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The Impact of the Digital Economy on Agricultural Green Development: Evidence from China

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Abstract: Whether the digital economy can effectively promote agricultural green development is crucial to the realization of agricultural rural modernization. This study empirically analyzes the impact of the digital economy on agricultural green development and the mechanism of action based on panel data of 30 Chinese provinces from 2011 to 2020. The results reveal that (1) the digital economy can significantly improve the green development level of China's agriculture; the dividends in the eastern region and central region are significantly higher than that in the western region, and there is regional heterogeneity. (2) The role of the digital economy in promoting agricultural green development has a nonlinear characteristic of increasing "marginal effect." (3) The digital economy has a significant spatial spillover effect, which can have a positive impact on agricultural green development in the surrounding areas. (4) The construction of "Broadband Countryside" can improve the development of the rural digital economy and indirectly promote agricultural green development. This study deepens our understanding of the internal effect and interval relationship of how the digital economy enables agricultural green development and provides the theoretical basis and practical suggestions for optimizing digital facility construction and high-quality agricultural development.

Keywords: digital economy; agricultural green development; threshold effect; space overflow; different-in-different

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1. Introduction

As the world's leading agricultural country, China constitutes 22% of the world population but feeds them off only 9% of the world's arable land, making an outstanding contribution to maintaining international food security [1]. China has also paid a huge environmental price. The bulletin of the second National Survey of pollution sources revealed that the total nitrogen, phosphorus, and ammonia nitrogen emissions from agricultural sources in China accounted for 46.5, 67.2, and 22.4% of the total water pollutant emissions, respectively [2]. The sustainable development of agriculture and rural areas is seriously restricted by the deterioration of the ecological environment. Therefore, China urgently needs to coordinate the relationship between agricultural production and the ecological environment and vigorously promote the green development of agriculture. In recent years, the digital economy and agricultural systems have continued to integrate, and with digitalization at its core, modern agriculture has brought new opportunities for agricultural green development. Agricultural green development is the trend of agricultural development worldwide. Therefore, it is of profound theoretical and practical significance to explore the internal effect of the digital economy on agricultural green development and how to effectively release the boosting power of the digital economy to solve resource and environmental problems and realize the sustainable development of agriculture worldwide.

With its high permeability, the digital economy helps to gradually achieve the integrated development of the agricultural industry. By improving agricultural development's efficiency and effectiveness [3], it provides new opportunities to optimize agricultural production elements and achieve high-quality agricultural development [4]. Digital technology penetrates the allocation system of agricultural elements, promotes the transformation of agricultural production methods [5], and promotes the greening of agricultural resources, thereby speeding up the promotion of agricultural total factor productivity [6]. Expanding digital financial services alleviates the financial constraints of rural production and promotes the intensification and specialization of agricultural production, thereby improving the efficiency of agricultural activities [7]. The digital economy innovates the rural economic development model and promotes sustainable rural development by improving the construction of agricultural databases [8]. The digital transformation of agriculture can also help it to better adapt to consumer needs, form a digital reproduction community [9], and effectively improve the quality and efficiency of the supply chain system [10]. The wide application of the digital economy in agriculture has gradually become a new driving force for the high-quality development of agriculture. The impact of the digital economy on the agricultural sector is also reflected in "output". In the field of ecological protection, digital technology can improve the early warning and perception of pollution sources and improve the efficiency of pollution control through precise monitoring of environmental data resources, such as air quality, river water quality, pollution discharge, and environmental carrying capacity [11]. The application of the digital economy can effectively integrate all kinds of information resources in production decision-making, which will help to reduce resource waste and improve environmental quality, effectively reduce the emission of environmental pollution, and realize the efficient advancement of production process [12]. Advances in agricultural technology brought about by the digital economy reduce harmful substances caused by agricultural production factors and reduce agricultural carbon emissions [13]. For the breeding industry, digital economy also plays an important role in improving animal health and productivity by monitoring changes in animal body parameters and taking corresponding measures in real time [14]. As an environmentally friendly industry, the digital economy also pushes forward the restructuring of industrial ecological rules by squeezing traditional high-pollution industries [15]. The widespread application of the digital economy in the agricultural field has become a new driving force for the realization of high-quality agricultural development. Green agriculture uses advanced digital technology and standardized production methods to run "green" through the whole agricultural production process [16], which can improve the development quality of green ecological technology [17], reduce agricultural supply-side risk [18], and accelerate the formation of a high-quality agricultural production model of sustainable development. Most of the available literature focuses on the relationship between the digital economy and high-quality agricultural development [19]. However, studies that explore the mechanism of the impact of the digital economy on green agricultural development are lacking. Long-term extensive agricultural development has brought about a serious situation of tightening resource constraints and ecological degradation, whereas the development of the digital economy has provided a new opportunity to break through the current bottleneck of agricultural development and realize the green development path of output safety, high efficiency, and environmental protection.

The contributions of this article are as follows: First, although agricultural green development has become a new concept and model advocated by the international community, many theoretical and practical problems still need to be solved. This study introduces the digital economy into the analysis framework of agricultural green development and discusses the promotion effect of the digital economy on agricultural green development from both theoretical and empirical perspectives to provide a scientific basis for agricultural green transformation worldwide. Second, using the panel data of 30 provinces in China from 2011 to 2020, this paper explains the mechanisms of how the digital economy affects agricultural green development from the dimensions of agricultural industry integration, production intelligent control, and managerial decision-making efficiency, and verifies the nonlinear and spatial effects between the digital economy and agricultural green development. The digital economy realizes the green development of agriculture by optimizing the allocation of agricultural industrial resources, ensuring the scientization of agricultural production and realizing the high efficiency of the management system. Third, the differences in digital dividends enjoyed by different regions may affect the positive impact of the digital economy on agricultural green development. Therefore, this study investigates the regional heterogeneity and reveals that location disadvantage is an important factor that restricts the digital economy from promoting agricultural green development, and the construction of "Broadband Countryside" provides a new idea for bridging the digital divide. This has important policy implications for alleviating the imbalance in regional digital economy development, narrowing the gap in agricultural green development, and realizing the sustainable development of agriculture worldwide.

2. Mechanism Analysis and Hypotheses Development

Agricultural green development is the way to overcome the constraints of resources and the environment and form a new pattern of coordinated development of agricultural production and ecology. This requires accelerating the transformation of agricultural development and eliminating the extensive agricultural development that relies on resource consumption. Furthermore, it is essential to coordinate the economic, social, and ecological benefits and enhance agricultural competitiveness [20]. Therefore, as agricultural green development puts forward higher requirements for agricultural technological innovation, it is urgent to change the direction of technological innovation and strengthen innovation-driven development. With its innate advantages of high penetration, increasing marginal effects, and network externalities, the digital economy promotes the efficient interconnection of agricultural production, operation, and consumption through deep integration with agriculture. Moreover, it realizes the agricultural development model of "controllable production, traceable quality, and measurable environment" and provides technical support for agricultural green development [21]. This section studies and demonstrates the intrinsic mechanism of the digital economy on agricultural green development from three dimensions—the basic mechanism of action, the nonlinear transmission mechanism, and the spatial spillover effect—and puts forward relevant hypotheses.

2.1. Influence Mechanism of the Digital Economy on Agricultural Green Development

The digital economy promotes agricultural green development by enhancing the integration of agricultural industries, ensuring intelligent production management and control, and improving the efficiency of agricultural operational decision-making. Figure 1 depicts the corresponding mechanism path diagram. In the agricultural industry, by penetrating into the agricultural industrial system, the digital economy promotes the change in industrial organization and structure and realizes the resource optimization and scale agglomeration effects of the agricultural industry. First, the replicability, renewability, non-consumption, and shareability of data lead to an unlimited replication of digital production factors at almost zero cost. Therefore, the digitization of agricultural production overcomes the scarcity and exclusivity of traditional resources, reduces energy consumption by sharing means of production, and realizes the optimal allocation of resources [22]. Second, as a "speed economy", the digital economy accelerates the circulation of information elements and saves information acquisition costs. This is because farmers can timely obtain market information on agricultural products; adaptively adjust the distribution of agricultural production factors, such as labor, land, and technology in real time; reduce the ineffective supply of agricultural products to minimize agricultural loss; and promote the greening of agricultural resource utilization. Third, due to the strong correlation of data, the agricultural industry relies on digital technology innovation and financial support to build an industry-wide organizational structure that integrates agricultural planting, production, and trading. This also helps to realize the transformation and upgrading of the industry-wide structure of agriculture through industrial collaboration and specialized production. In addition, by integrating with traditional agriculture, the digital economy has organically combined technological achievements and the agricultural industry, thus promoting the agricultural industry chain to accelerate the transformation to networking, digitalization, and intelligence, giving rise to new industries, such as smart agriculture [23], and empowering agricultural green development.

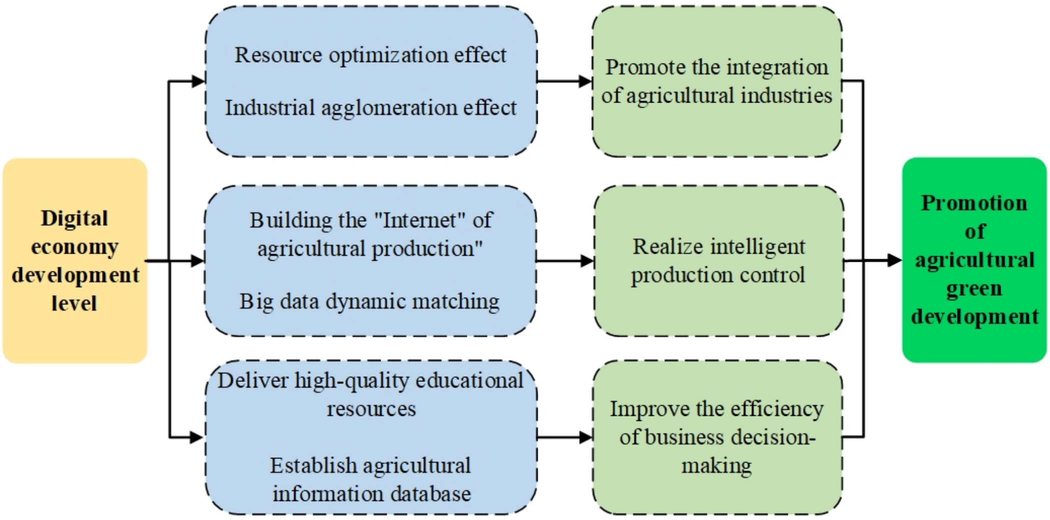

Figure 1. Mechanism path diagram.

By adopting the digital economy, agricultural production effectively promotes information interoperability and the intelligent operation and scientific management of agricultural production links, thus achieving controllability and science in all aspects of production and empowering green agricultural production. First, with new infrastructures, such as cloud computing and artificial intelligence, the digital economy has built an Internet system for agricultural production, providing efficient and accurate technical support for agricultural green development [24]. Second, it ensures rational adjustment of production layout, precise agricultural management, and real-time monitoring of the whole process of agricultural planting, production, and sales through data feedback. In the planting process, the digital economy can accurately analyze the ecological conditions, environmental capacity, and resource status of each region [25] and then determine the optimal amount of fertilizer and pesticide to achieve a dynamic balance between agricultural production and protecting the ecological environment. In the production process, big data dynamic matching can timely and accurately update user demand information, eliminate information asymmetry to a certain extent, and help farmers to speed up the production of agricultural products with local resources based on consumer demand. While meeting the needs of consumers, adopting the digital economy reduces transaction costs and increases the income of farmers. In the sales process, the combined online and offline sales model does not only expand the product coverage but also promptly addresses various problems in the product sales process, improves transaction efficiency and profitability, and improves the efficiency of the agricultural industry in all aspects.

The information integrity and scientific decision-making brought by the popularization of digital infrastructure can reduce the information and management costs of farmers in the production and operation decision-making process and realize the high efficiency of green agriculture operations. First, by relying on the Internet platform, the digital economy continues to deliver high-quality educational resources to rural areas and bring new ideas, knowledge, and technologies to agricultural production [26]. It does not only play a positive role in realizing agricultural scientific production and improving farmers' management and decision-making ability but also improves farmers' ecological awareness and promotes the green transformation of agriculture. Second, relevant government departments use digital technology to establish a database, which encompasses information services, such as technology development, market research, and agricultural production. Through precise analysis, the information will be announced to farmers in real-time so that agricultural business decision-makers can respond quickly and avoid business risks in the process of green agricultural transformation effectively [27]. Third, the integration of digital technology and the agricultural operation system can also promote the transformation of agricultural operation methods to be intelligent and refined. By accurately screening and organizing massive data, the cost inputs required in the agricultural production process can be controlled to a minimum, thereby minimizing the loss of resources. Therefore, the following hypothesis is proposed:

Hypothesis 1 (H1). *The digital economy has a significant positive effect on agricultural green development.*

2.2. Nonlinear Threshold Characteristics of the Digital Economy on Agricultural Green Development

First, the digital economy has the characteristics of strong network externality and positive feedback. The value of the platform expands with an increase in user scale, and once the number of users exceeds the critical scale, the value of the platform is magnified instantly. Specifically, the more the users on the digital platform, the more agricultural producers can obtain more data, thus breaking the "information silo" [28] and using factors and cost advantages to meet the different needs of consumers and improve the service quality of agricultural producers. This attracts more users and leads to the acquisition of more data to further improve the quality of products and services. This virtuous circle forms a user-based economy of scale or scope. With the continuous accumulation of digital production factors, the marginal cost of farmers' access to information, knowledge, and technology will continue to decrease, but the income will continue to increase to realize the nonlinear increase in agricultural marginal output.

Second, the digital economy is highly permeable and industry-related. With the deep integration of the digital economy and traditional agriculture, agricultural production has gradually changed to networking and digitization. This provides efficient and intelligent decision-making suggestions for agricultural production and operation and effectively improves the operation efficiency and service quality of all the stages of agricultural production [29]. While providing consumers with more high-quality, convenient, and high-end products and services, the digital economy accelerates the transformation and upgrading of traditional agriculture to green production. In addition, with the continuous growth of digital technology and infrastructure, the digital industry continues to experience high-speed upgrading and innovation. While optimizing the allocation of industrial resources, it accelerates the diffusion to other industries, thus forming data-driven and highly interrelated industrial clusters, realizing the integrated development of agriculture, manufacturing, and service industries, and ultimately leading to the power multiplier effect to empower agricultural green development [30]. This also means that there is no simple linear relationship between the digital economy and agricultural green development, and there may be a more complex nonlinear threshold effect.

Hypothesis 2 (H2). *The impact of the digital economy on agricultural green development has the nonlinear characteristics of increasing marginal effect.*

2.3. Spatial Spillover Effect of the Digital Economy on Agricultural Green Development

The digitization of production equipment enables the spread of agricultural production factors across time and space and at near-zero cost, which has a spatial impact on agricultural production. First, the open sharing and high permeability of data enable the production factors to compress the space–time distance, completely flow between different platforms and regions, improve the correlation of agricultural production factors between different regions, and reduce a series of problems caused by high information transaction cost and information asymmetry. Moreover, farmers can integrate and share resources on a larger scale, optimize resource allocation efficiency, and realize the synergistic development of green agriculture between different regions [31]. Second, relying on the Internet, cloud computing, and other information technologies, the digital industry cluster has significant technical knowledge characteristics. It can also strengthen the industrial relevance of digital agriculture between regions through the network effect, comprehensively break the industrial boundary [32], form a new open agricultural industry framework, and share agricultural technology and innovation achievements. In addition, the digitization of agricultural production has given rise to a group of elites that are proficient in digital agricultural technology, and the mobility of human capital has provided a new channel for the spatial spillover of knowledge elements. This has deepened the exchange and connection of agricultural knowledge between regions and driven the progress of agricultural technology in neighboring regions. Third, the combination of data and agricultural production elements constantly impacts the government's institutional framework and agricultural industrial structure and promotes the continuous transformation of the operation model of the government and relevant agricultural departments to digitization. In this way, more suitable policies, regulations, and digital infrastructure have been formed to provide institutional guarantees and technical support for the mobility of agricultural factors of production between different regions [33]. Therefore, the following hypothesis is proposed:

Hypothesis 3 (H3). *The digital economy can influence agricultural green development in neighboring regions through spatial spillover effects.*

3. Methodology and Data

3.1. Benchmark Model

To verify the hypotheses proposed, we test the mechanism of the impact of the digital economy on agricultural green development. Following the research method of Yang et al. [34], the basic econometric model constructed is as follows:

$$agri_{i,t} = \beta_0 + \beta_1 dige_{i,t} + \beta_i X_{i,t} + \lambda_i + \varepsilon_{it} \tag{1}$$

where $agri_{i,t}$ represents the level of agricultural green development in province i in year t; $dige_{i,t}$ represents the level of digital economy development in province i in year t; vector $X_{i,t}$ represents other control variables affecting agricultural green development; ε_{it} represents the random disturbance term; β_0 represents the model intercept term, and β_1 represents the coefficient of the digital economy variables.

Due to the existence of network externalities, there should also be a nonlinear contribution of the digital economy to agricultural green development. Thus, this study constructs a threshold model to test how the impact of the digital economy on agricultural green development differs at different stages of development. According to Zong et al. [35], the specific model is as follows:

$$agri_{i,t} = \Psi_0 + \Psi_1 dige_{i,t} \times \mathrm{I}(Adj_{i,t} \le \theta) + \Psi_2 dige_{i,t} \times \mathrm{I}(Adj_{i,t} > \theta) + \Psi_i X_{i,t} + \lambda_i + \varepsilon_{it} \tag{2}$$

where $Adj_{i,t}$ is the threshold variables, such as digital economy and population consumption level; $I(\cdot)$ denotes the indicator function, which is 1 if the condition in parentheses is satisfied and 0 otherwise; and θ is the threshold value to be estimated.

The externalities of the digital economy may transcend spatial and temporal constraints, which makes the benefits of neighboring regions affect each other. According to Uberti et al. [36], we introduce the spatial correlation term based on Equation (1) to set the spatial model.

$$agri_{i,t} = \beta_0 + \rho W agri_{i,t} + \Phi_I W dige_{i,t} + \beta_1 dige_{i,t} + \Phi_c W X_{i,t} + \beta_i X_{i,t} + \lambda_i + \varepsilon_{it} \tag{3}$$

where ρ is the spatial autoregressive coefficient, and W is the spatial weight matrix. ϕ_I and ϕ_c are the elasticity coefficients of the spatial cross-product terms of the core and control variables, respectively.

3.2. Variables

3.2.1. Measurement of the Development Level of the Digital Economy

Based on the digital economy index construction system of Kieti [37], Zou [38], and Song [39], this study measures the level of digital economy development in terms of the state of rural digital economy infrastructure construction, agricultural digitization, and rural digital industrialization, as presented in Table 1.

Table 1. Digital economy development level indicator system.

Primary Indicator	Secondary Indicator	Indicator Interpretation	Indicator Attribute	Weightings (%)
Digital Infrastructure	Rural Internet penetration rate	The proportion of rural broadband access users to the rural population in the region	+	7.6%
	Rural smartphone penetration rate	Average cell phone ownership per 100 rural households	+	1.7%
	Coverage of agricultural weather observation stations	Number of agricultural meteorological observation stations	+	2.9%
Digitalization of Agriculture	Digital trading scale of agricultural products	Online physical transaction volume	+	23.3%
	Agricultural infrastructure development	Investment in fixed assets in agriculture, forestry, animal husbandry, and fishery	+	6.3%
	Digital industry support	The proportion of urban IT service personnel	+	12.1%
Digitization of the Agricultural Industry	IoT technology applications	Number of postal outlets	–	0.7%
	Rural digital bases	Number of Taobao villages	+	45.2%

The construction of digital infrastructure is the foundation for the development of an agricultural digital economy. It needs Internet software, hardware, and mobile communication equipment to operate. Therefore, this study takes the rural Internet penetration rate, smartphone penetration rate, and the number of agrometeorological observation stations as the secondary indicators of digital infrastructure. Figure 2 shows the average variation trend of the three from 2011 to 2020. It can be seen that the rural Internet penetration rate, smart phone penetration rate, and number of agrometeorological observation stations have steadily increased in the past decade. Agricultural digitization mainly refers to the digitization of agricultural production, distribution, and operation using digital technology. This study uses the digital transaction scale of agricultural products and the construction of agricultural infrastructure to measure the degree of agricultural digitization.

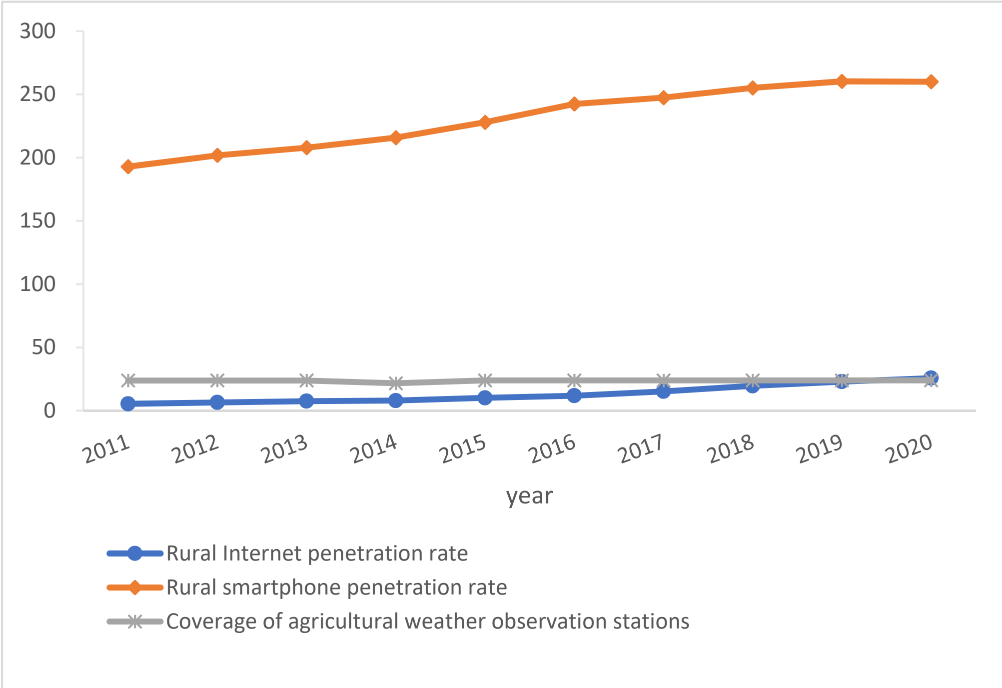

Figure 2. The rural Internet penetration rate, smartphone penetration rate and the average development level of agrometeorological observation stations in 2011–2020.

The digitization of the agricultural industry mainly refers to the degree of development of the digital industry in rural areas. Its development mainly benefits from the relevant technical support and the reduction of production and transportation costs. Therefore, this study selects the application of the Internet of Things and the number of Taobao villages to measure the digitalization of agricultural industry. The entropy method is used to assign values to each indicator, and then the measured weight values are used to measure the standardized data to obtain the digital economy development index of 30 provinces (except for Tibet) from 2011 to 2020 (due to the limitations of space, the specific principle and measurement process are omitted here). Figure 3 depicts the spatial distribution of digital economy levels in 2011 and 2020 by province.

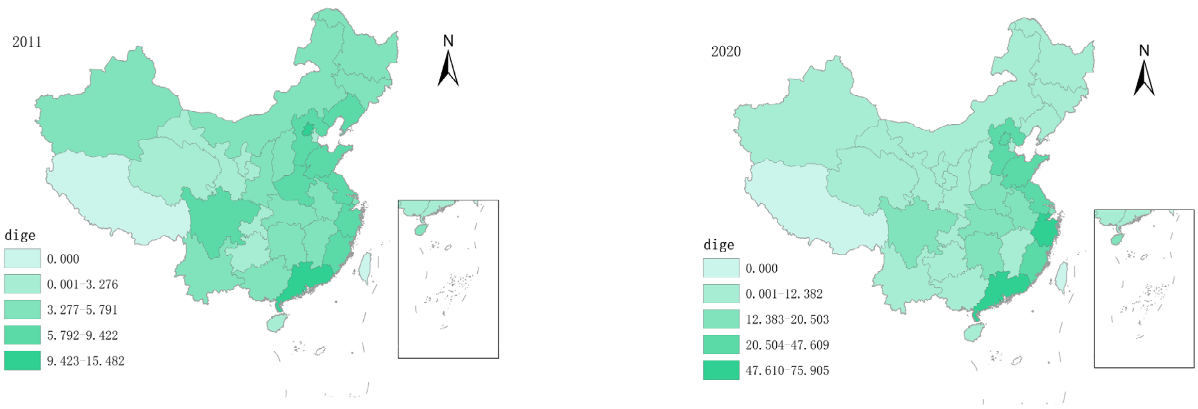

Figure 3. Digital economy development level by provinces in 2011 and 2020.

3.2.2. Measurement of the Level of Green Development in Agriculture

The focus of agricultural green development is resource conservation and environmental friendliness. While emphasizing the reduction of pollution, we should also improve the efficiency of resource utilization [40]. Based on the availability and practicability of data indicators and referring to the green agriculture index system constructed by Fang [41], as presented in Table 2, this study measures the development level of green agriculture in each province from seven perspectives—chemical fertilizer, pesticide, agricultural film, agricultural machinery, agricultural energy, water resources utilization, and total agricultural output. The index system highlights the characteristics of energy conservation, high efficiency, and sustainable development in the process of agricultural green production, which is consistent with the focus of agricultural green development. Among them, the reduction of chemical fertilizers, pesticides, and agricultural film in agricultural green production can not only reduce the direct greenhouse gas emissions, but also reduce the greenhouse gas emissions in the production of chemical fertilizers, pesticides, and agricultural film. Improving the utilization efficiency of water resources and machinery in agricultural production and reducing energy consumption are also important measures for the green and low-carbon development of agriculture. Maximizing agricultural output while minimizing pollution is more consistent with the concept of green agricultural development. As the direction of the effect of each indicator unit on agricultural green development is inconsistent, this study reduces the error by standardizing the extreme difference in each indicator to obtain dimensionless data with the same direction of effect and comparability. Finally, the entropy method is also used to assign the value of each index to obtain the agricultural green development index of 30 provinces in China (except for Tibet) from 2011 to 2020. Figure 4 depicts the spatial distribution of agricultural green development levels in various provinces in 2011 and 2020.

Table 2. Agricultural green development level index system.

Indicator	Indicator Interpretation	Indicator Attribute	Weightings (%)
Fertilizer use efficiency	Net amount of chemical fertilizer consumed by agriculture, forestry, animal husbandry, and fishery production	−	7.4%
Pesticide use efficiency	Pesticides consumed in agriculture, forestry, animal husbandry, and fishery production	−	7.1%
Agricultural film utilization efficiency	Agricultural film consumed by agriculture, forestry, animal husbandry, and fishery production	−	13.4%
Efficiency of agricultural machinery	Machinery input for agriculture, forestry, animal husbandry, and fishery production	−	11.4%
Energy consumption for agricultural production	Total carbon emissions from agricultural production	−	16.1%
Gross agricultural output	Gross output value of agriculture, forestry, animal husbandry, and fishery	+	6.8%
Water resources utilization efficiency	Ratio of effective irrigation area to total cultivated land area at the end of the year	+	37.7%

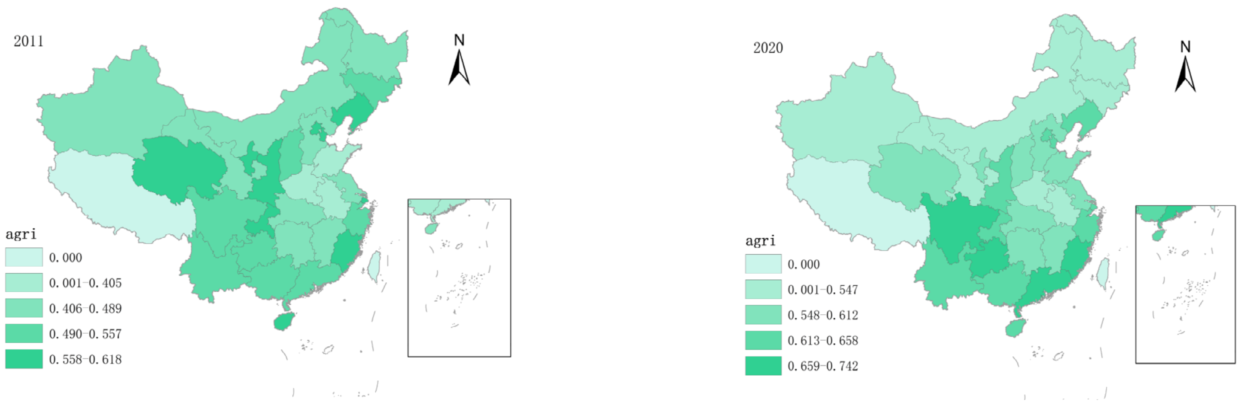

Figure 4. Green development level of agriculture by provinces in 2011 and 2020.

3.2.3. Control Variables

In addition to the development level of the digital economy, the green development of agriculture is also affected by human capital stock, rural economic growth level, degree of policy support, disaster rate, and other factors, which are set as control variables in this study. Among them, the stock of human capital follows the method of Yao [42] and is represented by the average number of students in higher education per 100,000 people. Referring to Zhao et al. [43], the added value of agriculture, forestry, animal husbandry, and fishery is used to measure the level of rural economic growth. The degree of policy support is measured using the proportion of science and technology expenditure in general public budget expenditure, referring to the method of Nan [44]. The method of Poggio [45] was adopted to measure the disaster rate using the ratio of the affected area to the total sown area of crops.

3.2.4. Data Sources

Based on data availability, this study empirically examines the impact of the digital economy on the green development of agriculture using balanced panel data of 30 Chinese provinces from 2011 to 2020. The data are mainly from China Statistical Yearbook, China Rural Statistical Yearbook, China Information Yearbook, and China Information Society Development Report. The "Broadband Countryside" list is from the official website of the Ministry of Industry and Information Technology, PRC.

4. Empirical Analysis

4.1. Measurement Results of Digital Economy and Agricultural Green Development Level

Table 3 shows the average level of digital economy development by region in China from 2011 to 2020. It can be seen that there is a big gap in the development level of digital economy in different regions. Among them, the development level of digital economy in the eastern region is higher than the national average, while the development level of digital economy in the central and western regions is lower than the national average. It can be concluded that there is a large "digital gap" in the development of the digital economy among regions in China. Table 4 shows the average level of green agricultural development in different regions of China from 2011 to 2020. The level of agricultural green development in the eastern and western regions is higher than the national average, while the development level in the central region is lower. On the whole, there are great differences in agricultural green development levels among different regions in China, which may be caused by the differences in agricultural production levels among regions. Figures 5 and 6 respectively show the average variation trend of digital economy and agricultural green development level in different regions of China. It can be seen that there are differences in the digital economy and agricultural green development levels in different regions, but both show a steady upward trend.

Table 3. Average development level of China's digital economy from 2011 to 2020.

Year	Total	Eastern Region	Central Region	Western Region
2011	5.534	7.389	5.009	3.851
2012	6.120	8.282	5.465	4.206
2013	7.139	9.876	6.180	4.860
2014	7.748	11.103	6.425	5.116
2015	9.217	13.734	7.267	5.864
2016	10.564	16.291	7.875	6.553
2017	12.382	19.921	8.680	7.280
2018	14.717	24.476	9.929	8.108
2019	16.867	28.821	10.940	8.844
2020	18.851	32.511	12.080	9.680

Table 4. Average development level of green agriculture in China from 2011 to 2020.

Year	Total	Eastern Region	Central Region	Western Region
2011	0.518	0.546	0.467	0.542
2012	0.525	0.555	0.473	0.545
2013	0.533	0.567	0.480	0.549
2014	0.536	0.573	0.483	0.550
2015	0.541	0.580	0.486	0.555
2016	0.551	0.591	0.497	0.563
2017	0.552	0.589	0.493	0.570
2018	0.564	0.602	0.506	0.581
2019	0.583	0.619	0.532	0.597
2020	0.604	0.636	0.560	0.614

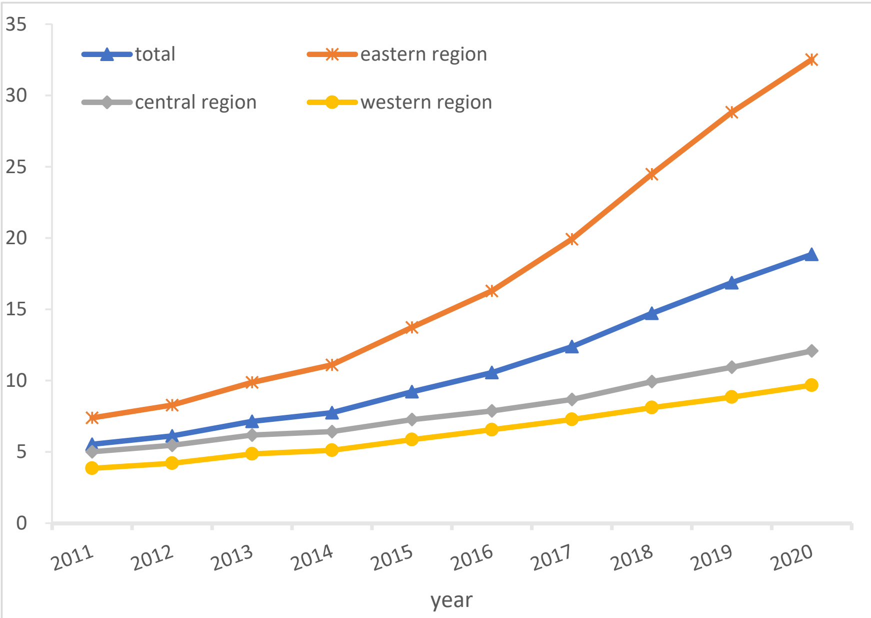

Figure 5. Trend of regional digital economy development level.

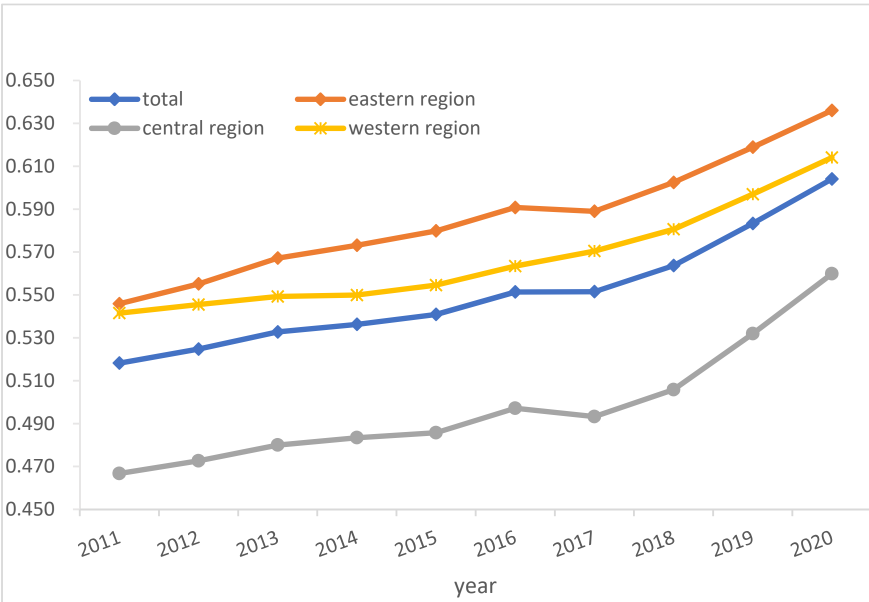

Figure 6. Trend of regional agricultural green production level.

4.2. Benchmark Regression Results

Table 5 presents the linear estimation results of the impact of the digital economy on agricultural green development. In Models (1) and (2), the regression coefficients of the core explanatory variable, i.e., the digital economy index, are positively significant at the 1% level. This indicates that the digital economy has significantly improved the level of agricultural green development. In addition, control variables are included in Model (2) and tested. The results indicate that the rural economic growth level, degree of policy support and agricultural disaster rate hinder agricultural green development. The reason may be that most of the income of farmers comes from migrant work, so they undertake less re-investment in improving agricultural production conditions, and the lag of government policies [46], which inhibits the efficiency of agricultural production. Natural disasters reduce agricultural output, increase agricultural production costs [47], and hinder the effective promotion of agricultural green development.

Table 5. Benchmark regression results.

Variable	Agri	
	(1)	**(2)**
dige	0.002 *** (0.000)	0.003 *** (0.001)
human		0.000 *** (0.000)
add		−0.000 *** (0.000)
policy		−0.642 ** (0.047)
dis		−0.065 ** (0.043)
Observations	300	300

Note: the values in brackets are T values; **, and *** are significant at the level of 5%, and 1%, respectively.

4.3. Nonlinear Effect Analysis

Before conducting the threshold regression, the Bootstrap method should be used to identify whether there is a threshold effect of digital economic development on agricultural green development. After 300 sampling checks, both the level of digital economy development and the level of population consumption significantly pass the double threshold test. Table 6 presents the results of the threshold model regression. There are significant differences in the effects of different levels of digital economy development on agricultural green development.

Model (1) takes the level of the digital economy development as the threshold variable. The results reveal that as the development level of the digital economy improves, its role in promoting China's agricultural green development has significant nonlinear dynamic characteristics. When the development level of the digital economy is lower than the threshold value of −1.08, the estimation coefficient of the digital economy is 0.011. This may be because at the initial stage of the integration of the digital economy and agricultural production, there are risks, such as high investment cost, long return cycle, and large trial and error cost, coupled with the rapid development and small scale of the digital economy, resulting in insufficient motivation for the digital transformation of agriculture [48]. In addition, the digital economy has a strong lag effect, and the application of digital technology leads to changes in the agricultural production model, resulting in an insignificant promotion of the digital economy. When the development level of the digital economy is between −1.08 and −0.92, the estimation coefficient is 0.044, which is significant at the 1% level. This demonstrates that with the continuous development of the digital economy, the integration barrier between digital technology and traditional agriculture has been gradually broken, thereby having a positive effect on agricultural green development.

When the level of the digital economy exceeds the threshold value of −0.92, the coefficient of the digital economy is still significantly positive. This indicates that the digital economy promotes agricultural green development only when it exceeds the first threshold. This may be because there is a process of absorption and integration of the positive effect of the digital economy on agricultural production. When the development of the digital economy reaches a critical point, the promotion effect of the digital economy on agricultural green development will appear, and the scale effect of the digital economy will further enhance the promotion effect. This supports H2.

Table 6. Threshold regression results.

Variable	**Threshold Variable**
	(1)
Threshold Value (Th_1)	−1.08
Threshold Value (Th_2)	−0.92
dige, t × I (Adj ≤ Th_1)	0.011 (0.227)
dige, t × I (Th1 < Adj ≤ Th_2)	0.044 *** (0.000)
dige, t × I (Adj > Th_2)	0.062 *** (0.000)
human	0.233 *** (0.000)
add	−0.013 (0.445)
policy	1.996 *** (0.000)
dis	0.046 (0.105)
Observations	300
R^2	0.819

Note: the values in brackets are T values; *** is significant at the level of 1%.

4.4. Spatial Spillover Effect Analysis

Before applying the spatial model to measure the spatial effect of the digital economy on agricultural green development, it is necessary to consider whether both the digital economy and the level of agricultural green development are spatially correlated. This study uses the adjacency matrix to calculate the Moran's I index of the digital economy index and the level of agricultural green development from 2011 to 2020 to verify the spatial autocorrelation between the two. As presented in Table 7, the Moran's I index of agricultural green development level is significantly positive, and there is an obvious spatial positive correlation. The Moran's I index values for the digital economy are also greater than 0, and the *p*-values are significant at the 1% and 5% levels, which indicates that the level of digital economy development also has a significant positive spatial correlation effect. Therefore, it is reasonable to test the spatial spillover effect of digital economy development on the level of green agriculture using a spatial model.

Table 7. Moran's I of the digital economy and agricultural green development under a geographical weight matrix.

Year	Agri			Dige		
	Moran's I	**Z-Value**	***p*-Value**	**Moran's I**	**Z-Value**	***p*-Value**
2011	0.221	2.291	0.011	−0.054	−0.174	0.431
2012	0.213	2.208	0.014	−0.013	0.197	0.422
2013	0.176	1.876	0.030	0.011	0.411	0.340
2014	0.141	1.565	0.059	0.055	0.800	0.212
2015	0.131	1.478	0.070	0.114	1.339	0.090
2016	0.137	1.526	0.064	0.149	1.660	0.048
2017	0.143	1.570	0.058	0.195	2.073	0.019
2018	0.163	1.757	0.039	0.250	2.581	0.005
2019	0.216	2.240	0.013	0.281	2.859	0.002
2020	0.286	2.885	0.002	0.295	2.971	0.001

Before selecting the specific spatial model, the LM Test was carried out on the panel data. Finally, we use the spatial error model (SEM) for spatial effect analysis. Based on the Hausman test, when the SEM model is selected, the fixed effect model is better, so the fixed effect model is used for the analysis. To improve the robustness of the results, this study also uses the spatial lag model (SAR) to test the robustness of the spatial regression results. Table 8 presents the spatial measurement results of the effect of the digital economy on the level of agricultural green development under the three weight matrices.

Table 8. Spatial model regression results.

Model	**SAR**			**SEM**		
Spatial Matrix	**Geographic Distance Matrix**	**Economic Distance Matrix**	**Adjacency Matrix**	**Geographic Distance Matrix**	**Economic Distance Matrix**	**Adjacency Matrix**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ρ	0.154 *** (0.004)	0.114 (0.124)	0.201 *** (0.000)			
λ				0.252 *** (0.009)	0.245 * (0.066)	0.376 *** (0.000)
dige	0.001 *** (0.000)	0.001 *** (0.000)	0.001 *** (0.000)	0.003 *** (0.000)	0.003 *** (0.000)	0.002 *** (0.000)
human	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)
add	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.293 (0.356)
policy	0.233 (0.127)	0.271 * (0.078)	0.224 (0.132)	−0.230 (0.486)	−0.329 (0.309)	−0.000 *** (0.000)
dis	0.014 (0.128)	0.012 (0.170)	0.017 * (0.054)	−0.029 (0.366)	−0.038 (0.235)	−0.008 (0.784)
Direct effect	0.001 *** (0.000)	0.001 *** (0.000)	0.001 *** (0.000)			
Indirect effect	0.000 *** (0.010)	0.000 (0.140)	0.000 *** (0.000)			
Total effect	0.001 *** (0.000)	0.001 *** (0.000)	0.001 *** (0.000)			
R^2	0.844	0.848	0.845	0.372	0.369	0.364

Note: the values in brackets are T values; *, and *** are significant at the level of 10%, and 1%, respectively.

In the SEM model, the coefficients of the digital economy under the three weight matrices are significantly positive at the 1% level, indicating that the higher the development level of the digital economy in the province, the higher the level of agricultural green development. The application of the digital economy in the region plays a positive role in accelerating the digitization of agricultural production and improving the consumption level of agricultural products and promoting the green development of regional agriculture from both supply and demand sides. The estimated values of λ are also significantly positive at the 1% and 10% levels, which indicates that the level of agricultural green development among regions has broken through regional barriers and has a certain relevance. To explain the marginal effect of the digital economy on agricultural green development, the direct, indirect, and total effects of the digital economy on regional agricultural green development are analyzed using the SAR model. The Table 6 indicates that under the three weight matrices, the direct, indirect, and total effects of the digital economy on the level of agricultural green development are significantly positive. This indicates that the development of the digital economy in the province not only plays a positive role in promoting the agricultural green development in the province but also is an effective way to promote agricultural green development in neighboring provinces. The positive spillover effect of the digital economy on agricultural green development has been verified again, thus supporting H3.

4.5. Robustness Tests

To further ensure the reliability of the above regression results, this study performs robustness tests in two ways:

(1) The panel quantile regression method is used to test whether there are differences in the impact of the digital economy on agricultural green development under different agricultural green development levels. The results are presented in Model (1) in Table 9. The three quantiles of 25%, 50%, and 75% indicate the low, medium, and high levels of agricultural green development, respectively. Under different levels of agricultural green development, the positive impact of the digital economy on China's agricultural green development is significant. This confirms the robustness of the empirical results.

(2) Add control variables. Increased openness to the outside world will promote the development of the rural economy, innovate the agricultural development model, and enhance agricultural green development. In addition, enhancing agricultural fiscal spending will also promote agricultural technology research and development, which will drive the transformation of agricultural production to greenization. Therefore, the degree of openness to the outside world (open) and the level of agricultural fiscal spending (fin) are added as control variables. The degree of external openness is measured by the proportion of total imports and exports to GDP, and agricultural fiscal expenditure is directly measured by its proportion to total regional fiscal expenditure. The regression results are presented in Model (2) in Table 9. The regression coefficient of the core explanatory variable, the digital economy, is still significantly positive at the 1% level. The robustness of the benchmark regression results is tested again.

Table 9. Robustness test results.

Variable	Agri			
		(1)		(2)
Quantile	**25%**	**50%**	**75%**	
dige	0.002 **	0.003 ***	0.004 ***	0.003 ***
	(0.024)	(0.000)	(0.000)	(0.000)
human	0.000 **	0.000	0.000 *	0.000 ***
	(0.033)	(0.385)	(0.092)	(0.000)
add	−0.000 ***	−0.000 ***	−0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
policy	−0.519	−0.106	−0.682 *	−1.352 ***
	(0.453)	(0.800)	(0.093)	(0.001)

Table 9. *Cont.*

Variable	Agri			
	(1)			(2)
Quantile	25%	50%	75%	
dis	−0.082 (0.196)	−0.109 * (0.050)	−0.034 (0.406)	−0.052 (0.105)
open				0.001 *** (0.007)
fin				−0.009 (0.955)
Observations	300	300	300	300

Note: the values in brackets are T values; *, **, and *** are significant at the level of 10%, 5%, and 1%, respectively.

5. Regional Heterogeneity Analysis and the Effect of the "Broadband Village" Policy

5.1. Regional Heterogeneity Analysis

Due to the differences in resource conditions and development status among the regions in China, there is obvious regional heterogeneity in the development level of the digital economy and agricultural green development. Therefore, there may be regional differences in the role of the digital economy in promoting the level of agricultural green development. To test this hypothesis, this study divides the 30 provinces into 3 regions—eastern region, central region, and western region—for regression analysis, as presented in Table 10.

Table 10. Regional heterogeneity test results.

Variable	Eastern Region	Central Region	Western Regions
dige	0.003 *** (0.000)	0.010 *** (0.000)	0.005 (0.185)
human	0.000 (0.931)	0.000 *** (0.000)	0.000 ** (0.014)
add	−0.000 *** (0.000)	−0.000 *** (0.000)	−0.000 (0.177)
policy	−0.477 (0.175)	−1.670 *** (0.002)	5.614 *** (0.000)
dis	−0.015 (0.678)	0.015 (0.770)	0.041 (0.512)
Observations	110	100	90
R^2	0.540	0.476	0.332

Note: the values in brackets are T values; **, and *** are significant at the level of 5%, and 1%, respectively.

From Table 10, the regression coefficient of the digital economy in the eastern region and central region are significantly positive, indicating that the digital economy effectively promotes the level of agricultural green development in the eastern region and central region. However, the effect is not significant in the western regions. It can be concluded that, overall, the development of China's digital economy has promoted the level of agricultural green development, but there are obvious differences in the promotion effect on different regions, with the positive effect in the eastern region and central region being more significant. The reason for this difference may be that the eastern and central provinces of China have relatively abundant capital and high-tech talent, good market development environment, and sufficient driving force for the development of the digital economy, so that the dividends of the digital economy can be more fully released. The western region is rich in energy resources, which guarantees China's energy supply. However, the proportion of industries with high energy consumption, high pollution, and high emissions is large. The cost of digitalization and green transformation is high, and the progress is slow, which does not significantly promote the green development of agriculture [49].

5.2. "Broadband Countryside" Policy Effect

According to the above results, the level of digital economy development in the central and western regions of China is relatively backward, resulting in an insignificant contribution to the level of agricultural green development. Moreover, in the central and western regions, the foundation of the digital economy is relatively weak, especially in rural areas, and the digital infrastructure required for the development of the digital economy is not yet in place. As an infrastructure network, broadband construction plays an indispensable role in accelerating the penetration and integration of digital technology into the economy and society. To speed up the construction of broadband in rural areas in central and western China and narrow the development gap of the digital economy, in 2014, the National Development and Reform Commission, the Ministry of Finance, the Ministry of Industry and Information Technology jointly decided to implement the "Broadband Countryside" pilot project in Sichuan and Yunnan. After being selected for the pilot project, the local area will expand network coverage, continuously increase the scale of broadband users, enhance broadband penetration, and vigorously promote broadband network speed-up, thus achieving high-speed growth of the digital economy. It is expected that the level of rural digital economy development would significantly improve in areas affected by the construction of "Broadband Countryside." This will have a positive impact on the technological progress and efficiency of local agricultural production, thus promoting the green development of local agriculture. The construction of "Broadband Countryside" also provides a new opportunity to bridge the digital economic development gap between the east and west.

This study introduces the difference in differences (DID) method to analyze the effect of the "Broadband Countryside" pilot project on rural green development. Due to the randomness of the approval of the pilot cities, the 2014 "Broadband Countryside" pilot is regarded as a quasi-natural experiment. Sichuan and Yunnan started the construction of "Broadband Countryside" in 2014, so they are set as "experimental groups." In addition, Chongqing and Guizhou are set as the "control group". The reasons are as follows: Chongqing, Guizhou, Sichuan, and Yunnan are geographically adjacent and have similar levels of economic development. They are relatively close in terms of agricultural resources, environment, production mode, and industrial structure, which have a certain comparability. Referring to the method of Wang [50], the specific form of the model is as follows:

$$agri_{i,t} = \alpha_0 + \alpha_1 treat_{i,t} + \alpha_2 time_{i,t} + \alpha_3 did_{i,t} + \alpha_j controls_{i,t} + \gamma_i + \mu_i + \varepsilon_{it} \quad (4)$$

In Formula (4), *agri* is the agricultural green development level of each province; *treat* is a grouping variable for cities, where if the city is a pilot city, it is assigned a value of 1 and 0 otherwise; *time* is a grouping variable for time; and *did* represents the intersection of group and time variables. In addition, *controls* are a series of control variables that may affect agricultural green development: γ is the individual effect, μ is a time effect, and ε is the disturbance term.

Table 11 reports the impact of "broadband rural" construction on agricultural green development. Model (1) is the regression result without control variables. The estimation coefficient of the effect of the "broadband rural" pilot project on agricultural green development is positive. This indicates that the construction of "Broadband Countryside" promotes the development of a regional digital economy and can improve the level of agricultural green development. Model (2) adds a series of control variables to Model (1). The regression coefficient of the "broadband rural" pilot project is significant at the 1% level, and compared with that of Model (1), the significance improves. According to the regression results, the "broadband rural" pilot project has a significant policy effect and can accelerate the green development of local agriculture by improving the development level of the digital economy.

Table 11. Regression results of DID between broadband construction and agricultural green development.

Variable	Agri	
	(1)	**(2)**
treat × post	0.035 (0.793)	0.136 *** (0.000)
human		0.262 *** (0.000)
add		−0.032 (0.255)
policy		22.616 *** (0.000)
dis		0.330 *** (0.000)
Observations	40	40
R^2	0.567	0.922

Note: the values in brackets are T values; *** is significant at the level of 1%.

To ensure that the causal effect between the "broadband rural" pilot project and agricultural green development identified by the double-difference method is not affected by other random factors, this study randomizes the years when each province is recognized as the "broadband rural" pilot city and constructs a placebo test to test the authenticity of the results obtained using the DID method. Figure 7 depicts the coefficient distribution of the estimation result of agricultural green development level as the explained variable. The estimated values of the coefficient kernel density of 500 random samples are concentrated around 0, and the estimation results are robust.

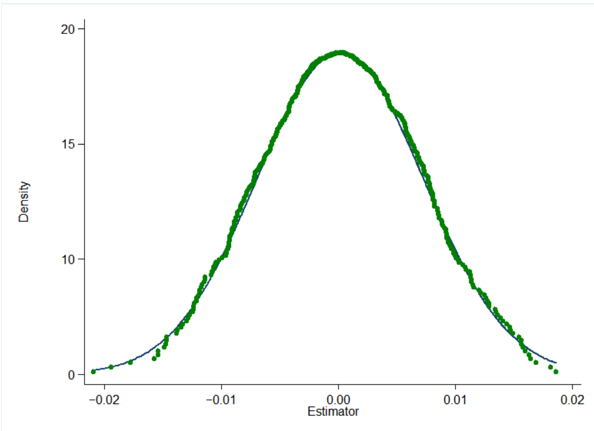

Figure 7. Placebo test.

6. Conclusions

6.1. Research Conclusions

This study empirically analyzes the transmission mechanism and impact effect of the digital economy on agricultural green development and draws the following conclusions. First, the digital economy can significantly improve the level of agricultural green development. By reconstructing the agricultural industrial chain and improving the efficiency of production and management decision-making, it has become the endogenous driving force for the development of green agriculture in China. After a series of robustness tests, this conclusion is still valid. Second, the digital economy has a significant nonlinear trend of having an increasing positive "marginal effect" on agricultural green development. The accumulation of platform users and the continuous improvement of digital technology will accelerate the transformation of agricultural technology achievements and continuously enhance the positive effect of the digital economy on agricultural green transformation. Third, the level of agricultural green development in China's provinces has a significant spatial correlation, and the digital economy has an obvious spatial spillover effect on China's agricultural green development. Government guidance and rational utilization will help to narrow the development gap of green agriculture among regions and form a new pattern of green coordinated development of regional agriculture. However, compared with the spillover effect of the digital economy, the direct effect of the digital economy on local agricultural green development is more obvious. Fourth, the positive effect of the digital economy on agricultural green development has regional heterogeneity. The eastern region enjoys more digital economic dividends, which means that the positive impact of the digital economy on agricultural green development in the central and western regions still needs to be strengthened. The construction of "Broadband Countryside" can improve the digital economy in rural areas in the central and western regions of China, accelerate the technological progress and efficiency improvement of local agricultural production, and have significant policy effects on agricultural green development.

6.2. Recommendations

Based on the above conclusions, this study proposes the following recommendations. First, we should vigorously develop the digital economy. Traditional agriculture should actively embrace the Internet platform and realize the integrated development of digital technology and agricultural production with the help of the new driving force of the digital economy. Digital technology continuously improves the modern agricultural industrial chain through intelligent monitoring and efficiency improvement. While improving the efficiency of agricultural production, digital technology promotes the digitization of all processes of agricultural production, thus realizing agricultural green development. Relevant departments should strengthen scientific top-level design, consolidate the foundation of digital technology, increase investment and support for the digital economy, encourage digital enterprises to innovate and develop smart agriculture, guide the development of "agriculture, rural areas, and farmers" enabled by the digital economy, and cultivate new driving forces to comprehensively promote agricultural green development.

Second, we should coordinate the development of the digital economy and agricultural green development. The integration of digital economy and regional agricultural green development does not exist in isolation but is indirectly related to potential factors, such as human capital and policy support. Therefore, a high-end intellectual talent guarantee and high-quality policy support are still effective ways to improve agricultural green development in China. When formulating education, consumption, and other related policies, policymakers should fully consider the positive impact of the digital economy and give full play to the catalytic role of regulatory factors on agricultural green development.

Third, the government should give full play to the radiating and driving role of the digital economy and share the dividends of the digital economy. The spatial radiation of a digital platform accelerates the spread of agricultural information elements in different regions, weakens the decreasing law of technology spillover effect caused by space–time constraints, and effectively improves the universality of relevant knowledge and information. Therefore, we should make full use of the network effect of the digital economy, strengthen the linkage of agricultural production between adjacent regions, and release its spatial contribution ability to agricultural green development. In particular, the central and western regions should take advantage of the spillover effect of the digital economy and make full use of the comparative advantages among regions to form a new pattern of coordinated development of green agriculture among regions.

Fourth, all regions should implement differentiated digital economy development strategies to narrow the digital divide. While consolidating the advantages of digital economic dividends, the eastern region should continue to play its exemplary and leading role in areas that have lower levels of digital economy development. The central and western regions should speed up making up for their shortcomings, constantly improve the construction of digital infrastructure, and break the constraints of the unbalanced development of the digital economy.

Fifth, we should make full use of the policy of "Broadband Countryside", promote the construction of rural digital infrastructure through policies, and empower agricultural green development. As a new opportunity for the development of rural digital economy, the "Broadband Countryside" project has greatly improved the coverage and transmission speed of rural communication networks and bridged the development gap between urban and rural digital economies. Therefore, it is necessary to strengthen the construction of the digital matching mechanism, increase investments in digital education in rural areas, and cultivate digital farmer elites by optimizing the digital training system to provide basic support for the implementation of agricultural digital transformation policies.

6.3. Research Limitations and Areas for Future Studies

The limitations of this study and the areas to be expanded mainly include the following:

First, the integrated development of the digital economy and green agriculture has been practiced in China for a short time, so a complete research framework and regular summary have not been established. This requires continuous exploration in future research and practice. After fully understanding and confirming the relevant conclusions, we expect to obtain more comprehensive and systematic research results.

Second, due to the complex internal composition of the digital economy and incomplete relevant data, this study only measures the development level of the digital economy from the aspects of the rural digital foundation, agricultural digitization, and rural industrial digitization, which may lead to a certain deviation from the measurement results and the current situation of rural digital economy development in China. With the continuous improvement of the availability of relevant data, the measurement system of the digital economy level can be further refined in future research to obtain more accurate statistical results.

Third, regarding the use of the DID method to verify the relevance of the "Broadband Countryside" pilot project to agricultural green development, limited by the number of pilot cities, only a few cities were selected as the experimental and control groups. The amount of data is small, which will affect the accuracy of the empirical results to a certain extent, but the overall relevance is acceptable. With the deepening of the "Broadband Countryside" pilot project, the correlation analysis between it and agricultural green development will be more convincing in the future.

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