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Digital Economy and Agricultural Green Total Factor Productivity: Influencing Mechanism and Empirical Test

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Abstract: Driven by the rural revitalization strategy, the development of digital economy has brought a new development path for agricultural green total factor productivity. Based on the panel data of 29 provinces and regions in China from 2014 to 2022, this paper systematically discusses the internal mechanism and implementation path of digital economy and green agricultural total factor productivity. The entropy method and super-efficiency SBM model were used to measure China's digital economy level and agricultural green TFP. and a bidirectional fixed effect model was constructed to explore the impact of digital economy on agricultural green TFP. The results show that (1) both China's digital economy and agricultural green TFP present an increasing trend, and the development of digital economy has a significant positive promoting effect on the improvement of agricultural green TFP and this conclusion is consistent in multiple robustness tests. (2) Through the intermediary effect, it is found that digital economy has an effect on agricultural green total factor productivity through labor transfer effect and agricultural industry agglomeration; (3) Heterogeneity analysis shows that digital economy has regional differences in agricultural green total factor productivity, and there is a phenomenon of increasing level from west to central to east; (4) The threshold effect of expansion analysis shows that regional economic development level plays a positive role in improving agricultural green TFP. is a region with higher economic development level, has a correspondingly higher agricultural green TFP. Based on this, it is proposed that a mechanism for agricultural green innovation and promotion should be established, the concept of ecological and green development should be adhered to, and the agriculture should develop in the direction of high digitalization, green ecology and intelligent innovation, so as to promote the high-quality development of China's agriculture.

Keywords: Digital economy, Agricultural green total factor productivity, Labor transfer, Agricultural industry agglomeration.

1. Introduction and Literature Review

The report of the 20th National Congress of the Communist Party of China pointed out the need to promote the modernization of agriculture and rural areas, accelerate the transformation of agriculture towards green direction, and in the new development stage of comprehensively promoting rural revitalization and building a socialist agricultural power, promoting green and low-carbon development is a realistic requirement for high-quality agricultural development. However, in the past decade, with the accelerated development of agricultural technology, the efficiency of agricultural resource allocation and the optimization of agricultural industrial structure have been accompanied by the intensification of agricultural pollution. As the second largest source of carbon emissions after industry, agriculture's annual greenhouse gas emissions account for 30% of the global anthropogenic greenhouse gas emissions (Shen Yang, 2022). Reducing carbon emissions from agriculture and promoting green development is urgently needed. In 2024, the "No.1 Central Document" put forward the road map of rural comprehensive revitalization, anchored "strengthening agricultural science and technology support, optimizing agricultural science and technology innovation, and promoting the transformation of traditional agriculture to digital agriculture", and pointed out the development direction of rural revitalization.

At present, the relationship between the digital economy and green total factor productivity has received widespread attention in the industrial and manufacturing fields. Literature is mostly focused on manufacturing, service industries, and other fields, with little research on traditional agriculture. Traditional productivity measurement emphasizes input-output ratio and neglects the role of resource and environmental factors in it. Therefore, incorporating the environment into the calculation of agricultural productivity to measure the quality of agricultural development has become the current practice of most scholars. However, there are certain differences in accurately measuring agricultural green total factor productivity and grasping the relationship between digitalization and agricultural green total factor productivity. In terms of measuring agricultural green total factor productivity, Lv Na (2019) used the SBM standard model to divide multiple decision-making units and overcome the problem caused by angle selection bias. Yang Zhiqing (2019) used the Tobit model to solve the problem of restricted dependent variables in the process of measuring agricultural total factor productivity. In terms of selecting indicators for agricultural green total factor productivity, Peng Bingzhong (2021) included agricultural research investment and agricultural human capital in the calculation of agricultural total factor productivity indicators, and empirically tested that research investment is conducive to improving agricultural green total factor productivity. Liu Chengkun (2021) adopts the population aging index in rural areasThe Durbin model analyzed the impact of human capital on regional total factor productivity and found a linear relationship between total factor productivity and the degree of population aging. From a research perspective, Fang Fang (2024) empirically tested the positive correlation between rural industry integration and fixed utility model and moment estimation method. From the perspective of environmental factors, Wang Pei (2022) believes that digitalization can improve the efficiency of agricultural resource allocation, thereby enhancing the total factor productivity of agriculture; From an institutional perspective, Wu Lei (2020) believes that the transfer of rural labor has accelerated the deepening of agricultural capital, guided the transfer of urban capital, technology, and talent to rural areas, thereby stimulating the endogenous driving force of rural development and improving total factor productivity; Bai Ziming and Xi Yu (2024) found from a spatial perspective that the promotion of the digital economy leads to the transfer of rural labor, uneven flow of production factors, and negative spillover effects on agricultural green total factor productivity.

At present, the relationship between the digital economy and total factor productivity has become a hot topic. However, many scholars have focused on theoretical research on industrial factor productivity, manufacturing factor productivity, and other fields. There is relatively little research on agriculture, and some studies ignore the unexpected output brought by agricultural production activities, exaggerate the green total factor productivity of agriculture, and cannot reflect the true performance of agricultural production. Exploring the impact of the digital economy on total factor productivity in agriculture is of great practical significance during the critical period of transition from traditional agriculture to green agriculture. Based on this, this study adopts a bidirectional fixed utility model, aiming to reveal the inherent mechanism and implementation path between the digital economy and agricultural green total factor productivity. Specifically, this article evaluates the mechanism of the digital economy in enhancing agricultural green total factor productivity from two dimensions: labor transfer and agricultural industry agglomeration, and expands the boundaries of related research. Meanwhile, based on heterogeneity research, it has been found that the impact of the digital economy on agricultural green total factor productivity shows an increasing trend from the west to the central and then to the east. Finally, incorporating the level of economic development into the analysis framework and conducting threshold effect analysis aims to explore the impact mechanism of economic development level on agricultural green total factor productivity in different time and space, and provide a practical and feasible path for rural revitalization.

2. Theoretical Analysis and Research Hypotheses

2.1. Digital Economy and Agricultural Green Total Factor Productivity

The widespread application of digital technology in the field of agriculture has profoundly reshaped the traditional production and lifestyle in rural areas (Chen Xiaodong, 2021). The large-scale use of agricultural tools based on digitalization, such as unmanned aerial vehicles for fertilization and spraying, and the application of automated sowing and harvesting technologies, has improved agricultural production efficiency, liberated surplus rural labor, helped to cross urban-rural boundaries, promoted the smooth flow of production factors such as capital, technology, and talent between urban and rural areas, and achieved a gradual balance of factor returns. In addition, the advantage of digital information matching can correct the mismatch of factors and improve the efficiency of production factors. The improvement of production and transaction efficiency can deepen industrial specialization, shorten the time from agricultural product production to sales, promote coordinated urban-rural division of labor, enable the rational allocation of various factors in rural areas, and increase the income of rural residents. Through digital technology, digital production, and digital management, we can promote the efficient allocation of production factors, break the factor monopoly of cities, promote the mobility of factors, and promote the circulation of production factors across regions. At the same time, digitalization can improve labor information, master market demand, and use digital Internet technology to collect and analyze agricultural market information, so as to provide scientific decisions for agricultural production, operation, and management. With the support of big data, we can achieve departmental connectivity and information sharing, accurately identify poor people, and effectively allocate medical, health, education and other public service resources, making government allocation of resources more refined and public services more inclusive. Digitization has significantly promoted the optimization and upgrading of rural industrial structure, especially the rise of the tertiary industry, injecting new vitality into the rural economy. This transformation not only creates abundant employment opportunities, effectively absorbs surplus rural labor, accelerates the flow of agricultural population to non-agricultural fields, greatly alleviates the contradiction between rural people and land, and paves the way for the intensive and large-scale operation of agriculture. The development of digitalization has provided strong impetus for the agglomeration of agricultural industries. With the increasing improvement and implementation of digital infrastructure, the modernization of agriculture has received solid technical and financial support. The agglomeration of agricultural industries thus demonstrates multiple advantages such as economies of scale, knowledge spillovers, and competitive effects (Du Chuanzhong, 2023). The economies of scale effect, through efficient integration and sharing of resources, reduces production and transaction costs, strengthens specialized division of labor and collaborative operations, thereby achieving a dual improvement in cost savings and resource utilization, and plays a key role in the growth of agricultural green total factor productivity. The knowledge spillover effect is reflected in the agricultural industry agglomeration promoting the rapid dissemination of knowledge and technology. The business entity has accelerated the promotion of advanced agricultural management experience and the integration of technological innovation through online learning, injecting fresh blood into the green development of agriculture. The emergence of competitive effects forces various agricultural entities to constantly innovate themselves, forming a two-way virtuous cycle between production methods and product quality, ultimately promoting the comprehensive improvement of agricultural green total factor productivity. Based on this, this article proposes the following hypothesis:

Assumption 1: The digital economy has a positive impact on agricultural green total factor productivity.

Assumption 2: The digital economy affects agricultural green total factor productivity by promoting the transfer of rural labor.

Assumption 3: The digital economy affects agricultural green total factor productivity by promoting agricultural industry agglomeration.

2.2. Economic Development, Digital Economy, and Agricultural Green Total Factor Productivity

The depth of the impact of digitization on agricultural green total factor productivity is to some extent constrained by the level of economic development in the region (Chen Huiqing, 2021). Specifically, the improvement of economic development level promotes the rapid flow of production factors, providing necessary financial support for the construction of digital infrastructure, and the improvement of digital infrastructure further promotes the improvement of agricultural production efficiency. On the other hand, economic development has also driven regional technological innovation, providing solid technical support for the digital construction process. This not only promotes the technology absorption and urbanization process of surrounding cities, but also guides the transformation of urbanization towards high-quality and sustainable models. At the same time, applying high-level technology to the entire process of agricultural production and operation can enhance the mechanization level of agriculture, reduce agricultural resource consumption, promote the improvement of pure technical efficiency in agriculture, and further improve the green total factor productivity of agriculture. Based on the above analysis, this article proposes the following hypothesis

Assumption 4: Economic development helps enhance the impact of digitalization on agricultural green total factor productivity

3. Research Design

3.1. Model Construction

Two-way fixed effect model: In order to test the impact of the development level of digital economy on agricultural green total factor productivity, the following benchmark regression model is constructed:

$$\mathrm{GTFP}_{i,t} = q_0 + q_1 \mathrm{Digital}_{i,t} + y\mathrm{ZJ}_{i,t} + p\mathrm{Controls}_{i,t} + v_t + e_t + \varepsilon_{i,t} \quad (1)$$

Where, $\mathrm{Digital}_{i,t}$ is the digital economy level of province i in year t, $\mathrm{GTFP}_{i,t}$ is the agricultural green total factor productivity, $\mathrm{Controls}_{i,t}$ is the control variable, and $\varepsilon_{i,t}$ is the random disturbance term.

Panel threshold model: Establish a single threshold model with agricultural green TFP as the explained variable, digital economy as the explanatory variable, and economic development as the threshold variable to explore the difference in the impact of digital economy development level on agricultural green TFP at a specific threshold value. The model is specified as follows:

$$y = \alpha H_{it} + \beta_1 x_{it} * I(edl_{it} \le \gamma_1) + \beta_2 x_{it} * I(edl_{it} \ge \gamma_2) + \varepsilon_{it} + \mu_i \quad (2)$$

Where, y represents agricultural total factor productivity, x represents the development level of digital economy, and the threshold variable represents economic development and a set of control variables.

3.2. Variable Selection

3.2.1. Explained variable: Agricultural green total factor productivity (GTEP)

Referring to the practice of Fan Dongshou (2023) and Min Jisheng (2024), the total amount of agricultural carbon emission (10,000 tons) is used as the non-expected output, and the input amount of each production factor in the agricultural production process and its carbon emission coefficient are used to calculate. The calculation formula is as follows: Carbon emission coefficient of each carbon source is determined as follows: Fertilizer (0.8956kg/kg), diesel (0.5927kg/kg), pesticide (4.9341kg/kg), irrigation (20.476kg/hm2), agricultural film (5.18kg/kg), actual sown area of crops (312.620.476kg/km2); At the same time, the specific input-output indicators are shown in Table 1 for reference to Du Jianjun et al.

Table 1. Selection of agricultural total

Indicator	Name	Meaning	Unit
Input index	Number of agricultural labor force	nvested in the primary industry	10,000
	Input indicators	primary industry	1000 hectares
	agricultural machinery	agricultural water input per	10000 tons
	The total power of agricultural machinery invested	converted to pure	megawatt
	Agricultural plastic film input,	lm usage of Pesticide input	10000 tons
	Agricultural fertilizer	factor indicators	10000 tons
	agricultural output	Effective irrigation area o	Thousandhectares
Output indicator	Expected output indicators:	expected to reach emissions of	100 million yuan
	Unexpectedly generated total	agricultural carbon	10000 tons

3.2.2. Core explanatory variable: Level of digital economy development (DIGITALL)

The digital economy emphasizes green and coordinated development. Following the principles of scientificity, comparability, and operability, this study draws on the research methods of Zhao Tao (2020) and others to establish a digital economy indicator system from three dimensions: digital infrastructure, industrial digitization, and digital services. The specific indicators are shown in Table 2.

Table 2. Selection of Digital Economy Indicators

Definition	level	indicator names
Digital infrastructure Internet accessibility	Internet accessibility	Rural per capita Internet access
	l device accessibility	Fixed digital device accessibility
	Mobile digital devices	administrative villages households
	Fixed digital device accessibility	rural computer ownership per 100 households
Digital infrastructure Internet	Agricultural Production	the Quantity of Machinery Used in Digital Agricultural Production
	Digitalization of Industry	computer ownership
	Digital Financial Services Digital Financial Coverage Breadth Index	Digital Finance Digitalization Index for the Financial Industry
Digital service, e-commerce service,	Digital service	Sales of digital Taobao villages as a percentage of administrative villages
	rural delivery frequency per week	Mobile Payment Level Mobile Payment Index

3.2.3. Control variable: Agricultural Industry Structure (AML)

Following the approach of Cao Fei (2021), the proportion of grain sowing area to total crop sowing area is used to measure. Environmental Protection Intensity (EPE). Following the approach of Chen Jiantao (2021), the proportion of environmental protection expenditure to total local fiscal expenditure is used as a measure. Environmental protection efforts can enhance the quality of environmental and economic development through measures such as strengthening investment in green elements, greening production processes, and technological innovation. Financial Support for Agriculture (FSA) level. Using the method of Lu Cheng (2019) to measure the proportion of agricultural fiscal expenditure to total fiscal expenditure. Rural Human Capital Level (RHCL). The average years of education in rural areas are used to measure the level of rural human capital. Referring to Han Haibin's (2015) research, the proportion of educated population in different regions is multiplied by the years of education to obtain the level of rural human capital.

Due to the lack of data in Hong Kong, Macao and Taiwan, Xizang and Xinjiang, 29 provinces and cities in China from 2014 to 2022 were selected for the study. The data mainly comes from the "China Statistical Yearbook" and statistical yearbooks of various provinces. The descriptive statistics of each variable are shown in Table 3.

Table 3. Descriptive Statistics of Digital Economy Variables in 29 Provinces of China

Variables	Mean	Standard	Minimum	Maximum
GTEP	0.297	0.285	0.0462	1.021
DIGITAL	0.368	0.103	0.154	0.692
AML	0.657	0.140	0.396	0.971
EPE	0.030	0.009	0.013	0.068
FSA	0.606	0.117	0.365	0.942
RHCL	11.910	0.151	11.530	12.230
ECL	27535	12533	10954	78027

4. Empirical Analysis

4.1. Benchmark Regression

To explore the impact of digital economy development level on agricultural green total factor productivity, provincial panel data from 2014 to 2022 were used, and a double fixed effects model was adopted for the study. The specific regression results are shown in Table 4, where model (1) is the regression result without control variables, and model (2) is the regression result with control variables such as agricultural industrial structure and fiscal support for agriculture. According to the regression results in Table 4, it can be seen that the regression results of Model (1) are significant at the 5% level, indicating that the level of digital economy development has a positive impact on agricultural green total factor productivity. On the basis of model (1), a series of control variables such as agricultural industrial structure and environmental protection intensity were added to obtain model (2). The regression results were still significant, and the estimated coefficient increased compared to the results without control variables. This indicates that the optimization and upgrading of agricultural industrial structure and the improvement of urbanization level play an important role in promoting agricultural transformation and improving agricultural green total factor productivity.

Table 4. Benchmark Regression Results

variables	(1)	(2)
DIGITAL	0.358**	0.924**
	(2.47)	(2.11)
AML		0.696***
		(2.89)
EPE		-0.237
		(-0.24)
FSA		0.864***
		(2.99)
RHCL		0.089
		(0.60)
Constant	0.195***	-3.873**
	(4.64)	(-2.20)
R^2	0.278	0.448

4.2. Robustness Test

In order to ensure the reliability of the above research conclusions, this study used exclusion method, replacement of explanatory variables, and tail reduction method for robustness testing: (1) excluded data from four municipalities directly under the central government, and the empirical regression results are shown in column (1) of Table 5; (2) Replace explanatory variables and use EBM method to re measure agricultural green total factor productivity. Substitute it into the regression model, and the empirical regression results are shown in column (2) of Table 5; (3) Consider the impact of extreme values on regression results. The first 2.5% and 97.5% values of each major variable were truncated, and the empirical regression results are shown in column (3) of Table 5. The regression results of each group in Table 5 indicate that, under the three adjustment methods of removing municipalities directly under the central government, replacing the dependent variable, and trimming, the estimated coefficient of the level of digital economic development on agricultural green total factor productivity is still significantly positive, consistent with the benchmark regression results mentioned earlier, and the conclusion is robust.

Table 5. Robustness Test

Variables	(1)	(2)	(3)
DIGITAL	0.248**	0.155***	0.352**
	(2.23)	(3.93)	(2.17)
AML	0.138**	-0.035	0.044
	(2.17)	(-0.17)	(0.51)
EPE	0.148	0.038	-0.074
	(0.50)	(0.40)	(-0.19)
FSA	0.234**	1.638***	-0.059
	(2.45)	(3.24)	(-0.55)
RHCL	-0.077**	-0.201	-0.091*
	(-2.16)	(-1.34)	(-1.68)
Constant	0.852**	0.820	1.293**
	(1.98)	(0.52)	(2.00)
R^2	0.396	0.5088	0.285

4.3. Heterogeneity Analysis

From the above analysis, it can be seen that the digital economy has a positive effect on agricultural green total factor productivity. However, considering factors such as economic structure and resource endowment, there may be differences between different regions, so the country is divided into three major regions: East, Central, and West. The regression results are shown in Table 6. According to the regression results, the coefficient in the eastern region is higher than that in the central and western regions. The reason for this may be that compared with the central and western regions, the eastern region has a higher level of high-quality economic development, more complete rural infrastructure construction, smaller urban-rural gap, more high-level universities, stronger digital technology research and development level, and faster improvement in rural human capital level, These advantages are all conducive to reducing the cost of agricultural production and management processes, thereby leveraging the benefits of information technology for agriculture and improving the level of green total factor productivity in agriculture.

Table 6. Heterogeneity test

Variables	(1)	(2)	(3)
	Eastern region	Central region	Western region
DIGITAL	2.012***	0.290***	1.092**
	(2.77)	(2.82)	(1.07)
AML	0.768**	-0.015	0.201
	(2.41)	(-0.23)	(0.23)
EPE	-0.498	0.470**	0.279
	(-0.34)	(2.13)	(0.11)
FSA	1.154***	-0.053	1.035
	(2.77)	(-0.69)	(0.87)
RHCL	0.235	0.019	-0.168
	(0.91)	(0.69)	(-0.38)
Constant	-6.097**	0.012	-0.254
	(-2.00)	(0.04)	(-0.05)
R^2	0.466	0.740	0.523

5. Mechanism Analysis

Based on the empirical analysis in the previous section, this section will use a mediation model to examine the possible mechanism by which the level of digital economy development affects agricultural green total factor productivity. This article draws on the approach of Wen Zhonglin et al. (2014), and the model is set as follows:

$$\mathrm{GTEP}_{it} = \alpha_0 + \beta_1 \mathrm{Digital}_{it} + \sum \varphi_{it} x_{it} + \mu + \varepsilon_{it} \quad (3)$$

$$\mathrm{mv}_{it} = \alpha_0 + a_1 \mathrm{Digital}_{it} + \sum \varphi_{it} x_{it} + \mu + \varepsilon_{it} \quad (4)$$

$$\mathrm{GTEP}_{it} = \alpha_0 + z_1 \mathrm{Digital}_{it} + z_2 \mathrm{mv}_{it} + \sum \varphi_{it} x_{it} + \mu + \varepsilon_{it} \quad (5)$$

5.1. Transfer of Rural Labor Force

Reasonable allocation of agricultural resources has a crucial impact on green total factor productivity in agriculture. Among them, human resources, as the core element of agricultural production and operation activities, are particularly important for their effective allocation. The transfer of surplus rural labor has effectively alleviated the contradiction of having more people and less land in rural areas, enabling more rational use of land resources and more efficient agricultural production. Thus enhance the green total factor productivity of agriculture. Therefore, this article selects rural labor force transfer as the mediating variable to test this mechanism. The transfer of rural labor force (LB) is measured by the difference between the rural economically active population and the primary industry employees. The inspection results are shown in Table 7. Using the transfer of rural labor as an intermediary variable and adding a benchmark regression equation, the estimated coefficient of the level of digital economic development on agricultural green total factor productivity decreases, confirming the role of the digital economy in improving agricultural green total factor productivity through the transfer of rural labor.

Table 7. Analysis of the Intermediary Effect of Rural Labor Transfer

Varibles	GTEP	LB	GTEP	GTEP
	(1)	(2)	(3)	(4)
DIGITAL	0.358** (2.47)	0.021*** (3.08)		0.135*** (3.34)
LB			0.233*** (5.83)	0.232*** (5.80)
R^2	0.278	0.419	0.474	0.474

5.2. Agricultural Industry Agglomeration

Based on the previous analysis and reference to literature such as Yin Xiyang, the Agricultural Industry Agglomeration (LQ) is expressed as the quotient obtained by dividing the ratio of a region's agricultural output value to the national agricultural output value by the ratio of the province's gross domestic product to the national gross domestic product. The regression results are shown in Table 8. The significance of the coefficients in columns (1) and (2) confirms that the development of the digital economy promotes industrial agglomeration, thereby enhancing agricultural green total factor productivity. By using agricultural industry agglomeration as a mediator variable and adding a benchmark regression equation, the estimated coefficient of the level of digital economic development on agricultural green total factor productivity decreases, further confirming the existence of this mechanism.

Table 8. Analysis of the Intermediary Effect of Agricultural Industry Agglomeration

Varibles	GTEP	LQ	GTEP	GETP
	(1)	(2)	(3)	(4)
DIGITAL	0.358**	0.025*		0.201***
	(2.47)	(1.70)		(3.39)
LQ			0.114**	0.0014**
			(2.24)	(2.22)
R^2	0.278	0.460	0.374	0.474

6. Conclusion and Suggestions

Improving the green total factor productivity of agriculture is a practical requirement for building a socialist agricultural power. This article is based on provincial panel data from 2014 to 2022, using a two-way fixed effects model to explore the impact of the digital economy on agricultural green total factor productivity, and using a panel threshold model to explore the threshold effect of regional economic development level. Through empirical analysis, the following conclusions can be drawn: firstly, from 2014 to 2022, China's digital economy and agricultural green total factor productivity showed a growth trend; Secondly, the digital economy has a significant positive promoting effect on agricultural green total factors, and the promoting effect shows regional heterogeneity, with a decreasing effect from the east to the west. Thirdly, the promotion effect of the digital economy on agricultural green total factor productivity is limited by the single threshold effect of regional economic development level, and its promotion effect gradually strengthens with the improvement of economic development level. Based on this, the following policy recommendations are proposed:

First, strengthen the construction of digital infrastructure, continue to increase investment in rural digital infrastructure, improve the penetration rate and quality of Internet, mobile communication and other services, and provide a solid foundation for the development of digital agriculture. Especially in the central and western regions, we will strengthen policy and funding support, improve digital infrastructure, and narrow the digital divide between regions. Promote the digital transformation of agriculture, encourage and support agricultural production and operation entities to adopt digital technology, and improve agricultural production efficiency and resource utilization efficiency.

Secondly, promote the agglomeration of agricultural industries, rely on the advantages of the digital economy, guide the development of agricultural industry agglomeration, and through measures such as building modern agricultural industrial parks, promote the coordinated development of the upstream and downstream of the agricultural industry chain, and enhance the overall competitiveness of agriculture. Strengthen the cultivation and introduction of agricultural talents, and improve the digital literacy and skill level of agricultural practitioners. By organizing training courses, remote education, and other methods, we aim to popularize knowledge of digital agriculture and cultivate a group of versatile talents who understand both agriculture and digital technology.

Thirdly, pay attention to regional coordinated development and implement differentiated development strategies. The eastern region should continue to play a leading role in promoting the deep integration of digital economy and agriculture; The central and western regions should increase policy support, accelerate infrastructure construction, and enhance the level of agricultural digitization. Through regional cooperation and resource sharing, achieve comprehensive improvement of agricultural green total factor productivity. Improve the policy support system, formulate and refine policy measures to support the development of the digital economy, including fiscal subsidies, tax incentives, financial support, etc. At the same time, establish and improve the legal regulations and standard system for green development in agriculture, and guide agricultural production and operation entities to follow the path of green, low-carbon, and circular development.

References

[1] Shen Yang, Zhou Pengfei. Measurement and Convergence Analysis of Agricultural Green Total Factor Productivity: Based on the Dual Perspectives of Carbon Sequestration and Carbon Emissions [J]. Research World, 2022, (04): 58-68.

[2] Lv Na, Zhu Lizhi. Research on the Efficiency of Agricultural Environmental Technology and the Growth of Green Total Factor Productivity in China [J]. Agricultural Technology and Economics, 2019, (04): 95-103.

[3] Yang Zhiqing. How Education Affects Agricultural Green Productivity: An Empirical Analysis Based on Different Forms of Education in Rural China [J]. China Soft Science, 2019, (08): 52-65.

[4] Peng Bingzhong, Yi Junyu. Research on the Impact of Digital Economy on the Upgrading of Industrial Structure in the Yangtze River Economic Belt [J]. Hunan Social Sciences, 2021, (06): 51-57.

[5] Liu Chengkun. Regional Heterogeneity of Rural Population Aging and Agricultural Total Factor Productivity [J]. Journal of South China Agricultural University (Social Sciences Edition), 2021, 20 (06): 46-55.

[6] Fang Fang, Zhang Lijie, Zhao Jun. Multi path analysis of improving agricultural green total factor productivity from the perspective of institutional configuration: panel data analysis based on dynamic QCA [J]. China Rural Economy, 2024, (02): 44-66.

[7] Wang Pei, Huang Shan, Yang Zhijie, et al. Study on the Impact of Environmental Protection Tax on Enterprise Green Total Factor Productivity [J]. Taxation Research, 2022, (11): 66-73.

[8] Wu Lei, Jia Xiaoyan, Wu Chao, et al. The impact of heterogeneous environmental regulation on China's green total factor productivity [J]. China's Population, Resources and Environment, 2020,30 (10): 82-92.

[9] Bai Ziming, Zhang Xiaochen, Li Cuixia. The impact of cross regional operation of agricultural machinery on green total factor productivity in agriculture: based on the perspective of spatial spillover effects. Agricultural Modernization Research, 2024, 45 (03): 443-454.

[10] Xi Yu, Sun Yudong. Economic Development, Vertical Fiscal Imbalance, and Deviation from Budget and Final Account Revenue: Empirical Analysis Based on Threshold Regression of China's Provincial Panel Data from 2007 to 2017. Finance and Trade Research, 2021, 32 (06): 1-11.

[11] Chen Xiaodong, Yang Xiaoxia. The Impact of Digital Economy Development on Industrial Structure Upgrading: A Study Based on Grey Relational Entropy and Dissipative Structure Theory [J]. Reform, 2021, (03): 26-39.

[12] Du Chuanzhong, Liu Shutong. Measurement and Path Analysis of the Effect of Digital Economy Empowering Total Factor Productivity of China's Manufacturing Industry [J]. Economic and Management Research, 2023, 44 (09): 43-65.

[13] Chen Huiqing, Chen Guosheng, Wei Xiaobo, et al. The income increasing and poverty reducing effects of digital inclusive finance: an empirical analysis based on inter provincial panel data [J]. Economic Geography, 2021, 41 (03): 184-191.

[14] Fan Dongshou, Yang Fuxia, Zheng Xin, et al. The fertilizer reduction effect and impact mechanism of green agriculture subsidies: evidence from the pilot policy of organic fertilizer subsidies [J]. Resource Science, 2023, 45 (08): 1515-1530.

[15] Min Jisheng, Chen Jingwen. Has the promotion and application of modern agricultural technology increased farmers' income--Quasi natural experiments based on the pilot of national modern agriculture demonstration zones [J]. Financial Research, 2024, 50 (04): 94-108.

[16] Zhao Tao, Zhang Zhi, Liang Shangkun. Digital Economy, Entrepreneurial Activity, and High Quality Development: Empirical Evidence from Chinese Cities [J]. Management World, 2020, 36 (10): 65-76.

[17] Cao Fei, Nie Ying. Industrial integration, upgrading of agricultural industrial structure, and growth of farmers' income: an empirical analysis based on panel data of counties in Hainan Province [J]. Agricultural Economic Issues, 2021, (08): 28-41.

[18] Chen Jiantao, Wu Yinyin, Chen Jiandong. Impact of Environmental Protection Tax on Environmental Investment in Heavy Pollution Industries [J]. Tax Research, 2021, (11): 44-49.

[19] Lu Cheng. A Further Study on the Impact of Fiscal Support for Agriculture Policies on Agricultural Production: Based on Fixed Observation Point Data of Rural Areas in China from 2009 to 2015 [J]. Rural Economy, 2019, (02): 88-94.

[20] Han Haibin, Zhang Li. Threshold Effect Analysis of Agricultural Informatization on Total Factor Productivity Growth in Agriculture [J]. China Rural Economy, 2015, (08): 11-21.

[21] Wen Zhonglin, Ye Baojuan. Mediating Effect Analysis: Method and Model Development [J]. Advances in Psychological Science, 2014, 22 (05): 731-745.