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Study on the Impact of Digital Agricultural Technology on Green Total Factor Productivity in Agriculture

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Abstract

Digital agricultural technology empowers the development of agricultural production and has become an important way to promote the green development of agriculture. In order to explore the impact of digital agricultural technology on agricultural green total factor productivity and help China's agricultural digitalization and green transformation, we constructed an indicator system based on the panel data of 30 administrative districts in China from 2011 to 2020, measured the level of development of digital agricultural technology and agricultural green total factor productivity respectively, and introduced the fixed effect model and threshold effect model to empirically analyze the impact of digital agricultural technology on agricultural green total factor productivity. factor productivity. The results show that: 1) digital agricultural technology will produce significant promotion results on agricultural green total factor productivity; 2) there is a single threshold effect in the promotion of digital agricultural technology, and after the level of digital agricultural technology exceeds 0.074, its promotion effect on agricultural green total factor productivity is more significant; 3) the promotion effect of digital agricultural technology on agricultural green total factor productivity in different regions shows significant heterogeneity.

Keywords

Digital agricultural technology; Green total factor productivity in agriculture; Threshold effect.

1. Introduction

The green development of agriculture is the basic requirement for realizing Chinese-style modernization and the inevitable requirement for realizing high-quality development of agriculture [1]. Since the reform and opening up, China's agricultural gross domestic product has grown at an average annual rate of 4.6%[2]. However, the contradiction between China's past backward agricultural production technology and the demand for high output has kept China's agricultural production in a crude growth mode of high factor input, high waste of resources, and high emission of pollution[3]. This unreasonable resource allocation mode leads to resource waste and ecological environment damage problem is becoming more and more serious, China's sustainable development of agriculture is facing a serious test. 2024 Central Document No. 1 puts forward “adhere to the industry to develop agriculture, quality to develop agriculture, green to develop agriculture” policy, and specifically deployed to strengthen the rural ecological civilization construction measures Such as fighting a good battle against pollution in agriculture and rural areas, promoting the reduction of chemical fertilizers and pesticides to increase efficiency, etc.[4]. At this time, how to realize the transformation of traditional agriculture and promote the quality and efficiency of the agricultural industry has become an urgent problem of agricultural green development. The arrival of the digital and intelligent era has caused changes in the traditional economic model, providing a new direction

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and opportunity for the development of traditional industries. Then, what is the impact of digital agricultural technology on agricultural green total factor productivity? And how does digital agricultural technology affect agricultural green total factor productivity? These are the questions to be addressed in this study. In the critical period of transition from traditional agriculture to green agriculture, it is of great practical significance to explore the impact of digital agricultural technology on agricultural total factor productivity to promote the green transformation of agriculture.

In the relevant studies on the impact of digital agricultural technology on agricultural production at home and abroad, Lio et al[5] empirically demonstrated that there is a positive relationship between ICT and agricultural productivity through the agricultural production function, and that this positive effect is twice as much as that of the poor countries in the rich countries.Al-Hassan et al[6] showed that IT-based MLS services have a facilitating effect on the use of advanced technologies in agricultural production in a study of farmers in the eastern part of the Ghanaian empire. utilization has a facilitating effect. Sun Zhongfu et al[7] analyzed the demand for big data in agriculture, its main application areas and its key position in digital agriculture, taking into account the characteristics of agriculture. In the empirical research, Han Haibin et al[8] studied the nonlinear effect of agricultural informatization on agricultural total factor productivity through the threshold model. Zhu Qiubo and other scholars conducted empirical analyses through models such as the multiplier method and mediation effect, respectively[9][10]. Some scholars also pay attention to the green development and sustainable development of agriculture in the research process. Gao Yang et al[11] measured and studied the impact of agricultural informatization on agricultural green total factor productivity through the SBM-GML index method, and concluded that agricultural informatization has a driving effect on agricultural green total factor productivity. Its main pathway is technological progress, and the spatial correlation of this role is gradually increasing.

In summary, in the research on digital agricultural technology, domestic scholars are more concerned about the theoretical analysis of research, and less about the quantitative measurement and empirical analysis of digital agricultural technology; in the research on the impact of digital agricultural technology on the agricultural sector, the research object is more focused on the impact of digital agricultural technology on agricultural productivity, and fewer scholars are concerned about the relationship between digital agricultural technology and green total factor productivity in agriculture. productivity. Based on this, this study utilizes provincial panel data from 2011 to 2020, and applies tools such as the SBM model, GML index and entropy weighting method to measure the agricultural green total factor productivity and the level of development of digital agricultural technology in 30 provincial-level administrative districts across the country, to examine the impact of digital agricultural technology on agricultural green total factor productivity and regional heterogeneity. The impact of digital agriculture technology on agricultural green total factor productivity and regional heterogeneity are examined, with a view to providing theoretical support for promoting the synergistic development of agricultural intelligence and agricultural greening, and enhancing the level of agricultural green total factor productivity.

2. Theoretical Analysis and Research Hypothesis

2.1. Analysis of the impact of the digital agricultural technology industry on green total factor productivity in agriculture

The high-tech applications of digital agricultural technology, such as precision agriculture technology, Internet of Things equipment, big data analysis and artificial intelligence decision support systems, can directly affect the efficiency of resource utilization, reduce the excessive use of pesticides and fertilizers, and thus enhance green total factor productivity. First of all,

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digital agricultural technology can realize the dissemination of information and technology across time and space through the science and technology innovation platform. On the one hand, the science and technology innovation platform can be combined with agricultural production to bring the green production concept into agricultural production; on the other hand, agricultural enterprises with the help of the science and technology innovation platform can quickly learn the cutting-edge production technology and apply it to green agricultural production[12], which can reduce the frequency of the use of pesticides and chemical fertilizers and other traditional means of agricultural production and the emission of agricultural pollution, and promote the green total factor productivity of agriculture. Secondly, the information traceability function of digital agricultural technology can strengthen the government's environmental regulatory function, prompting agricultural producers to control the amount of fertilizer application, and reduce agricultural surface pollution[13]. Thirdly, digital agricultural technology can redistribute fertilizers and pesticides according to the comparative advantages of the supply side and demand side of production factors through the information coordination function of the e-commerce platform, improve the efficiency of land operation, and increase the green total factor productivity of agriculture. This is because the e-commerce platform can realize the efficient docking of market supply and demand information, alleviate the problem of information asymmetry in agricultural production, so that farmers can use the acquired information to make more thorough decisions, which can reduce the degree of resource waste caused by the mismatch of land and machinery factors, and effectively promote the growth of green total factor productivity in agriculture[9].

Accordingly, this study proposes hypothesis H1: digital agriculture technology can enhance agricultural green total factor productivity.

2.2. Analysis of the effect of digital agricultural technology on green total factor productivity in agriculture

When the development level of digital agricultural technology is low, it often means that the utilization rate of agricultural production factors is low and agricultural production methods are primitive. At this time, although the development of digital agricultural technology, but limited by the backward agricultural production facilities and low level of human capital, the promotion effect of digital agricultural technology on the green total factor productivity of agriculture will also be at a low level[14]. With the continuous improvement of the level of digital agricultural technology, the construction of agricultural infrastructure and the level of human capital of agricultural producers are also gradually improved, so that the development results of digital agricultural technology can be applied to agricultural production, to realize the upgrading of green production technology and pollution emission monitoring efforts, so as to reduce the pollution emissions in the case of factor inputs remain unchanged[15], and to ensure that the agricultural output, which in turn will enhance the agricultural green total factor productivity.

Through the above analysis, this study proposes the hypothesis H2: the promotion effect of digital agricultural technology on agricultural green total factor productivity will be further enhanced after crossing the threshold.

3. Model Construction and Variable Selection

3.1. Modeling

3.1.1. Benchmark regression model

Theoretical analysis shows that digital agriculture technology will have an impact on green total factor productivity in agriculture, therefore, this study constructs the following regression model:

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$$Agtfp_{it} = \beta_0 + \beta_1 Dat_{it} + \beta_2 X_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

Where: i is the region, t is the year, Agtfp is the agricultural green total factor productivity; Dat (Digital agricultural technology) is the level of development of digital agricultural technology; X is the control variable; μ_i is the unobservable province fixed effect; and ε_{it} is the random disturbance term. After adding time dummy variables and individual dummy variables for regression, the P-value of the time dummy variables are all greater than 10%, and the individual dummy variables are all significant at 5% significance, which indicates that the time fixed effect is not significant in the sample, therefore, this study adopts the individual fixed effect model.

3.1.2. Threshold effect model

In order to further analyze whether there is a threshold effect on the impact of digital agricultural technology development on agricultural green total factor productivity in each administrative region of China, the level of digital agricultural technology development is chosen as the threshold variable and the following threshold regression model is set:

$$Agtfp_{it} = \chi_0 + \chi_1 Dat_{it} \times I(Dat_{it} \leq \psi) + \chi_2 Dat_{it} \times I(Dat_{it} > \psi) + \chi_3 X_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

Where: ψ is the threshold value to be estimated; χ_1 and χ_2 represent the impact coefficients of the level of digital agricultural technology development on China's agricultural green total factor productivity when it is located in different variable domains; $I(Dat_{it} \leq \psi)$ is the indicative function; the meanings of other characters are the same as those of the benchmark regression model.

3.2. Selection of variables

3.2.1. Explained variables

This study refers to the measurement method of Ma Guoqun et al[16], and chooses the SBM super efficiency model and GML index to measure agricultural green total factor productivity, agricultural green technology efficiency, agricultural green technology progress, and the input and output data are from the EPS global database. Overall, China's agricultural green total factor productivity has been increasing from 2011 to 2020, with an average annual growth rate of 15.42%, of which the growth rate of agricultural green technology efficiency is 3.19% and the growth rate of agricultural green technology progress is 17.22% (Table 1).

Table 1 Changes in green total factor productivity and its decomposition in Chinese agriculture, 2011-2020

Year	Agtfp	AGEC	AGTC
2011	1.192	0.993	1.201
2012	1.338	1.003	1.335
2013	1.534	1.046	1.526
2014	1.657	1.043	1.654
2015	1.785	1.036	1.878
2016	1.960	1.017	2.105
2017	2.004	1.213	2.099
2018	2.499	1.268	2.735
2019	3.048	1.267	3.655
2020	4.189	1.295	4.820

3.2.2. Core explanatory variables

This study draws on the indicator construction system and measurement method of Zhang Jinsong et al[17], establishes digital agriculture technology level indicators based on the pressure-state-response model, and adopts the entropy weight-fuzzy comprehensive evaluation method for measurement. Specific indicators are selected as shown in Table 2, in

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which the scale of agriculture is measured by the arable land area of state-owned farms and the number of state-owned farms; the greening of agriculture is measured by the amount of pesticide use, the amount of fertilizer application, the amount of agricultural plastic film use and the area of water-saving irrigation; the development of e-commerce is measured by the e-commerce sales and the proportion of e-commerce trading activities to the total number of enterprises; the mechanization of agriculture is measured by the total power of agricultural machinery, the number of large and medium-sized tractors, and the total number of enterprises in the agricultural sector. Agricultural mechanization is measured by the total power of agricultural machinery, the number of large and medium-sized agricultural tractors and the effective irrigated area; rural living standard is measured by the per capita disposable income of rural households and the Engel's coefficient of rural residents; Internet communication infrastructure is measured by the number of broadband access subscribers of rural residents, the number of mobile telephones per 100 households in rural areas and the number of web sites per 100 enterprises; the production capacity of agriculture is measured by the total food output, the proportion of the added value of the primary industry in the GDP of the region and the total output value of agriculture, forestry, livestock and fisheries. agricultural, forestry, animal husbandry and fishery output value; agricultural financial service support is measured by the agricultural budget expenditure and agricultural, forestry, animal husbandry and fishery fixed asset investment growth over the previous year; agricultural talent cultivation base is measured by the public financial budget expenditure on education, the per capita education, culture and recreation consumption expenditure of rural residents, and the number of students enrolled in ordinary schools of higher education; scientific and technological innovation capacity is measured by the local financial science and technology expenditures, the number of patents applied and authorized, and the expenditure on research and experimental development of industries above designated size. Scientific and technological innovation capacity is measured by local financial expenditure on science and technology, the number of patents applied for and authorized, and the expenditure on research and experimental development of industries above designated size.

Table 2 Indicator system for measuring the level of digital agriculture technology

Subsystem	Weight	Level 1 indicators	Weight
Strain	0.416	Scale up of agriculture	0.188
		Greening of agriculture	0.047
		Status of development of e-commerce	0.080
		Mechanization of agriculture	0.102
Statuses	0.268	Rural living standards	0.021
		Internet communications infrastructure	0.055
		Agricultural production capacity	0.192
Responsive	0.316	Agricultural financial services support	0.125
		Agricultural manpower training base	0.051
		Science, technology and innovation capacity	0.140

Figure 1 gives the distribution map of the level of digital agriculture technology development in 30 administrative regions from 2011 to 2020 divided into five levels through the natural discontinuity analysis method, the overall point of view of the level of digital agriculture technology in 2020 compared to 2011 has a greater increase in the level of digital agriculture technology, the level of digital agriculture technology in the higher areas are mainly concentrated in the central and eastern parts of the region, Xinjiang region is the reason for the

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higher data is because of the Xinjiang has a vast area of arable land and rich light resources, is one of the important cotton production bases. The reason why Xinjiang has higher data is that Xinjiang has a vast arable land area and abundant light resources, and is one of the important cotton production bases, and the high mechanization of cotton production makes the measured level of intelligence relatively high.

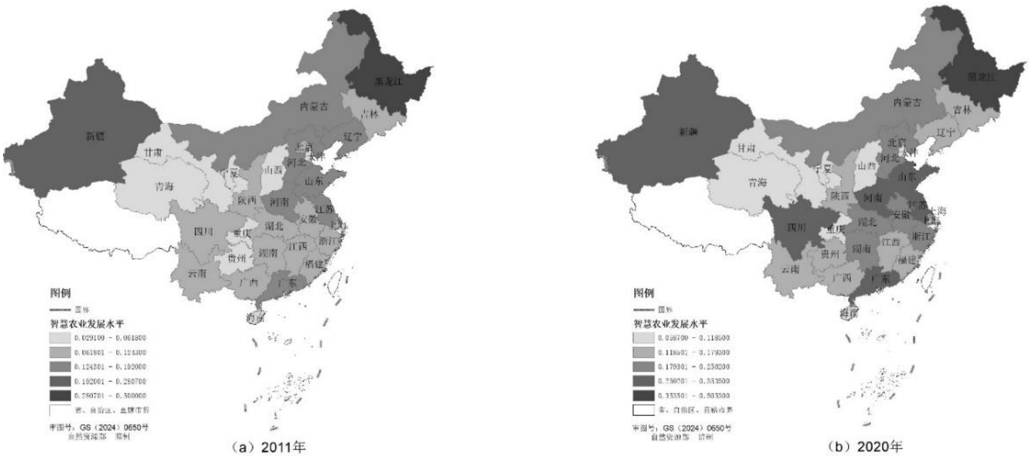

Figure 1 Level of development of Digital Agricultural Technology in 2011 and 2020

3.2.3. Control variables

Drawing on existing research[18][19][20], this paper introduces the following control variables: 1) Disaster rate, measured by the proportion of disaster-affected area to the sown area of crops.2) Agricultural machinery operation level, expressed as the and total power of agricultural machinery in each administrative district.3) Cultivation scale, expressed as the sown area per capita by dividing the sown area of crops by the number of agricultural employees in each administrative district.4) Human capital, expressed as the share of high school population in the rural population aged 6 and above. The statistical characteristics of each variable are shown in Table 3.

Table 3 Descriptive statistical characteristics of the variables

Variable	Symbol	Mean value	SD	Min	Max
Green total factor productivity in agriculture	Agtfp	1.781	1.178	0.296	9.836
Level of technological development in digital agriculture	Dat	0.161	0.096	0.029	0.544
Disaster rate	affir	0.153	0.119	0.001	0.695
Level of operation of agricultural machinery	mech	3411.086	2922.604	93.970	13353.020
Planting scale	are	5.721	3.902	0.880	23.245
Human capital	human	0.101	0.034	0.037	0.239

Note: Sample size is 300

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4. Empirical Analysis

4.1. Test results of digital agricultural technology and green total factor productivity in agriculture

In this study, based on the results of LM test, F test and Huasman test, the fixed effect model was used for regression analysis. After adding time and individual dummy variables to the regression, the individual fixed effect of the sample is significant, and the time fixed effect is not significant, therefore, this study determines to use the individual fixed effect model. The results of the baseline regression of the impact of digital agriculture technology on green total factor productivity in agriculture are shown in Table 4.

Table 4 Benchmark regression results

Variable	Agtfp
Dat	0.991***
affir	-0.321*
mech	0.062
are	0.496***
human	0.358***
_cons	1.378***
N	300
R^2	0.745

Note: Models are baseline regression results; *, ** and *** indicate significant at the 10%, 5% and 1% statistical levels, respectively.

In Table 4, the regression coefficient of digital agricultural technology on agricultural green total factor productivity is positive and significant at the 1% confidence level, indicating that the development of digital agricultural technology helps to improve agricultural green total factor productivity, and hypothesis H1 is confirmed. The reason for this phenomenon is that, first, with the gradual development of digital agricultural technology, the allocation efficiency of agricultural green production factors will gradually improve, which will not only reduce the amount of pesticides and fertilizers applied, but also realize the popularization of agricultural green production technology through the technology demonstration effect and technology transfer effect, and then enhance the agricultural green total factor productivity. Secondly, the application of digital agricultural technology promotes agricultural innovation and knowledge dissemination, facilitates the knowledge updating and skill upgrading of farmers' groups, and strengthens their environmental protection awareness, thus reducing soil pollution, which is ultimately reflected in the improvement of AGTFP. Third, the government's incentive policies for digital agricultural technology and green agricultural subsidies, combined with the growing consumer demand for green and healthy food, together constitute a key driving force to promote the popularization of digital agricultural technology, and this double-driven mechanism of market and policy effectively promotes the enhancement of green total factor productivity in agriculture.

Among the control variables, the disaster rate has a significant inhibitory effect on agricultural green total factor productivity, with an overall impact coefficient of -0.321. The reason for this is that, on the one hand, natural disasters directly reduce crop output by destroying the agricultural infrastructure, which in turn reduces the efficiency of agricultural production and the adaptability of the environment; on the other hand, frequent disaster events also exacerbate the uncertainty of agricultural production, which inhibits the farmers in the On the other hand,

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frequent disaster events also increase the uncertainty of agricultural production and inhibit farmers' willingness to invest in green technology innovation and eco-friendly agricultural practices. The above negative effects are not only limited to short-term yield loss, but also involve long-term agro-ecosystem degradation and a decline in the economic vitality of the agricultural community, which together constitute comprehensive constraints on the green total factor productivity of agriculture. The coefficient of agricultural machinery operation level on agricultural green total factor productivity is 0.062, with a certain positive promotion effect, but the effect is not significant, agricultural mechanization can significantly improve labor productivity, reduce the labor cost per unit of output, and promote the precision and intensification of agricultural production. Human capital on agricultural green total factor productivity promotion effect is significant and it is mainly through the technological progress pathway, the impact coefficient of 0.358, but its inefficiency of China's agricultural technology does not play a significant role. The popularization of education has improved the quality of China's labor force, and the high-quality labor force can better absorb and utilize advanced technology in agricultural production.

4.2. Threshold panel model analysis

In order to study whether there is a threshold effect on the impact of digital agricultural technology development on agricultural green total factor productivity in each administrative region of China, the level of digital agricultural technology development was chosen as the threshold variable to do a threshold regression (Table 5).

Table 5 Threshold test results

Threshold variable	Threshold type	P value	Threshold value	BS iterations	Critical value		
					1%	5%	10%
Dat	Single threshold	0.040	0.074	300	37.54	27.523	19.383
	Double threshold	0.653	0.111	300	29.236	29.128	21.037
	Triple threshold	0.293	0.241	300	34.931	23.096	15.498

As can be seen from the P-values in Table 5, the level of digital agriculture technology development plays a significant single threshold effect in the impact on green total factor productivity in agriculture. The specific threshold regression estimation results are shown in Table 6:

Table 6 Threshold regression estimates

Variable	Agtfp
Dat(intensity < 0.074)	1.276**
Dat(intensity ≥ 0.074)	1.590***
Control variables	Control
Individual fixed effects	Control
N	300
R^2	0.452
F test	32.860

As can be seen from Table (6), when the level of digital agricultural technology development is <0.074, digital agricultural technology shows a positive effect on agricultural green total factor productivity, with a regression coefficient of 1.276, which is significant at the 5% level; and when the level of digital agricultural technology development is greater than or equal to the threshold, digital agricultural technology exerts an even more significant positive effect on agricultural green total factor productivity, with its regression coefficient grows to 1.590 and is significant at the 1% level. This is because in the early stage of the development of digital agricultural technology related infrastructure construction requires a lot of investment, and the construction cycle is long and slow, the promotion effect of digital agricultural technology on agricultural green total factor productivity is relatively small; in the level of development of digital agricultural technology is higher than 0.074, the main reason for the significant increase in the impact of digital agricultural technology on agricultural green total factor productivity is that, first, the scale effect makes the digital Agricultural technology construction investment is mainly concentrated in the first stage, its second stage of the input is relatively small, that is to say, into the digital agricultural technology development to the second stage began to amortize the high cost of the first stage; Second, the network external effect of digital agricultural technology is based on a certain scale as a prerequisite, only to reach the critical value of the two stages of the 0.074, the network effect of digital agricultural technology began to appear positive feedback mechanism, three, the higher level of development of digital agricultural technology and the agricultural industry combined to play the multiplier effect also plays a positive role in the process of digital agricultural technology to enhance the total factor productivity of agricultural green. Hypothesis H2 is confirmed.

4.3. Robustness Tests

This study adopts the following four approaches to conduct the robustness test: 1) Replacement of the explanatory variables. This study refers to Yang Xiuyu et al.'s[21] method of accounting for green total factor productivity in agriculture and replaces the explanatory variables to verify the robustness of the baseline regression results. 2) Tailoring the data. In order to minimize the effect of extreme values, the data in this study were trimmed, i.e., 5% of the observations at the ends of each variable were removed to minimize the effect of outliers on the regression results. 3) Elimination of time samples. To assess potential anomalies in the time series, this study excludes data from 2018 to check whether data from a specific year adversely affects the overall results. Through the above three robustness tests, this study finds that the positive impact of digital agricultural technology on green total factor productivity in agriculture is robust.

Table 7 Robustness test results

Variable	Model 1:Agtfp new	Model 2: 5% data shrinkage	Model 3: Excluding the 2018 time sample
Dat	0.479***	0.983***	1.054***
	(0.044)	（0.079）	(0.100)
_cons	1.631**	-4.994	-5.783
	(0.660)	（1.341）	(1.543)
Control variables	Control	Control	Control
Individual fixed effects	Control	Control	Control
N	300	300	270
R^2	0.742	0.755	0.740

4.4. Endogeneity test

Although the baseline model controls for variables that may have confounding effects on green total factor productivity in agriculture, there may be measurement errors in the digital agricultural technology indicators, which may lead to an inaccurate estimation of the effect

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between digital agricultural technology and green total factor productivity in agriculture; at the same time, the level of regional economic development may inversely affect the development of digital agricultural technology, and thus the estimation results of the baseline model may be biased due to endogeneity problems. bias. Therefore, this paper searches for appropriate instrumental variables to test the robustness of the benchmark model. Drawing on the idea of constructing instrumental variables in existing studies, the historical data of Internet penetration rate is chosen as the instrumental variable of Internet development. On the one hand, this data can effectively portray the level of regional informatization, which meets the requirement of relevance; on the other hand, it has little effect on the green total factor productivity in agriculture, which meets the exclusivity assumption and is not correlated with the disturbance term in the current period. Therefore, the historical data of Internet penetration rate basically satisfy the conditions of instrumental variable correlation and exogeneity. To ensure the validity of the estimation results, control variables are still added and regressed under the individual fixed effects model. Table 8 reports the regression results of instrumental variables. In terms of the validity of the instrumental variables, the K-Paark LM statistic for the identifiable test, which rejects the original hypothesis at the 1% level, satisfies the identifiability of the instrumental variables, and the weak instrumental variable test (C-D Wald F) value is greater than the Stock-Yogo critical value at the 10% level, and the model passes the weak instrumental variable test. The regression coefficient of digital agricultural technology on green total factor productivity in agriculture is significant at the 1% level after considering the endogeneity issue, indicating that the results of the benchmark model are robust.

Table 8 Instrumental variable regression results

Variable	Agtfp
Internet penetration	1.028*** (0.106)
Dat	1.311*** (8.180)
_cons	-6.095*** (0.678)
Weak IV test	436.18 (16.380)
Identifiable test (P-value)	17.420 (0.000)
Control variables	Control
Individual fixed effects	Control
N	300
R^2	0.577

Note: Weak IV tests use the Cragg-Donald Wald F statistic, with values in parentheses reporting Stock-Yogo's critical value at the 10% level. The identifiable test uses the K-Paark LM statistic, and the p-value for the corresponding statistic is reported in parentheses.

4.5. Heterogeneity test

The impact of digital agricultural technologies on green total factor productivity in agriculture may also vary depending on the level of government attention in different regions,

The impact of digital agriculture technology on agricultural green total factor productivity also varies according to the degree of government attention, natural environmental characteristics

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and population density in different regions. In regions with a higher degree of importance, the government will promote the digitalization and intelligent transformation of agriculture through a series of fiscal and tax policies, which will further accelerate the digitization of agriculture in the region, and the impact of digital agriculture technology on the green total factor productivity of agriculture in the region may be more obvious. For regions with different natural environmental characteristics, different land resources, environmental conditions, and agricultural economic structures have their own characteristics, and these widely differing cultivation methods and technologies will affect the level of green agricultural development, and there may be differences in the promotional effects of digital agricultural technology. In addition, diversified consumer demand, industrial structure and infrastructure will also have an impact on the relationship between digital agricultural technology and agricultural green total factor productivity.

Therefore, this study examines the regional heterogeneity of the impact of digital agricultural technology on agricultural green total factor productivity from the perspectives of policy, natural environment and population density[22], and divides China into east-central-west, north-south and south-south sides of the Qinling-Huaihe River, and south-east and north-west sides of the Hu Huanyong Line, based on geographic location, Qinling-Huaihe River Line and Huanyong Line (Table 9). As can be seen from Table 9, the impact of digital agricultural technology on agricultural green total factor productivity is significantly positive in the east and central regions, while the impact on the western region is less obvious. This is because the information infrastructure is better in the eastern and central regions, and the government's financial investment is also relatively large. Therefore, digital agricultural technology has to some extent facilitated the digital-intelligent transformation of the agricultural sector and boosted the growth of green total factor productivity in agriculture. Digital agriculture technology on both sides of the Qinling-Huaihe River line shows a boosting effect on the green total factor productivity of agriculture, which is due to the fact that the areas on both sides of the Qinling-Huaihe River line are located in different climatic zones, and the main crops in the areas on both sides of the line are also different. At the same time, there are big differences in the agricultural production methods and the overall industrial construction planning of agriculture on both sides. Against the background of the gradual rationalization of the factor flow state on both sides of the Qinling-Huaihe River, the promotion effect of digital agricultural technology on green total factor productivity in agriculture is not significantly different between the two sides of the region. The positive effect of digital agricultural technology on agricultural green total factor productivity is significant in the southeast side of the Hu Huanyong line, and the effect is not significant in the northwest side of the Hu Huanyong line. The reason is that the northwest side of the Hu Huanyong Line has less than 5% of the population, and the level of key factors promoting the development of digital agriculture technology, such as labor, market, and industrial scale, is relatively low, and it is difficult to achieve the goal of green agriculture development only by expanding local digital agriculture infrastructure. On the other hand, the southeastern side of the line, which accounts for 95% of the population, has a larger market size, diversified consumer demand, and a better infrastructure environment, all of which synergistically contribute to the growth of total factor productivity in agricultural greening.

Table 9 Estimated results of the impact of digital agricultural technologies on green total factor productivity in agriculture in different regions

Variable	Easten region	Central region	Western region	South of the 'Qinling-Huaihe line'	North of the 'Qinling-Huaihe line'	Southeast of the 'Hu line'	Northwest of the 'Hu line'

Dat	1.324***	1.467***	0.785	1.184***	1.073***	1.205***	0.282
	(0.182)	(0.309)	(0.154)	(0.136)	(0.158)	(0.105)	(0.233)
_cons	-6.728**	2.222	-5.053	-0.038	-8.282***	-5.363***	-4.012
	(2.936)	(4.503)	(3.908)	(2.739)	(2.582)	(1.548)	(4.930)
Control variables	Control	Control	Control	Control	Control	Control	Control
Individual fixed effects	Control	Control	Control	Control	Control	Control	Control
N	120	70	110	150	150	240	60
R^2	0.746	0.707	0.768	0.822	0.592	0.771	0.610

5. Conclusions and recommendations for response

Based on the SBM model and the GML index to measure green total factor productivity in agriculture, this study analyzes the effect of digital agricultural technology on green total factor productivity in agriculture by using the panel data of 30 provinces in China from 2011 to 2020. And the threshold effect model is applied to further test the effect of the role. The empirical evidence shows that: digital agricultural technology has a significant promotion effect on agricultural green total factor productivity; after exceeding the threshold value of 0.074, digital agricultural technology further enhances the promotion effect on agricultural green total factor productivity; the enhancement effect of digital agricultural technology on agricultural green total factor productivity shows significant regional heterogeneity in different regions, and the enhancement effect of digital agricultural technology on agricultural green total factor productivity is significant in the east-central region. The effect of digital agricultural technology on the enhancement of agricultural green total factor productivity is significant in the east-central region, with 1.324 and 1.467, respectively, while it is not significant in the western region, with the significant coefficient of enhancement on both the north and south sides of the “Qinling-Huaihe Line” of 1.184 and 1.073, and the significant coefficient of enhancement on the south-eastern side of the “Huanyong Line” of 1.205, respectively. The southeast side of the Hu Huanyong Line is significant and the enhancement coefficient is 1.205, while the northwest side of the Hu Huanyong Line is not significant. This indicates that the development of digital agricultural technology promotes the improvement of green total factor productivity in agriculture in the east-central region, the north and south sides of the Qinling-Huaihe River, and the southeast side of the Hu Huanyong Line.

Based on the above research, the following four measures are recommended to improve the efficiency of China's agricultural production and promote the development of agricultural modernization. First, considering the promotion effect of digital agricultural technology on the existence of green total factor productivity in agriculture, the development of digital agricultural technology should be further accelerated, information technology should be applied to agricultural production, and new technology should be used to transform traditional agriculture, so as to realize the synergistic development of digital agricultural technology and green agriculture through the concept of green production and green production, and then to improve the green total factor productivity in agriculture. Secondly, China's digital agriculture technology development level of inter-regional differences, but also there is a certain correlation characteristics, there is a large space for development. Therefore, it is recommended that in the development of green agriculture, we should pay attention to the exchange and collaboration of green agriculture experience in different regions, popularize digital agriculture, green agriculture, ecological agriculture and other basic concepts to traditional agricultural producers, and guide agricultural producers to change the traditional mode of thinking to the new mode of thinking in the era of digitization and intelligence. Promote farmers' understanding and recognition of new digital agriculture technology, and promote the application of digital agriculture technology in traditional agriculture. Third, the eastern region of China is a leading region with a developed green agriculture economy, advanced technology and obvious spillover effect of scientific and technological benefits, and while giving full play to the advantages of its green agriculture talents and continuously optimizing the development of high technology, it should increase the output of technology and help the central and western regions to actively attract the flow of relevant high-quality talent areas. Fourth, the development of China's green agriculture is affected by a variety of factors, should be strengthened through the full use of a variety of power factors to enhance the popularization of green agricultural infrastructure conditions, narrowing the regional development differences, and strengthen the central and western regions of the green agricultural digital construction to increase the positive role of agricultural green total factor productivity. China's western region is inconveniently located and sparsely populated, and a reasonable green agriculture plan should be formulated in accordance with regional characteristics to solve the basic network and road transportation problems while promoting the smooth connection between green agricultural production areas and consumer markets. Through policy subsidies and concessions to attract relevant Internet enterprises and agricultural enterprises to station, promote the integration of digital agriculture industry and local characteristics of the agricultural industry, increase the efficient circulation of various market factors across the country, and give full play to the network effect and multiplier effect of digital agriculture on the positive impact of green agriculture.

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