions. In addition to direct promotion, digital economy also promotes high-quality agricultural development by promoting the development of green agriculture. We should actively promote the construction of digital economy and promote the deep integration of digital economy and agriculture. Secondly, government should improve the digital economy governance to create a good legal environment for the green development of agriculture and, at the same time, help farmers establish digital economic awareness and train farmers in digital economy vocational skills. Finally, digital agriculture development policies should be formulated according to local conditions.

Keywords: digital economy; high-quality development of agriculture; green agriculture; panel data analysis; China

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1. Introduction

The world today is faced with food shortages, climate change, resource waste, and soil degradation in some regions, which pose challenges to the high-quality development of global agriculture and are also an important challenge for rural revitalization and development in China. In 2022, China's total grain output will reach 687 million tons, more than 650 million tons for eight consecutive years [1]. China has long topped the world in the output of meat, eggs, vegetables, fruits, and fish, which has played an important role in ensuring China's food security and effective supply of important agricultural products. However, from the perspective of China's agricultural production resources input, China has invested about 22.87% of the national labor force in agriculture, but its per hectare yield is far lower than that of developed countries in Europe and the United States. In addition, the use of chemical fertilizers and the rapid development of other crop inputs have greatly increased crop yield, but they also bring more serious environmental pollution. It is estimated that, globally, farmers apply around 115 million tons of nitrogen to our crops every year. Only around 35% of this is used by them, meaning 75 million tons of nitrogen runs off into our rivers, lakes, and natural environments [2], which puts enormous pressure on ecological protection and soil management. At the same time, China's agricultural trade has been running a record deficit for years, and it has reached USD 137.8 billion in 2022, an increase of 1.73% year on year [3], which means that China's agricultural production is not yet sufficient to meet the needs of its people. Therefore, to create a "sustainable food future", China must increase food production while reducing greenhouse gas emissions and maintaining the 120 million hm^2 "arable land red line" (in 2006, the Tenth Five-Year Plan for National Economic and Social Development adopted at the Fourth Session of the Tenth National People's Congress of China proposed that 120 million hm^2 of arable land is a legally binding indicator and an insurmountable red line) to improve the agricultural value chain based on the rational use of existing agricultural resources, and to build on the strengths of those resources to improve efficiency and environmental sustainability. In this context, digital agriculture, an emerging agricultural production model based on the development of the digital economy, has emerged. In recent years, the use of digital technology to enhance agricultural capacity has helped improve the efficiency and quality of agricultural production, and agricultural informatization has become an important driving force for the development of high-quality agriculture [4]. Meanwhile, the development of the digital economy has greatly eliminated the information asymmetry between producers and consumers, providing the possibility for producers to produce special agricultural products according to consumer demand [5]. The report of the 20th National Congress of the Communist Party of China clearly puts forward the need to form a green mode of production and life, and to build a modernization in which people and nature live in harmony [6]. Developing green agriculture is an inevitable requirement for Chinese agriculture to modernize. In this context, it is of great theoretical value and practical significance to study the relationship between digital economy, green development of agriculture, and high-quality development.

At present, there are two views on the digital economy. One view emphasizes the interconnection of digital network applications and the global economy. For example, some scholars believe that the digital economy depends on the application of digital networks and the increase of human capital, which is characterized by digitalization and intelligence, and can realize the interconnection of the global economy through self-learning and innovation [7]. Another view emphasizes the integration of information technology and the traditional economy, namely, "digital technology plus". The digital economy enables data information and its transmission technology to penetrate into the conventional economy, realizing the coordinated development of economic "quality" and "quantity" [8]. In China, e-commerce of agricultural products has developed rapidly and many agricultural production and technology promotion websites have emerged. In this context, data and information and its transmission technology have widely penetrated into the production and consumption of agricultural products, having a profound impact on the development of agriculture. The digital economy refers to "digital technology+". In other words, it is a new form of economy formed by the penetration of digital technology into traditional economic sectors.

Driven by the digital economy, the deep integration of digital technologies such as the Internet, big data, and the Internet of Things with the real economy has created opportunities for the development of digital agriculture. High-quality agricultural development driven by the digital economy has become an important way to achieve rural revitalization. Through the review of existing literature, it can be found that research on digital empowerment to help the high-quality development of agriculture mainly focuses on the following aspects: (1) The development of the digital economy, which has promoted the digital transformation and reform of agricultural production systems and the value chain management mode [9]. The integrated development of digital economy and agriculture can optimize the allocation of factors, reduce transaction costs, and promote innovative financial service models, realizing economies of scale, and effectively alleviating information asymmetry, thus promoting the higher-quality development of agriculture [10]. (2) The digital economy has improved the efficiency of resource allocation, reduced resource mismatch and promoted the high-quality development of agriculture. Data and information are the key production factors of the digital economy. A large number of data and information sharing based on digital technology promote the communication and trust between farmers and other entities in the industrial chain, reduce information asymmetry and market transaction costs, and provide the possibility for the rapid development of precision agriculture. Precision agriculture is aimed at improving crop yield and quality, and improving the ecological environment, and it considers the application of technologies and strategies in all aspects of agricultural production in both the time and space dimensions. Precision agriculture uses technology to determine what is right, and in turn, to do the right thing at the right time and in the right place, using the right method [11]. The development of the digital economy has promoted the application of precision technology in modern agriculture [12,13]. Precision technology changes economic activities by reducing the cost of copying, transmitting, tracking, verifying, and searching data. Digital technology can improve the efficiency of the entire agricultural value chain by reducing agricultural production and operation costs. For example, precision agriculture technology can minimize the input required for a given output, improve the allocation efficiency of physical capital within and between farms, and promote the low-cost dissemination of agricultural knowledge and skills [14]. (3) The impact of digitalization on farmer identity, farmer skills, and farm work [11]. Compared with traditional agriculture, digitalization of agriculture requires more knowledge, skills, and management of labor and other aspects of farming, which promotes the transformation of agricultural production mode from traditional "hands-on" and experience-driven to data-driven [15]. (4) The phenomenon of the digital divide leads to an individual and regional imbalance in the impact of digital economic development on agricultural development. Studies have shown that agricultural enterprises lacking expertise and digital technology have relatively high production costs due to a lack of access to specialized databases, up-to-date software, and information services, which may result in their loss of competitive advantage in local and global markets [16–18]. Agribusiness and rural areas suffer the most from digital discrimination, which also contributes to the decline in profitability and competitiveness of the agricultural sector [19].

Green development of agriculture is a way of agricultural development that is in harmony with production, life, and ecology. It is led by the vision of green development, aims at sustainable supply of green agricultural products and ecological services, is supported by green technology, green inputs, green production, and green logistics, and is guaranteed by green consumption, green culture, and green system [20]. High-quality development of agriculture means that agricultural production aims at consumer demand using resource-saving technology, avoiding pollution of the environment, pursuing high social, economic, and ecological benefits of agricultural development, and achieving sustainable development of agriculture. The development of the digital economy has improved the efficiency and coverage of information dissemination and reduced farmers' information search costs. Its promotion of high-quality agricultural development is mainly reflected in the following aspects: (1) Optimizing the supply of agricultural products. Supply information affects the efficiency of competitive markets because it affects price dispersion, arbitrage, and farmer/consumer welfare. Since the marginal cost of delivering information digitally is close to zero, digital agriculture has the potential to spread supply information [21,22]. Therefore, farmers can easily access information about product supply and demand via the Internet, and consumers of agricultural products can send market demand information (e.g., price of specific commodities, market location, product demand, etc.) directly to agricultural sales agents (e.g., agricultural e-commerce platforms) and farmers via digital platforms, thus connecting buyers and sellers of agricultural products. In this way, farmers and commodity buyers can avoid intermediate links to achieve accurate matching between buyers and sellers, and reduce ineffective supply in production. (2) Promoting and popularizing advanced agricultural production technologies. Farmers can visit the agricultural technology extension website to learn advanced agricultural production technology. To improve the output and quality of agricultural products, farmers can also exchange production experience via telephone, QQ, WeChat, etc. [23]. (3) Creating a new marketing model for agricultural products. The online transaction mode is gradually accepted by farmers.

Through e-commerce platforms, farmers can not only buy seeds, fertilizers, pesticides, and other basic inputs needed for production but also sell their agricultural products. Farmers can connect directly with input producers and consumers, bypassing middlemen. This changes the unfavorable situation of buying inputs at high prices and selling output products at low prices under the traditional marketing model and is conducive to improving the economic benefits of agricultural production [24]. (4) Changing the ideology of farmers. Through the Internet, farmers can easily understand the market's demand for high-quality, healthy, and green agricultural products and the country's environmental protection requirements for agricultural production, and realize the importance of green agricultural products. Only by improving the quality of agricultural products can we win more consumers and obtain greater returns on economic benefits, which is conducive to improving the ecological benefits of agricultural production [25]. (5) Improving the organization of agricultural production. Farmers can meet more like-minded colleagues through the Internet. They may move towards horizontal alliances based on common interests to form professional cooperatives. They can also communicate and collaborate more deeply with the corresponding upstream and downstream links in the industry chain to improve the level of vertical collaboration. This horizontal integration and vertical collaboration improve the organization of agricultural production and may enable greater benefits from economies of scale. At the same time, it also promotes the integration of the entire agricultural industry chain, which can effectively avoid ineffective output and waste of resources [26]. (6) Promote the development of green agriculture. With the development of the economy and the improvement of living standards, people's consumption demand for agricultural products has gradually changed from "eat enough" to "eat well" and "eat healthily". On the one hand, the development of the digital economy has created conditions for farmers to keep abreast of consumer needs and their changes; on the other hand, it has also provided consumers with information on the production and processing of agricultural products, to identify whether agricultural products are "green" and "healthy" [27]. (7) Green agricultural development for high-quality agricultural development. Green agricultural development means consuming fewer resources to produce more high-quality agricultural products that better meet consumers' needs, which indirectly also improves the quality of agricultural development. It can be seen that the digital economy, in addition to directly promoting high-quality agricultural development, also indirectly contributes to high-quality agricultural development by promoting green agricultural development [28].

To sum up, the application of digital technology in agriculture has a long history from concept to theoretical discussion, which guides the study of the digital economy on the high-quality development of China's agriculture in this paper. However, due to the heterogeneity of the digital economy's impact on agricultural development, it remains to be tested whether and how the digital economy can effectively promote high-quality agricultural development in China. Given this, based on panel data of 30 provinces in China from 2013 to 2020, this paper establishes some econometric models to empirically test the impact of the digital economy on high-quality agricultural development, to provide decision-making guidance for the regional development of the digital economy to achieve high-quality agricultural development. Compared with the previous studies [10,22,28], this paper offers new explorations of at least three aspects: Firstly, it has constructed a measure of agricultural green total factor productivity which considers economic, social, and ecological benefits to systematically evaluate the high-quality agricultural development level of China's provinces. Secondly, it analyzes the influence of the digital economy on agricultural high-quality development, and heterogeneity testing was carried out on the influence of the digital economy on agricultural high-quality development in eastern and central, and western regions, respectively. Thirdly, it verifies the mediating effect of green agricultural production between the digital economy and high-quality agricultural development.

2. Materials and Methods

2.1. Measurement of High-Quality Agricultural Development

2.1.1. Measurement Method

At present, China's economy is entering a stage of high-quality development from a stage of high-speed growth and is in a critical period of transforming its development mode, optimizing its industrial structure and adjusting its growth momentum. Compared with the traditional agricultural development model, which emphasizes scale, production increase, and environmental impact, high-quality development of agriculture can keep pace with the times and embody the new development concept, which is carried out under the constraints of multiple objectives such as effective supply of important agricultural products, common prosperity, and environmental friendliness. From a theoretical perspective, high-quality agricultural development is a manifestation of adhering to the main character of the people, an inevitable choice to realize agricultural and rural modernization, and an important support for the Chinese modernization road. From the practical point of view, the promotion of high-quality agricultural development should take into account the dual value orientation of quality and efficiency, which includes not only the upgrading of agricultural products, but also the continuous improvement of the quality of industrial development and the continuous expansion of agricultural functions. As a measure of factor quality, total factor productivity is the core indicator of national wealth growth, especially in developing countries [29–31]. It has become an important indicator to measure the high-quality development of the agricultural economy. However, agricultural total factor productivity only considers capital laborers and ignores the environmental factors of green agricultural development, so it cannot better reflect the ecological benefits in the process of high-quality agricultural development [32]. Under the guidance of the development concept of "lucid waters and lush mountains are invaluable assets", it is necessary to rely on technological progress to improve resource utilization efficiency under the tight constraints of the environment and resources to achieve high-quality agricultural development [33]. This prioritizes not only pursuit of social benefits but also the realization of economic and ecological benefits. Therefore, this paper uses agricultural green total factor productivity to measure agricultural resource input and agricultural green development efficiency. On the one hand, it can better respond to the goals of "prospering agriculture with a green approach" and "prospering agriculture with quality", and on the other hand, it is helpful for in-depth analysis of the impact path of digital agriculture on the high-quality development of agriculture. Comparing existing studies, it can be found that stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are mainly used to measure agricultural total factor productivity. SFA requires setting the probability distribution from a random error term, and the frontier production function is susceptible to the influence of individual regions [34,35]. However, the DEA approach does not require setting a specific production function. It applies to the multi-input, multi-output boundary production function, the result of which is endogenous from the data, which avoids the bias caused by the function setup and has become the main measure of total factor productivity. At the same time, in order to minimize the drawbacks of the inherent assumptions of the data envelopment method on the proportion and direction of input–output increase or decrease, which are inconsistent with the research scenario of the model in this paper, the non-radial and non-angular SBM directional distance function was selected to measure the total factor productivity of green agriculture in China's provinces. Its expression is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{M}\Sigma_{i=1}^{M} \frac{S_m^x}{x_{m0}}}{1 + \frac{1}{S_1+S_2}\left(\Sigma_{r=1}^{S_1} \frac{S_r^r}{y_{r0}^g} + \Sigma_{r=1}^{S_1} \frac{S_k^b}{b_{k0}^b}\right)} \tag{1}$$

$$\begin{cases} \sum_{j=1}^{J} \lambda_j^t Y_{ij}^t - S_r^g = y_{rj}^t, r = 1, \cdots, S_1; \\ \sum_{j=1}^{J} \lambda_j^t b_{kj}^t + S_k^b = b_{bj}^t, K = 1, \cdots, S_2; \\ \sum_{j=1}^{J} \lambda_j^t b_{mj}^t + S_m^x = x_{mj}^t, m = 1, \cdots, M; \\ \sum_{j=1}^{J} \lambda_j^t = 1, \lambda_j^t \geq 0, j = 1, \cdots, J \\ S_k^b \geq 0, S_r^g \geq 0, S_m^x \geq 0, j = 1, \cdots, J \end{cases} \tag{2}$$

In the above equation, S^x, S^g, and S^b are slack variables, which respectively represent excessive input, insufficient green output, and equivalent ecological damage. M, S_1 and S_2 represent the input–output quantity of each independent decision-making unit (DMU), respectively. λ_j^t represents the corresponding weight value of each decision-making unit in the construction of green production technology. The two constraints that the sum of the weight variables is equal to 1, and the weight variables are non-negative which indicate that the green production technology has variable returns at scale. The objective function is $\rho \in [0, 1]$ when $\rho = 1$; that is, $S^x = S^g = S^b = 0$, which means that each decision-making unit is completely efficient, and there is no slack situation of input, undesired output excess, or desired output insufficiency. When $0 < \rho < 1$, that is, at least one of S^x, S^g, and S^b is not 0, this indicates that the DMU has the phenomenon of efficiency loss and can be further improved in terms of input and output.

When agricultural production involves multiple inputs and outputs, DEA can only calculate the Malmquist Index (MI) instead of total factor productivity directly because of the unknown production function, as shown in Equation (3):

$$MI_{t-1,t} = \frac{TFP(x_t, y_t)}{TFP(x_{t-1}, y_{t-1})} = \frac{TFP(x_t, y_t)/TFP(benchmark)}{TFP(x_{t-1}, y_{t-1})/TFP(benchmark)} \tag{3}$$

In Equation (3), $t-1$ period is used as the frontier reference in both numerator and denominator. $TFP(x_t, y_t)/TFP(benchmark)$ is the DEA efficiency value obtained by referring (x_t, y_t) to the front of period $t-1$. $TFP(x_t, y_t)/TFP(benchmark)$ is the DEA efficiency value obtained by referring (x_t, y_t) to the front of period $t-1$. $TFP(x_{t-1}, y_{t-1})/TFP(benchmark)$ is the DEA efficiency value obtained by referring (x_{t-1}, y_{t-1}) to the front of period $t-1$. Therefore, this paper takes $TFP(x_t, y_t)/TFP(benchmark)$ as the descriptive index of agricultural green total factor productivity in period t.

2.1.2. Input–Output Index

(1) Expected output index

This paper takes agriculture as the research object and considers that the high-quality development of agriculture includes not only the pursuit of an effective supply of grain and important agricultural products, but also the prosperity of farmers. In this paper, the added value of agriculture and the total disposable income of rural residents are used as expected output indicators. The added value of agriculture reflects the value created by agriculture for the whole society and reflects the social benefits of agriculture. The total disposable income of rural residents reflects the economic income obtained by farmers from the development of agriculture and reflects the economic benefits of agriculture (since the ecological benefit factor has been included in the calculation of agricultural green total factor productivity, this paper no longer considers a separate ecological benefit index in the expected output). To eliminate the influence of price factors, this paper removes inflation from the above indexes according to the consumer price index.

(2) Input index

Based on previous studies and combined with the actual situation of agricultural production [36,37], this paper selects the people employed in agriculture, land acreage appropriate amount, agricultural machinery total power, consumption of fertilizers (purified amount), effective irrigation area, the usage of pesticides, etc., in green total factor productivity of agriculture input indexes.

(3) Undesired output index

The undesired output index is the total agricultural carbon emissions. Considering the existing research [38,39], this paper uses chemical fertilizers, pesticides, agricultural diesel, agricultural film, diesel, agricultural farming, and agricultural irrigation as carbon emission sources. The consumption of fertilizers (purified amount), pesticide application amount, agricultural diesel oil, land sowing area, effective irrigation area, and agricultural film application amount were selected to measure the total agricultural carbon emissions. The specific calculation formula for total carbon emissions from agricultural production is as follows:

$$E = \sum E_i = \sum T_i \delta_i \quad (4)$$

In Equation (4), E represents the total agricultural carbon emissions. E_i is the emission of carbon source (i). δ_i refers to the carbon emission factor of a carbon source (i). Carbon emission sources and emission coefficients are shown in Table 1:

Table 1. Carbon emission sources and emission coefficients.

Carbon Emission Sources	Carbon Emission Coefficients	Data Sources
Consumption of fertilizers (purified amount)	0.8956 kg/km^2	Oak Ridge National Laboratory in the U.S.A. (Wang et al. [40])
Pesticides	4.9341 kg/km^2	Oak Ridge National Laboratory in the U.S.A. (Wang et al. [40])
Agricultural diesel oil	0.5927 kg/km^2	IPCC (Tian et al. [41])
Soil tillage	312.6 kg/km^2	Wu et al. [42]
Agricultural irrigation	25 kg/km^2	Maheswarappa et al. [43]
Agricultural film	5.18 kg/km^2	Institute of Resource, Ecosystem and Environment of Agriculture, Nanjing Agricultural University (Tian et al. [41])

Note: The above data on the proxy variables for the measurement of high-quality agricultural development were obtained from national and provincial statistical yearbooks.

2.2. Measuring the Development Level of the Digital Economy

2.2.1. Construction of Evaluation Index System

In terms of the selection of evaluation indicators for the development level of the digital economy, under the guidance of previous research, this paper constructs an evaluation index system for the development level of the digital economy from three dimensions: the development of informatization, the development of the Internet, and the development of digital transactions, as shown in Table 2.

2.2.2. Measurement Method

In the comprehensive evaluation of multiple indicators, the determination of weights in existing studies mainly uses principal component analysis (PCA), analytic hierarchy process (AHP), factor analysis, and the entropy method. Among these, both PCA and factor analysis are the idea of dimensionality reduction, trying to reflect the main information of the original variables by using a few factors. This reduces the difficulty of processing data, but only the weights of each factor can be obtained without the actual weights of the measurement items (a measurement item is usually composed of several measurement factors). AHP decomposes the research problem into a few influencing factors and aggregates them at different levels according to their interactions to form a multi-level analysis model.

Subsequently, the expert scoring method is used to assign weights to each influencing factor, which is more subjective. Compared with the above three methods, the entropy method is more objective. It determines the weights of indicators based on their relative change degree in the system, and is more suitable for evaluating different research objects in multiple periods [44,45]. Therefore, this paper uses the entropy method to determine the index weight and measure the digital economy development level comprehensive index of different regions and different years. The specific calculation steps are as follows.

Table 2. Index system of digital economy development degree evaluation.

Core Indexes	First-Class	Second-Class	Measurement Index	Attribute
Digital Economy Develop-ment Index	Information development	Information infra-structure	Cable line density (km/sq km)	Positive
			Mobile phone exchange capacity per capita (household/person)	Positive
			Employment in information transmission, software, and information technology services in urban units (%)	Positive
			Telephone penetration (including mobile phones) (per 100 people)	Positive
		Influence of informati-zation	Proportion of total telecom business in regional GDP (%)	Positive
			Proportion of software business revenue in regional GDP (%)	Positive
	Internet development	Internet infra-structure	Internet broadband access port density (per person)	Positive
			Number of domain names (unit: 10,000)	Positive
			Broadband access per person (per person)	Positive
		Influence of Internet	Number of web pages (unit: 10,000)	Positive
	Digital transaction development	Infra-structure of digital trading	Number of websites per 100 enterprises	Positive
			Proportion of enterprises with e-commerce transactions (%)	Positive
		Influence of digital trading	Proportion of e-commerce sales in regional GDP (%)	Positive
			Proportion of e-commerce purchases in regional GDP (%)	Positive
			Express delivery per capita	Positive
			Online payment quantity and scale	Positive

Note: The data used in this table, unless otherwise noted, are from the website of the National Bureau of Statistics of China.

Step 1: Since the dimensions and orders of magnitude of each index are different, it is necessary to standardize each original index to eliminate the influence of different dimensions on the evaluation results. In this paper, the range method is used to de-dimesionalize and synchronize the original indicators to keep the data size between [0, 1]. The details are as follows:

$$\text{Positive indexes}: \ x_{ij} = \frac{a_{ij} - \min a_{ij}}{\max a_{ij} - \min a_{ij}} \tag{5}$$

$$\text{Negative indexes}: \ x_{ij} = \frac{\max a_{ij} - a_{ij}}{\max a_{ij} - \min a_{ij}} \tag{6}$$

Equations (5) and (6) represent the original value of the second indicator in the *i* primary indicator, and the standardized value of the second indicator in the *i* primary indicator, respectively.

Step 2: To avoid zero value in the de-dimensionalization process, add 0.00001 to the equation. That is, let $y_{ij} = x_{ij} + 0.00001$. Then, the data are normalized:

$$p_{ij} = \frac{y_{ij}}{\sum\limits_{i=1}^{m} y_{ij}} \tag{7}$$

In the above equation, m represents the year of evaluation.

Step 3: Calculate the entropy coefficient e_j and difference coefficient d_j of the index x_j:

$$\begin{aligned} e_j &= -\tfrac{1}{\ln m}\sum\limits_{i=1}^{m} p_{ij} \ln p_{ij} \\ d_j &= 1 - e_j \end{aligned} \tag{8}$$

The smaller the entropy value e_j is, the larger the differential coefficient d_j is, indicating that this index is more important.

Step 4: The weight of the index x_j can be further obtained; below, n is the number of indexes:

$$w_j = \frac{d_j}{\sum\limits_{j=1}^{n} d_j} \tag{9}$$

Step 5: Then, obtain the comprehensive score of the development evaluation of the i first-level indexes:

$$S_i = \sum_{j=1}^{n} w_j p_{ij} \tag{10}$$

Step 6: After obtaining the comprehensive score of the development evaluation of the i first-level index, the comprehensive index of the digital economy development level in different regions and different years is obtained by using the equal weight method.

2.3. Model Construction and Index Selection

The explained variable of this paper is the high-quality development of agriculture (namely, agricultural green total factor productivity, AGTFP). The core explanatory variable is the digital economy development level (DIG). Comparing previous studies, it can be found that there are many factors influencing the quality development of agriculture. To alleviate the endogeneity caused by the omission of important explanatory variables, industrialization rate (IR) and rural household fixed asset investment (FAI) are selected as control variables. In addition, this paper selects the number of green foods with three-year useful labels in the" Green Food Statistical Annual Report" from 2013 to 2020 as the descriptive variable to produce green agricultural products. The purpose of the empirical test is to explore whether the development of the digital economy can promote the high-quality development of agriculture. To alleviate possible heteroscedasticity, this paper conducts logarithmic processing of the agricultural green total factor productivity (AGTFP) farmer fixed asset investment (FAI) indicator.

Based on the panel data of 30 provinces (limited by data availability; Tibet was excluded from the data acquisition in this paper) in China from 2013 to 2020, this paper establishes an econometric analysis model as shown in Equation (11):

$$\ln AGTPF_{i,t} = \beta_0 + \beta_1 DIG_{i,t} + \beta_2 IR_{i,t} + \beta_3 \ln FAI_{i,t} + v_i + \varepsilon_{i,t} \tag{11}$$

In Equation (11), the subscripts i and t represent provinces and years, respectively. v_i denotes unobservable individual fixed effects for each province. $\varepsilon_{i,t}$ represents the random interference term, which is normally distributed, and v_i is uncorrelated. β_i is the parameter to be estimated.

In addition, to reveal the mechanism by which the digital economy promotes the high-quality development of agriculture, this paper selects the production of green agricultural products as the mediating variable, and adopts the method of step-by-step testing of the regression coefficient to construct the following mediation effect model:

$$\ln AGTPF_{i,t} = \alpha + c_2 DIG_{i,t} + \sum \delta_i \mathrm{Ctrl}_{i,t} + \varepsilon_{i,t} \quad (12)$$

$$GREEN_{i,t} = \beta + aDIG_{i,t} + \sum \delta_i \mathrm{Ctrl}_{i,t} + \varepsilon_{i,t} \quad (13)$$

$$\ln AGTPF_{i,t} = \gamma + c_1 DIG_{i,t} + bGREEN_{i,t} + \sum \delta_i \mathrm{Ctrl}_{i,t} + \varepsilon_{i,t} \quad (14)$$

In Equations (12)–(14), α, β, and γ are constant terms; $\varepsilon_{\mathrm{it}}$ is the random disturbance term; $\sum \delta_i Ctrl_{i,t}$ represents the sum of the products of the control variables and their regression coefficients. $\ln AGTPF_{i,t}$ is the explained variable—high-quality agricultural development. $DIG_{i,t}$ is the explanatory variable—the level of development of the digital economy. $GREEN_{i,t}$ is the mediating variable—green agricultural production. Equation (12) is used to test whether the digital economy has a significant impact on the high-quality development of agriculture, and its impact coefficient is c_2. Equation (13) is used to test whether the digital economy has a significant impact on the production of green agricultural products, and the influence coefficient is denoted as a. Equation (14) is used to explore whether the digital economy and green agricultural production have a significant impact on high-quality agricultural development at the same time. c_1 and b are the impact coefficients of the digital economy and green agricultural product production, respectively. If the coefficients a, b, and c_2 are all significant, it indicates that the production of green agricultural products has a mediating effect on the relationship between them. Further, check the coefficient D. If c_1 is significant, there is a partial mediating effect. If c_1 is not significant, there is only a mediating effect, that is, a complete mediating effect. Finally, the bootstrap method was used to test the existence of a mediating effect and calculate the proportion of mediating effect in the total effect.

3. Model Testing and Estimation Results

3.1. Analysis of Main Effects Test

The pooled OLS, fixed effects model, and random effects model are the more popular models for panel data analysis. As shown in Table 3, both the F-test and LM-test reject the original hypothesis of using the mixed regression model at the 1% (“***”, “***”, and “*” denote significance at 1%, 5%, and 10% confidence levels, respectively (same below)) significance level. The Hausman test indicates that the random effects model should be used for optimal estimation. As shown in Table 3, the estimated coefficient of the level of development of the digital economy is 2.19 and significant at a 1% confidence level, which indicates that the digital economy has a significant positive impact on the high-quality development of agriculture.

Table 3. Estimation results of the model.

Variables	FE	RE	G2SLS	2SLS	SYS-GMM
L.AGTFP					0.7284 ** (0.2857)
DIG	1.9844 *** (0.4992)	2.1900 *** (0.4420)	4.3181 *** (0.5829)	4.1032 *** (0.9679)	1.0381 * (0.5819)
IR	−0.0274 ** (0.0103)	0.0224 *** (0.0075)	0.0079 (0.0098)	0.0056 (0.0047)	−0.0141 (0.0092)
lnFAI	0.2043 *** (0.0727)	0. 2107 *** (0.0680)	0.1408 ** (0.0736)	−0.2826 ** (0.0577)	0.2311 * (0.1255)

Table 3. *Cont.*

Variables	FE	RE	G2SLS	2SLS	SYS-GMM
Constant	−1.5358 ** (0.6909)	−1.8071 *** (0.6639)		−3.2744 ** (0.5173)	−1.58911 (1.0052)
AR (1)					0.1090
AR (2)					0.2783
Sargan–Hansen statistic			3.53 *	2.633	
Sargan			2.34		28.4120
Cragg–Donald Wald F statistic			70.98		
F test	39.58 ***				
Score chi2 (1)				0.16	
Wald chi2 (3)				51.17 ***	
Wald chi2 (4)					176.10 ***
LM test		263.82 ***		87.06 ***	245.30 ***
Hausman test	2.70				
N	240	240	210	180	210
R^2	0.6114	0.5680	0.5125	0.4966	

Note: "***", "**", and "*" indicate that they are significant at the level of 1%, 5%, and 10%, respectively. The values in brackets are the standard error of estimation. Hausman test is the robust Hausman test. The 2SLS corresponds to the F-statistic of the first stage.

3.2. Consideration and Resolution of Endogeneity

Endogeneity is usually caused by measurement errors, omission of important explanatory variables, and reciprocal causality. The analysis in this paper is based on authoritative data released by national statistical departments and appropriate control variables were selected to avoid endogeneity problems arising from measurement errors and omission of important explanatory variables, but the analysis results still face the threat of mutual causal endogeneity problems. On the one hand, the development of the digital economy eliminates the information asymmetry that may exist in production and consumption activities, which improves the accuracy of production and management decisions and consumption choices as well as reducing the waste of resources, thus improving the quality of economic development. The combination of digital economy and agriculture has promoted the high-quality development of agriculture [36,46]. On the other hand, to ensure the effective supply of grain and major agricultural products, increase farmers' income, modernize agriculture, and revitalize rural areas, the country sees the digital economy as an important strategic driving force to promote high-quality agricultural development and build beautiful villages [47]. Based on the above analysis, it can be found that there may be a mutually causal relationship between the digital economy and high-quality agricultural development. Therefore, in this paper, instrumental variable analysis and system GMM are used to overcome the possible endogeneity, respectively.

3.2.1. Instrumental Variable Analysis

When endogeneity arises in the model because the endogenous variables are correlated with the error terms, a common solution idea is to find a proxy variable that is correlated with the explanatory variables but not with the random error terms. This is the instrumental variable [48]. Government policy has an impact on the achievement of its goals, but the goals pursued have no effect on policy. In China, new agricultural business entities such as family farms and farmers' professional cooperatives are not sufficiently developed. Agriculture is also dominated by ultra-small-scale operations of farmers' families. Therefore, it is unrealistic to rely on private investment to develop digital agriculture. Meanwhile, due to the special nature of information consumption, the infrastructure construction of rural communication networks, information services, and e-commerce service sites and logistics support has obvious characteristics of public products and public services, which require government investment to support the development of digital agriculture. Therefore, the strength of government financial support to agriculture affects the degree of development of digital agriculture. At the same time, government financial support for agriculture depends on the government budget, especially the financial resources at the government's disposal and the government's judgment on the priority of several policy objectives. For example, less economically developed regions have weak financial resources and may not be able to provide sufficient financial support for local digital agriculture construction. The practice of digital agriculture rural construction in China's counties shows that insufficient financial investment is an important issue facing the current development of digital agriculture. In addition, the 117 digital rural construction pilots announced in 2020 have no central financial support, and the investment for digital agriculture accounts for only 0.8% of the financial support for agriculture expenditure, and is mainly concentrated in the rich eastern region ministries. Therefore, the government's financial support for agricultural expenditure is exogenous.

In this paper, we used the average labor government expenditure on agriculture (GOV, measured by the average local fiscal expenditure on agriculture, forestry, and water of the employed population in agriculture) and the ratio of government expenditure on agriculture to fiscal expenditure as instrumental variables (the above instrumental variables are taken as logarithmic values), and we also used G2SLS to deal with endogeneity [49]. In addition, the impact of the digital economy on high-quality agricultural development may have a time lag. The development of the digital economy in the current period may have an impact on the development of high-quality agriculture in the next period or even two periods, but the development of high-quality agriculture in the current period will not affect the development of the digital economy in the previous period. Therefore, this paper selected the first lag period and the second lag period of the digital economy development as the instrumental variables of the current digital economy development, and conducted the two-stage least squares method (2SLS) analysis. As can be seen from Table 3, the Sargan–Hansen test does not reject the null hypothesis that "all instrumental variables are exogenous" at the 5% significance level. Additionally, the Cragg–Donald Wald F-statistic for the weak instrumental variables test exceeds the maximum critical value (19.93), which indicates that the instrumental variables selected for the panel instrumental variables approach (G2SLS) are not weak instruments. Therefore, based on the above two conditions, it can be determined that the instrumental variables selected by the panel instrumental variables method (G2SLS) are valid instrumental variables. Therefore, the instrumental variables selected in the paper are valid. In addition, the two-stage least squares (2SLS) first-stage F-statistic > 10 and over-identification test (Score chi2 test) indicate that the selected instrumental variables are valid. The estimated coefficients of the level of digital economy development are all significantly greater than 0. It is evident that the positive impact of digital economy development on high-quality agricultural development still exists after the endogeneity problem is eliminated.

3.2.2. System GMM

System GMM can not only obtain consistent estimation in some cases of endogenous sources such as omitted variables and measurement errors, but also improve the efficiency of estimation. Therefore, this paper introduces the lagged first order of the explanatory variables as explanatory variables, constructs a dynamic panel data model, and uses a systematic GMM for estimation. As shown in Table 3, the *p*-Values of AR1 and AR2 are greater than 0.1, indicating that there is no first-order and second-order serial autocorrelation of the disturbance terms. The *p*-Value of the Sargan test is greater than 0.1, which indicates that the selected instrumental variables can eliminate the endogeneity problem better. From the estimation results, the estimated coefficient of digital economic development is 1.2744 and significant at a 5% confidence level, which is consistent with the findings of the analysis using the instrumental variables method.

3.3. Robustness Check

To ensure the robustness of the regression results, the following methods are selected for robustness testing. The results are shown in Table 4.

Table 4. Results of the robustness check.

Variables	Model 1	Model 2	Model 3
DIG	1.3523 ***	2.1378 ***	2.1901 ***
	(0.2382)	(0.4982)	(0.4465)
IR	−0.0142 ***	−0.0218 **	0.0224 ***
	(0.0036)	(0.0088)	(0.0071)
lnFAI	0.0684	0.3037 ***	0.2107 **
	(0.0452)	(0.0801)	(0.0687)
Constant	−0.5149	−2.6272 ***	−1.8072 **
	(0.4355)	(0.7026)	(0.6682)
LM test	632.71 ***	462.19 ***	560.87 ***
N	240	208	240
R^2	0.6311	0.5839	0.5573

Note: "***" and "**" indicate that they are significant at the level of 1% and 5% respectively. The values in brackets are the standard error of estimation.

3.3.1. Replace the Explained Variable (Model 1)

The input and output variables in the actual agricultural production process often have both radial and non-radial characteristics. A simple non-radial model may not fully describe the actual process of agricultural production. Based on this, some scholars have proposed a hybrid distance function with radial and non-radial characteristics (based on epsilon measurement), which can more comprehensively evaluate the relationship between input and output [50]. To test the robustness of the model, this paper used the epsilon-based measure for random effect estimation to replace the green total factor productivity under the non-radial, non-angular SBM directional distance function.

3.3.2. Change the Sample Size (Model 2)

Given that China's municipalities have greater policy tilt and independent decision-making, the development of the digital economy may vary greatly from its province. Therefore, to make the sample more accurate and make the test conclusion more robust, in this paper, the random effect estimation was carried out after eliminating the sample of municipalities.

3.3.3. Robust Standard Errors Obtained Using the Bootstrap Method (Model 3)

Panel data models usually assume that the disturbance terms between different individuals are independent of each other. There is no autocorrelation between the same individual and the contemporaneous disturbance term. Considering that the data used in this paper are short panel data, the sample size is not large, which may create heteroscedasticity and autocorrelation problems. The cluster robust standard errors at the provincial level may still be inaccurate, and using the bootstrap method to obtain standard errors can yield more accurate results. Therefore, this paper replaces the cluster robust standard error with the bootstrap standard error. In practice, the bootstrap times are set to 1000 times. In Table 4, the correlation between the digital economy development level and the high-quality agricultural development of all models has not changed, so we can infer that the benchmark regression results are robust and the conclusion is reliable.

3.4. Spatial Heterogeneity Analysis

Spatial heterogeneity refers to the differences shown by the same thing in different spatial locations. Specifically, in the research model of economics, it can be expressed as the same explanatory variable, and the model setting parameters and errors show significant differences with the change in spatial location. China has a vast territory, and its natural environment, human resources, social and cultural resources, and economic development levels are quite different in regional places, showing significant heterogeneity. Compared with the eastern region, the development foundation of digital technology and digital economy in the central and western regions is relatively weak, the development level is relatively lagging behind, and there is a big difference compared with the developed eastern regions [51]. Therefore, it is necessary to conduct a regional heterogeneity test for the digital economy to promote the high-quality development of agriculture. Drawing on the division method of the National Bureau of Statistics, this paper divides the 30 provinces involved into the eastern, central, and western regions and tests them, respectively. The test results are shown in Table 5:

Table 5. Results of spatial heterogeneity test.

Variables	East	Midwest
DIG	2.8013 *** (0.5409)	2.0115 *** (0.5927)
IR	−0.0165 *** (0.0052)	−0.0229 ** (0.0106)
lnFAI	0.1255 ** (0.0576)	0.2760 ** (0.1224)
Constant	−1.1782 ** (0.4281)	−2.4188 ** (1.1088)
LM test	125.01 ***	333.43 ***
N	88	152
R^2	0.5825	0.5461

Note: (1) The eastern region includes 11 provinces (cities and autonomous regions), including Beijing, Tianjin, Liaoning, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan, and the central and western regions include 19 provinces (cities and autonomous regions), including Heilongjiang, Jilin, Henan, Hubei, Hunan, Anhui, Jiangxi, Inner Mongolia, Shanxi, Shaanxi, Sichuan, Chongqing, Yunnan, Guizhou, Gansu, Xinjiang, Ningxia, Qinghai, and Guangxi. (2) In brackets are estimated standard errors (robust standard errors), and "***" and "**" indicate that they are significant at the level of 1% and 5%, respectively.

In Table 5, it can be seen that although the development of the digital economy in the eastern, central, and western regions has had a significant positive impact on the high-quality development of agriculture, the central and western regions are weaker than the eastern regions in terms of influence. In addition, from the impact of control variables, whether in the east or the central and western regions, the industrialization rate and the fixed asset investment of farmers have had a significant impact on the high-quality development of agriculture. Among these factors, the impact of increasing the industrialization rate is negative, and the impact of farmers' fixed asset investment is positive. In terms of influence, the impact of the industrialization rate and farmers' fixed asset investment on the eastern region is lower than that in the central and western regions, which is related to the higher level of agricultural infrastructure construction in the eastern region and the smaller income gap between urban and rural residents. To be specific, from the perspective of the 30 provinces involved in this study, the per capita financial support for agriculture in the eastern part of the country from 2013 to 2020 was 2.96 times that of the central and western regions during the same period. The fixed asset investment of rural households in the east was 1.59 times that of the central and western regions during the same period. Government and private agricultural capital investment reflect the gap in the level of agricultural infrastructure construction between the eastern, central, and western regions. During the same period, the ratio of disposable income of urban and rural residents was significantly lower in the east than in the central and western regions.

3.5. Test of the Mediation Effect of Green Agricultural Production

To test the mechanism of digital economy development in promoting high-quality agricultural development, this paper uses gradual regression to verify the mediating effect of green agricultural production. The test results are shown in Table 6.

Table 6. Mediation test results.

Variables	lnAGTPF	GEEN	lnAGTPF
DIG	2.1901 *** (0.4421)	3.7368 *** (0.6727)	1.6449 *** (0.5086)
GEEN			0.1363 *** (0.0434)
Constant	−1.8072 *** (0.6638)	5.3668 ** (2.1107)	−2.5035 *** (0.7012)
Control variables	Control	Control	Control
LM test	560.87 ***	573.83 ***	567.12 ***
R^2	0.5573	0.4617	0.5955
N	240	240	240

Note: "***" and "**" indicate that they are significant at the level of 1% and 5%, respectively. The values in brackets are the standard error of estimation.

In Table 6, it can be seen that the digital economy has had a significant role in promoting the production of green agricultural products. The production of green agricultural products has a significant role in promoting the high-quality development of agriculture. When the production of green agricultural products is not introduced, the development of the digital economy has a positive impact on the high-quality development of agriculture, with a total effect of 2.19. When the production of green agricultural products is introduced, the development of the digital economy also has a positive impact on the high-quality development of agriculture, with a direct effect of 1.6449. Therefore, there is a partial mediation effect between the production of green agricultural products and the relationship between the development of the digital economy and the high-quality development of agriculture. The development of the digital economy can promote the high-quality development of agriculture by promoting the production of green agricultural products. The mediating effect of green agricultural product production is 23.26%.

4. Conclusions and Discussion

Based on the data related to digital economy development and agricultural production from 2013 to 2020, this paper firstly constructs an evaluation index system for high-quality agricultural development that takes into account economic, social, and ecological benefits. Secondly, the panel data model was used to test the promotion of digital economy development on high-quality agricultural development. At the same time, based on the spatial heterogeneity of China's resource endowment, the country was divided into the eastern region and the central and western regions to explore the role of the digital economy in different regions in promoting the high-quality development of agriculture. Finally, step-by-step regression was used to verify the mediating effect of green agricultural production in the development of a digital economy and high-quality agricultural development. Research shows that the digital economy has promoted the high-quality development of agriculture, and its effect in the eastern region has been significantly stronger than that in the central and western regions. In addition to direct promotion, the digital economy also promotes the high-quality development of agriculture by promoting the production of green agricultural products.

Based on the above analysis, this paper puts forward the following suggestions. First of all, we should increase the infrastructure construction and digital development of the digital economy, promote the deep integration of the digital economy and the agricultural industrial chain, and promote the high-quality development of agriculture. There are several ways to achieve these goals: (1) Moderately advance the construction of digital economy infrastructure. Increase investment in information industry infrastructures such as wireless optical cables, broadband networks, and base stations of 5th Generation Mobile Communication Technology. Vigorously build big data, cloud computing, and artificial intelligence platforms to improve the hardware and software levels of the digital economy. Actively promote the application of 5th Generation Mobile Communication Technology, remote sensing technology, and spatial positioning technology in the agricultural industry chain. These can narrow the "digital divide" between urban and rural areas while accelerating the construction of digital villages, thereby improving the efficiency of high-quality agricultural development. (2) Accelerate the application of remote sensing satellite data technology in agriculture and rural areas, and build a basic database of the entire agricultural industry chain. In particular, it is necessary to achieve full coverage of the processing and sales of the entire industrial chain of agricultural products to consolidate the foundation for the digital economy and to promote the high-quality development of agriculture. (3) Improve the public service level of government agriculture and rural digital economy. Build a supply and demand information release platform for agricultural products to provide an information guarantee for the forecast and early warning of market demand for agricultural products, to be a market consultant for farmers' agricultural production. Build a good agricultural technology promotion website to promote the promotion and popularization of advanced and practical green agricultural production technology to provide technical support to produce green agricultural products.

Secondly, improve the governance mechanism of the digital economy to create conditions for the development of green agriculture. Green agriculture plays an intermediary role between the development of the digital economy and the high-quality development of agriculture, so we should promote the development of green agriculture through the development of the digital economy, and then promote the high-quality development of agriculture. Government agencies should establish and improve laws and regulations in the field of the digital economy, and strengthen the norms and supervision of data collection and release to ensure the authenticity and reliability of data. In particular, it is necessary to strengthen the control over the release and disclosure of self-media data and information to prevent misinformation from misleading the public. At the same time, relevant departments should strengthen the protection of intellectual property rights in the digital economy. On the one hand, it is conducive to safeguarding the legitimate rights and interests of information providers, users, and consumers. On the other hand, it creates a good legal environment for the production and consumption of green agricultural products.

Thirdly, help farmers establish digital economy awareness and train farmers' professional skills in digital economy. Farmers are the main body of agricultural development and the main users of digital technology in agricultural production and management. At present, the digital literacy and digital awareness of Chinese farmers are relatively low, so we should strengthen the publicity of the digital economy, make farmers aware of the importance of the digital economy to agricultural production and operation, guide farmers to form the habit of obtaining production and operation information and advanced practical production technology through the Internet, and establish the awareness of using e-commerce platform to purchase agricultural production inputs and sell agricultural products, improve farmers' ability to obtain useful data, and identify the authenticity of data through vocational skills training in the digital economy.

Finally, the government should formulate digital agriculture development policies according to local conditions. Compared with the eastern region, the development level of the digital economy in the central and western regions is not high. Therefore, the government should focus on the construction of digital economy infrastructure and the cultivation of farmers' awareness of the digital economy, and vigorously develop rural e-commerce. The digital economy infrastructure in the eastern region is relatively complete, farmers' awareness of the digital economy is strong, and their innovation ability is high. Therefore, the government should focus on the innovation of digital economy products/services and the mastery and breakthrough of the core capabilities and key technologies of the digital economy. According to the new situation and new problems in the development of agriculture and the rural economy, it is necessary to keep pace with the times, and adopt innovative digital economy products and services to better serve the high-quality development of agriculture.

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