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How does digital technology innovation drive agricultural sustainability? A mechanism study based on green total factor productivity

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Facing environmental pollution challenges in agricultural production, digital technology innovation—serving as the core driver of China’s “Digital China” strategy—emerges as a promising new force for promoting agricultural green development. This study utilises panel data from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) covering 2009–2022, employing the SBM-BML model to measure agricultural green total factor productivity (AGTFP) and applying a two-way fixed effects model to examine the impact of digital technology innovation on AGTFP and its underlying mechanisms. The findings demonstrate a significant positive relationship between digital technology innovation and AGTFP. Digital technology innovation enhances AGTFP primarily through optimising resource allocation. Moderating effect analysis reveals that appropriate environmental regulations can strengthen this positive impact. Heterogeneity analysis further indicates that the enhancing effect of digital technology innovation is more substantial in coastal regions and areas with higher financial development levels. Additionally, the study finds that digital technology innovation can promote local high-quality economic development and help address wastewater discharge issues by improving AGTFP. These research findings provide both theoretical foundations and practical guidance for China to better advance agricultural green development in the era of digital intelligence.

KEYWORDS

digital technology innovation, agricultural sustainability, agricultural green total factor productivity, resource allocation, environmental regulation

1 Introduction

Since the reform and opening-up, China’s agricultural economy has experienced rapid development, but this growth has been accompanied by significant energy consumption and environmental pollution challenges. Confronted with increasingly severe resource and environmental issues, the report of the 20th National Congress of the Communist Party of China emphasised the principle that “lucid waters and lush mountains are invaluable assets.” Furthermore, the Guiding Opinions on Accelerating the Comprehensive Green Transformation of Agricultural Development and Promoting Ecological Revitalization of Rural Villages, issued by the Ministry of Agriculture and Rural Affairs in 2024, explicitly called for continued efforts to advance agricultural green development and facilitate the transition of industrial models towards low-carbon and circular patterns. Agricultural Green Total Factor Productivity (AGTFP) serves as a crucial indicator for assessing the level of agricultural green development. Unlike conventional measures, AGTFP comprehensively accounts for energy consumption,

pollution emissions, and other environmental factors, while integrating both input–output efficiency and ecological considerations.

The digital economy is gradually becoming the core force driving economic development. China has established the world's largest 5G network system, which provides solid support for the development of the digital economy, while in the field of smart agriculture, advanced technologies such as big data and the Internet of Things (IoT) have greatly improved the efficiency of agricultural production. The “Overall Layout Plan for the Construction of a Digital China” has also provided strong policy guidance and support for the development of the digital economy. Currently, digital technological innovation is spreading at an unprecedented rate across all sectors, becoming a key driver for high-quality development, as well as a new tool for building an ecological civilisation and promoting green economic development. However, the environmental challenges triggered by digital technological innovation should not be ignored, and the problem of e-waste pollution will also pose a greater threat to the ecological environment. Then, what is the mechanism of the impact of digital technological innovation on AGTFP in the context of the current rapid development of digital economy?

In view of this, the article measures AGTFP based on the SBM-BML method, and examines the impact of digital technological innovation on provincial AGTFP and the intrinsic mechanism of resource allocation efficiency; at the same time, it examines the moderating effect of environmental regulation on the enhancing role of digital technological innovation based on the theory of the Porter's hypothesis. In addition, the sample is divided into two groups of coastal and inland areas, as well as two groups of high and low financial development levels, to analyse the geographical heterogeneity of the promotion of digital technological innovation. Finally, the economic consequences of digital technology innovation to enhance AGTFP are explored.

The exploration of this issue can provide scientific support for the purpose of synergistic increase of agricultural economic and ecological benefits, and at the same time echo the strategic needs of high-quality development in the new era.

2 Literature review

The term “digital technology” was first coined by Tapscott (1996) with characteristics such as self-growth and convergence (Yoo et al., 2012). Since technological innovation is regarded as a key factor in driving economic growth, academics are increasingly focusing on digital technological innovation. Yoo et al. define digital technological innovation as an innovative behaviour in developing new products, services and business models (Yoo et al., 2010). Current research mainly focuses on the study of the economic consequences of digital technological innovation, at the enterprise level, it is considered to have a positive effect on the efficiency of resource use (Acemoglu and Restrepo, 2018) and the energy structure (Liao et al., 2024), etc.; at the industrial level, it is pointed out that it is able to promote the integration of industries (Yoo et al., 2012), and to promote industrial upgrading (Oskam, 1991).

Current research on green total factor productivity (GTFP) focuses on measurement and influencing factors. GTFP is mainly measured by Solow's residual method (Oskam, 1991), beyond logarithmic method (Rezek and Richard, 2004; Wang et al., 2023), and

stochastic frontier distance function method (Wang et al., 2012). In the improvement of productivity dynamics assessment, the combination of SBM model (Tone, 2001) and Malmquist-Luenberger (ML) index (Chung et al., 1997) based on DEA framework (SBM-ML) is an important breakthrough. However, the traditional ML index suffers from the problem of estimating volatility. For this reason, Simar and Wilson used the Bootstrap resampling technique to construct a statistical framework to form SBM-BML (Simar and Wilson, 1999), the method effectively improves the robustness of the assessment, and can more accurately assess the dynamic efficiency of the output containing non-expected outputs. In terms of influencing factors, the early period revolves around the progress of green technology in agriculture (Meng et al., 2019) and agricultural mechanisation (Wang et al., 2023), etc. More recently, scholars have focused on the facilitating role of STI (Ge et al., 2017) and agricultural digitisation, but some scholars have pointed out the existence of the ‘STI dilemma’ (Usman et al., 2021; Zhao et al., 2023) or a non-linear relationship (Chen et al., 2025). It is worth noting that cutting-edge international agricultural research is providing key evidence and new research directions on these topics: in terms of digitalisation practices, Kovács et al. rely on Eurostat data to reveal the transformation path of the agri-food industry (Kovács et al., 2024), and Beach et al. use meta-analyses to confirm the potential of digital tools to increase yields for smallholders, but their conclusions are limited by the bias in the geographical coverage of the sample (mainly in Asia and Africa) and the timeliness of the data, predominantly and data timeliness gaps (not including post-2021 data), and their generalisability to Southern countries such as Latin America and the Caribbean is doubtful (Beach et al., 2025); in terms of productivity-driving mechanisms, cross-country comparisons by Fuglie and Rada show that developed countries rely on TFP to boost agricultural output, whereas developing countries have become the mainstay of global TFP growth since 1990, but sub-Saharan Africa, for example, remains mired in low growth (Fuglie and Rada, 2013).

Although the impact of digital technology innovation on green total factor productivity (GTFP) has been widely explored, there are three limitations in the existing research: first, most of the literature focuses on the industrial or service sectors, and pays little attention to the digital driving mechanism of agricultural GTFP; second, it ignores the central intermediary role of resource allocation efficiency in the pathway of digital technology innovation to agricultural GTFP, and it seldom examines the dynamic moderating effect of environmental regulations; third, it lacks an integrated analytical framework that integrates the economics of innovation and environmental sustainability. Second, the central mediating role of resource allocation efficiency in the pathway of ‘digital technological innovation to agricultural GTFP’ is neglected, and the dynamic adjustment effect of environmental regulations is less examined; third, there is a lack of an integrated analytical framework that integrates innovation economics and environmental sustainability. Compared with the existing literature, the marginal contributions may lie in the following: first, breaking through the limitations of the existing literature focusing on industrial or service sector GTFP, and incorporating digital technological innovation, resource allocation efficiency, and agricultural green total factor productivity into a unified analytical framework, which deepens the theoretical understanding of the role of digital technological innovation in the green development of agriculture, and provides an important policy basis for promoting the

practice of green transformation of China's agriculture. Secondly, we integrate Schumpeter's innovation theory, endogenous growth model and other theories to explain the internal logic of digital technology driving agricultural GTFP through the paths of "creative destruction" and "knowledge spillover effect," and introduce the dynamic regulatory role of environmental regulation to construct a systematic theoretical model of "technology-institution-green efficiency." Third, the breakthrough of causal identification. The DID model captures the exogenous shocks of the digital pilot policy, reveals the intermediary contribution of resource allocation efficiency through the causal intermediary effect test, and overcomes the endogeneity by adopting the instrumental variable method; at the same time, we design an asymmetric environmental regulation intensity index to analyse its moderating effect on the adoption of green technology by enterprises.

3 Theoretical analysis and research hypothesis

3.1 Analysis of the impact of digital technological innovation on agricultural green total factor productivity

Schumpeterian innovation theory clearly points out that innovation or technological progress is the core force of economic growth. It emphasises that entrepreneurs, by breaking the established economic equilibrium, introduce a new production function and realise the recombination of production factors, thus opening up a new round of economic growth cycle and injecting a steady stream of power for economic development. Porter's theory, on the other hand, further elaborates from the micro level of industrial competition, arguing that technological innovation can help enterprises to build unique competitive advantages, and make them stand out in the fierce market competition by improving production efficiency, reducing costs, and enhancing product differentiation, which in turn promotes the upgrading and development of the whole industry. Fichman et al. regard digital technological innovation as the core driver of new business models, products and processes (Fichman et al., 2014). Digital technology innovation is also seen as a technological innovation process that aims to improve the digitalisation and intelligence level of industries, and uses new generation of information technology such as big data as a tool to change the technological system and carry out integration and application (Meng et al., 2021). Under the wave of the digital information era, the role of digital technological innovation for AGTFP is mainly reflected in the following aspects:

The extensive use of digital technological innovation in rural areas greatly improves the management efficiency of enterprises, promotes the popularity of intelligent office and management systems, and accelerates the process of information sharing. In recent years, China's innovative application of digital technology has shown obvious results in areas such as meteorological information monitoring and crop rotation and fallow management. The construction of agricultural big data systems based on big data and the Internet of Things (IoT) has accelerated the process of informatisation and transformation of the agricultural industry chain, injecting digital vitality into traditional agriculture. This not only promotes the efficient allocation and

utilisation of resources, but also effectively reduces ineffective inputs and alleviates environmental burdens, thus enhancing the green total factor productivity of agriculture.

Digital technology innovation to promote the transformation of traditional industries, help agriculture towards green and sustainable development. With the emergence of modern digital agricultural models such as "smart agriculture" and "Internet + agriculture," traditional agriculture is being promoted to the transformation of the green development path. Through the analysis of big data on e-commerce platforms, farmers can be helped to accurately match market demand, thus achieving the optimal allocation of resources and optimal management of the supply chain (Frank et al., 2019). These innovations not only strengthen the efficiency of agricultural operations and production, but also inject vigour into promoting the growth of green total factor productivity in agriculture.

The application of digital technology innovations has improved the digital skills of farmers and effectively narrowed the digital gap between urban and rural areas. By adopting new technologies, farmers have enhanced their productivity while improving the efficiency of agricultural output. In addition, the use of digital technologies promotes the efficient reuse of straw and livestock waste, thereby effectively mitigating environmental pollution problems. With the help of an integrated intelligent monitoring system, farmers are able to keep track of the total output of livestock and poultry waste in real time and formulate optimal treatment plans based on the data collected, including converting it into biogas for power generation or making it into organic fertiliser, etc., so as to achieve efficient recycling and reuse of resources, which will help to reduce the burden on the environment, thereby promotes green total factor productivity in agriculture.

H1: There is a significant positive association between digital technology innovation and green total factor productivity in agriculture.

3.2 Analysis of the mechanism of digital technology innovation on agricultural green total factor productivity

The improvement of resource allocation efficiency depends not only on the optimal allocation of physical capital and labour, but also on the rational allocation of research and development factors. According to endogenous growth theory, the core driving force of long-term economic growth lies in the accumulation of knowledge and the spillover effects it generates, which fundamentally determines the efficiency of resource allocation and the quality of economic development. The innovation and application of digital technologies such as the Internet and cloud computing have significantly optimised resource allocation by strengthening this endogenous mechanism (Tian and Li, 2022). On the one hand, the core of knowledge accumulation and its spillover effect lies in efficient human capital allocation, while digital technologies (such as big data and cloud computing) significantly reduce the mismatch of research and development personnel by lowering information barriers and optimising R&D management. Its efficient data analysis and value extraction capabilities can provide precise decision support for agribusinesses or farmers (Wolfert et al., 2017), which not only

directly improves the efficiency of capital allocation, but more importantly promotes the extensive spillover of knowledge, enabling the rapid diffusion of best practices and innovations. On the other hand, digital technology has profoundly changed the way of factor allocation and realised endogenous ‘Pareto improvement’. It has driven the restructuring of traditional industries (e.g., agriculture): the use of intelligent machinery has reduced simple human inputs, while creating highly skilled jobs and optimising the allocation of human capital. The data analysis capability of digital technology can accurately identify the marginal output differences of R&D personnel, enabling a more efficient allocation of highly skilled personnel to key innovation segments (e.g., precision agriculture technology R&D), thus improving overall R&D capital efficiency (Porter and Linde, 1995). This optimisation of R&D resource allocation further promotes the growth of agricultural green total factor productivity (AGTFP). On the one hand, reducing R&D mismatch can accelerate the innovation and diffusion of green agricultural technologies (e.g., smart irrigation, bio-fertiliser) (Xu and Ying, 2021) and improve resource utilisation efficiency. This not only improves food production, but also reduces resource waste, which is important for the green development of agriculture. On the other hand, the efficient allocation of R&D capital releases redundant costs and makes firms more inclined to invest in sustainable agricultural technologies (e.g., soil remediation, renewable energy applications), thus contributing to AGTFP in the long run. Therefore, digital technology indirectly enhances the green technology innovation capacity of agricultural production by optimising the allocation efficiency of R&D personnel and capital, and becomes a key mechanism to promote AGTFP growth.

H2: Digital technology innovations may provide a boost to green total factor productivity in agriculture by optimising resource allocation.

3.3 Analysis of the regulatory effect of digital technology innovation on agricultural green total factor productivity

Environmental regulation is one of the important means for the government to implement environmental protection strategies, the core of which lies in limiting pollutant emissions through legal and policy tools to promote the development of industries in the direction of greener and low-carbon. Porter’s hypothesis suggests that a certain level of environmental regulation can drive firms to innovate, which not only compensates for the extra cost of complying with environmental regulations, but also enhances the firm’s market competitiveness (Jiang, 2022). In the field of agriculture, environmental regulation can guide the transition of agricultural production towards sustainability. At the same time, the application of digital technology can not only help enterprises reduce environmental pollution, but also improve the production efficiency of agriculture and the quality of products through intelligent and precise management. Digital technology can also help enterprises collect and analyse huge amounts of data and optimise the allocation of resources, so as to meet the requirements of environmental regulation without increasing costs.

Under the combined effect of environmental regulation and digital technology innovation, green total factor productivity in

agriculture has been significantly improved. As an external constraint, environmental regulations drive enterprises to shift to more environmentally friendly production modes (Bustos et al., 2016). Meanwhile, digital technology innovation provides key technological means for enterprises to achieve efficient green transformation. The combination of the two not only facilitates the realisation of environmental objectives, but also promotes the advancement of agriculture in the direction of greater efficiency and sustainability, reduces resource wastage and environmental pollution, and improves the quality of yields and products, ultimately realising a win-win situation in terms of both economic and ecological benefits.

H3: Environmental regulation reinforces the positive effect of digital technology innovation on green total factor productivity in agriculture.

4 Research design

4.1 Model construction

4.1.1 Benchmark regression model construction

Considering the estimation bias caused by regional heterogeneity and time factor, the dynamic panel model with two-way fixed effects is adopted as the benchmark model in this chapter. The model is as follows:

$$AGTFP_{it} = \alpha_0 + \alpha_1 DTI_{it} + \alpha_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (1)$$

Where the subscript i is used to represent different provinces, and the subscript t represents different periods, the explanatory variable $AGTFP$, i.e., agricultural green total factor productivity; the core explanatory variable DTI indicates the provincial level of digital technological innovation; and X is a control variable. Province fixed effects μ_i and year fixed effects ϑ_t are also introduced. ε_{it} are random error terms.

4.1.2 Mechanism testing model construction

On the basis of the theoretical analysis of the role mechanism in the previous section, in order to test hypothesis H2, resource allocation efficiency is taken as a mechanism variable to deeply investigate its role mechanism between digital technology innovation and agricultural green total factor productivity. According to the test method proposed by Jiang (Tang et al., 2020), the following model is established:

$$RAE_{it} = \alpha_0 + \alpha_1 DTI_{it} + \alpha_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (2)$$

In Equation 2, RAE represents the level of resource allocation efficiency, which is the mechanism variable of the model, and other variables are described as above.

4.1.3 Moderating effect model construction

In order to test hypothesis H3, which is to explore the moderating effect of environmental regulation between digital technology innovation and agricultural green total factor productivity. The steps taken are: add the moderating variable ER into the model (1). Secondly, an interaction term $DTI_{it} \times ER_{it}$ is added to the model to

capture the interaction between the two; finally, the Equation 3 is constructed as follows:

$$AGTFP_{it} = \alpha_0 + \alpha_1 DTI_{it} + \lambda_{it} (DTI_{it} \times ER_{it}) + \alpha_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

4.2 Description of variables

4.2.1 Explained variables

Agricultural green total factor productivity (*AGTFP*). Based on the previous research on green total factor productivity measurement, the article adopts the SBM-BML method to measure agricultural green total factor productivity (Zhai and Liu, 2023). In order to reduce the skewness of the values and the influence of extreme values, the logarithm of the original variables is used. Among them, the specific indicator system is shown in Table 1.

To illustrate the spatial and temporal distribution of agricultural green total factor productivity, spatial heat maps of agricultural green total factor productivity for each province in China in 2010, 2015, and 2020 are presented (see Figure 1). Overall, the eastern coastal regions have consistently maintained higher productivity levels. However, from 2010 to 2020, productivity in the central, western, northern, and northeastern regions gradually improved, with regional disparities narrowing and overall levels rising. This may be attributed to factors such as policy support, technological advancements, and resource optimization driving agricultural green development.

4.2.2 Core explanatory variables

Digital Technological Innovation (*DTI*). At present, academics mainly build their own indicator system or adopt authoritative indicators for alternative measurement. Among them, R&D input and patent output are the main ways to measure innovation activities, which are widely used in the quantitative research of digital technological innovation. Therefore, in order to ensure the reasonableness of the selection of indicators, the article uses the data from Digital Economy Research Database (DERD), a professional database developed based on the development of digital economy and related researches, which displays China's economic development in three modules, namely, digital innovation, digital industry and digital platforms, including digital patents of each province. DERD is a professional database developed by the Institute of Digital Economy Development and Related Research, which shows China's economic development in three modules: digital innovation, digital industry and digital platforms, including digital patent applications and grants by province. Considering that it is more appropriate to use the data of patent innovation output as a measure of the technological innovation level of enterprises (Bai and Liu, 2018), this paper selects the number of digital economy-related invention patents granted in the DERD library as a representative of the Digital Technology Innovation Indicator (*DTI*), which is standardised and logarithmised to ensure the comparability and accuracy of the data.

4.2.3 Control variables

Meanwhile, based on the existing research, the control variables selected in this paper are as follows, while the logarithm of the original

variables is used to reduce the skewness of the values and the influence of extreme values.

(1) Level of tax burden (*Tax*). Measured as the ratio of tax to GDP. (2) Level of economic development (*PGDP*). Measured by the natural logarithm of per capita GDP to test the environmental Kuznets curve hypothesis. (3) Social Consumption Level (*Consume*). The ratio of retail sales of consumer goods to GDP. (4) Industrial structure (*Indstru*). It is obtained by multiplying the ratio of value added of primary industry to GDP by 1, the ratio of secondary industry to GDP by 2, and the ratio of tertiary industry to GDP by 3, and then adding these three values together. (5) Income gap between urban and rural residents (*Incomegap*). Measured by the ratio of disposable income per capita in urban and rural areas. (6) Population density (*Popden*). The natural logarithm of the ratio of total population to land area. (7) Level of transport infrastructure (*Trl*). The total volume of freight transport is taken in logarithmic terms. (8) Technology market development level (*Tel*). It is the ratio of technology market turnover value to regional GDP. (9) Informatisation level (*Infor*). The ratio of postal and telecommunication business volume to GDP. (10) Research and Development Intensity (*Rd*). Ratio of internal expenditure on R&D to GDP. (11) Openness to the outside world (*Open*). Ratio of total import and export of goods to GDP. (12) Industrialisation level (*Indlevel*). Is the proportion of industrial added value in the regional GDP. (13) Human Capital Level (*HUM*). The ratio of the number of students in higher education to the city's population.

4.2.4 Mechanism variables

Capital allocation efficiency level (*RAE*). Referring to the research of Bai Junhong and Liu Yuying (He et al., 2024), this paper measures the R&D staff mismatch index τ_{Lit} that indicates the level of regional capital allocation efficiency as follows:

$$\gamma_{Li} = \frac{1}{1 + \tau_{Lit}} \quad (4)$$

The γ_{Li} in Equation 4 is the absolute distortion coefficient of R&D factor price, which is usually replaced by the “relative price distortion coefficient”:

$$\hat{\gamma}_{Li} = \left(\frac{L_i}{L} \right)^{\beta_L} \left(\frac{s_i \beta_{Li}}{\beta_L} \right) \quad (5)$$

In Equation 5, s_i is the innovation output of region i , and β_{Li} is the output elasticity of R&D personnel in region i . In order to estimate the output elasticity of β , it is assumed that the innovation production function is a C-D production function with constant returns to scale, that is:

$$Y = AK_{it}^{\beta_{K_i}} L_{it}^{1-\beta_{K_i}} \quad (6)$$

In Equation 6, for innovation output expressed as Y , the number of patents is selected to measure; K_{it} is R&D capital investment, measured by the actual R&D expenditure input of each province; L_{it} is R&D personnel input, measured by the full-time equivalent of R&D personnel.

TABLE 1 Indicator system of green total factor productivity in agriculture.

Variables	Indicator	Unit	Nature of indicators
Green total factor productivity in agriculture	Number of people employed in the primary sector	Ten thousand people	Agricultural labour input
	Crop sown area	Thousand hectares	Agricultural land input
	Fertiliser application	Million tonnes	Agricultural fertiliser input
	Agricultural plastic film use	Million tonnes	Agricultural plastic film input
	Pesticide use	Million tonnes	Pesticide input
	Irrigated area	Thousand hectares	Agricultural water input
	Gross output value of agriculture, forestry, animal husbandry and fishery	Billion yuan	Expected output
	Agricultural carbon emissions	Million tonnes	Undesired output
	The total equivalent discharge of agricultural non-point source pollution (converting the discharge of total phosphorus, total nitrogen and chemical oxygen demand into equivalent pollutant discharge, with the pollutant discharge evaluation standards being 0.2 mg/L, 1 mg/L, and 20 mg/L respectively, and finally obtaining the total amount of agricultural non-point source pollution)	One billion cubic metres	Undesired output

4.2.5 Moderating variables

Environmental regulation intensity (*ERI*). Based on the government work reports of each province, referring to, the text of the government work reports was crawled using Python software, and the frequency of keywords closely related to environmental regulation was counted.

Environmental regulation intensity (*ER2*). This article also measures the intensity of environmental regulations by using the amount of pollution discharge fees paid. Specifically, the amount paid from 2009 to 2017 represents the amount deposited into the treasury, while the amount from 2018 to 2022 represents the environmental protection tax.

4.3 Data sources

In order to ensure the completeness and operability of the data sources, the panel data of 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan and Tibet) from 2009 to 2022 were finally used as the research sample. The data on digital technological innovation come from the China Research Data Service Platform (CNRDS). The data on green total factor productivity in agriculture are synthesised from the China Statistical Yearbook, the China Environmental Statistical Yearbook, the China Energy Statistical Yearbook, and the statistical yearbooks of each province. Data for other variables are derived from provincial statistical yearbooks. Missing data were interpolated. The descriptive statistics are shown in Table 2, and all the variables are within reasonable ranges. Pearson's correlation coefficient matrix¹ indicates that digital technology innovation and agricultural green total factor productivity are positively correlated at the 1% level, and the correlation coefficients of the variables do not have any serious covariance problems.

4.4 Model validation

The multicollinearity test results are shown in Table 3. The results indicate that the VIF values are all less than 10, which also indicates that there are no serious multicollinearity issues between the variables. In Table 4, the F-test significantly indicates that the model is effective overall, and the explanatory variables have joint significance for the explained variable. The Hausman test significantly supports the use of a fixed-effects model rather than a random-effects model. The heteroscedasticity test indicates that the error term variance is not constant, and robust standard errors or other methods should be used for correction.

5 Empirical results and analyses

5.1 Benchmark regression analysis

Table 5 demonstrates the results of the benchmark regression. Column (1) reports the results of the panel OLS regression model. The

¹ Specific test results are available from the authors due to space limitations.

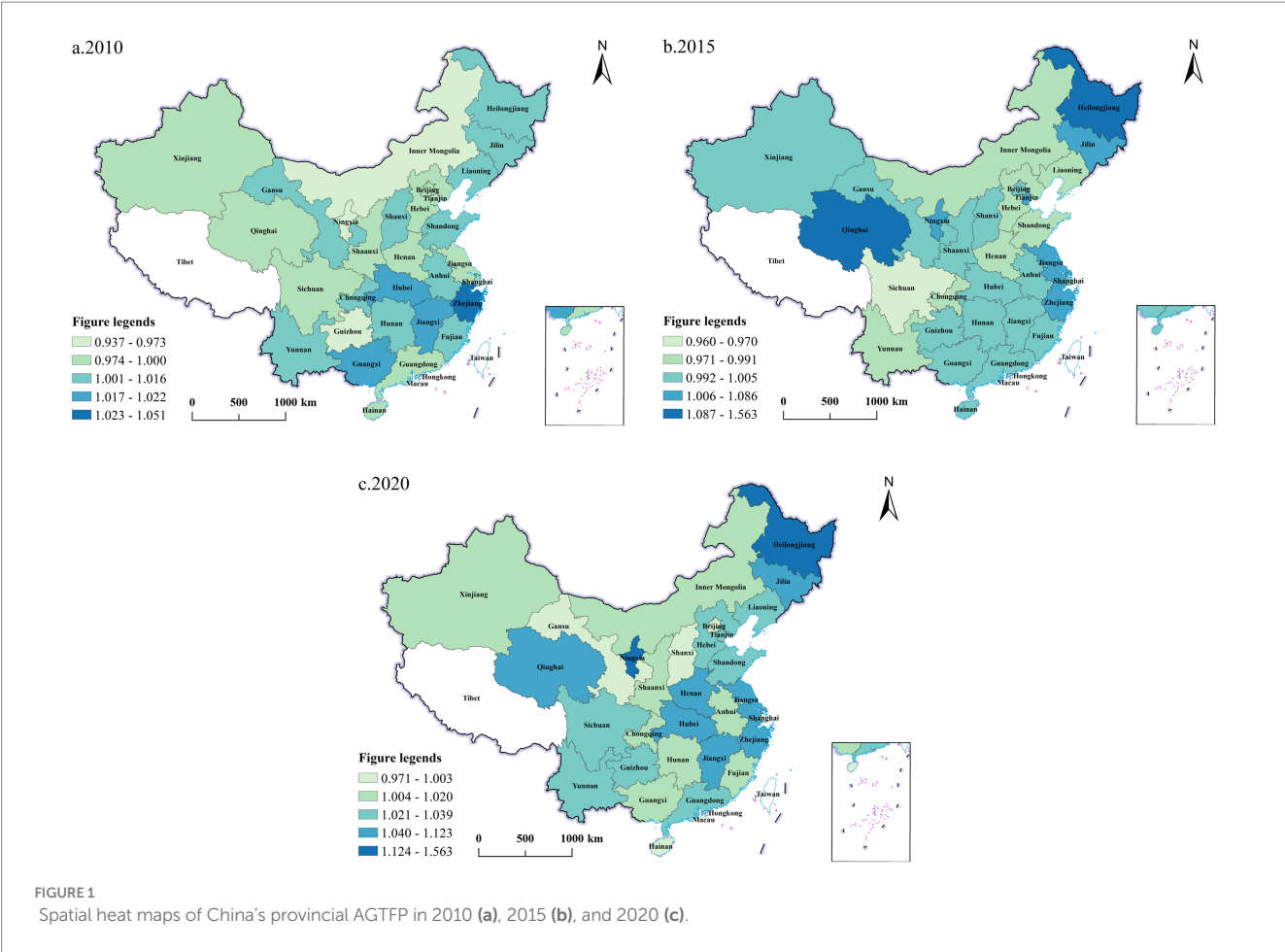


TABLE 2 Descriptive statistics.

Variables	Sample size	Mean	Standard deviation	Minimum value	Maximum value
AGTFP	420	1.0259	0.0573	0.9565	1.4111
DTI	420	2.8510	0.8670	0.4770	4.6300
Tax	420	0.0827	0.0279	0.0421	0.1720
PGDP	420	54,305	30,023	10,814	164,158
Consume	420	0.3890	0.0637	0.2220	0.5510
Indstru	420	2.3860	0.1270	2.1460	2.8230
Incomegap	420	2.5970	0.4080	1.8520	3.9090
Popden	420	466.4000	699.4000	7.8660	3929.0000
Trl	420	11.5800	0.8380	9.3110	12.9000
Tel	420	0.0166	0.0272	0.0002	0.1500
Infor	420	0.0633	0.0501	0.0190	0.2400
Rd	420	0.0207	0.0150	0.0022	0.0671
Open	420	0.2770	0.2940	0.0175	1.4640
Indlevel	420	0.3410	0.0819	0.1170	0.5420
HUM	420	0.0204	0.0058	0.0079	0.0378

specific results of the two-way fixed effects model are shown in Table 3, column (2). In this case, for every 1 per cent increase in digital technology innovation, green total factor productivity in

agriculture increases by 0.0500 per cent and passes the 1 per cent significance level. Hypothesis H1 is verified. With the application of big data and the Internet of Things, digital technological innovation

has promoted the transformation of traditional agriculture into green and sustainable development, which not only helps to improve production efficiency, but also further reduces environmental pollution, thus enhancing the green total factor productivity of agriculture. From a theoretical perspective, Schumpeter's innovation theory points out that innovation is the core driving force of economic growth, and digital technological innovation breaks the traditional balance of agricultural production with the help of big data and the Internet of Things to realise the recombination of production factors. Big data integration of soil, weather and other information to help accurate decision-making, real-time monitoring and intelligent control of the Internet of Things to enhance the accuracy of production, in line with Porter's theory of technological innovation to build a competitive advantage and enhance efficiency. In terms of policy, governments are actively promoting and China has introduced a series of supportive policies to create a favourable environment for the integration of digital technology and agriculture. In addition, the results in column (3) of Table 5 further indicate that digital technology innovation also contributes to technological efficiency progress at the provincial level. Most of the control variables reach statistical significance.

5.2 Endogeneity test

Given the possible causal relationship between digital technological innovation and AGTFP, and taking into account the possibility that some common factors may have been overlooked, thus

causing endogeneity problems. For this reason, the following four methods are used to address the endogeneity problem.

5.2.1 Lag effect of digital technology innovation

Considering that it takes a certain amount of time for digital technological innovations in the provinces to be widely used and absorbed in the agricultural sector. There may be a time interval from the generation of technological innovation to its practical application in agricultural production. Considering also that agricultural production is cyclical and it takes time to adapt and adjust to new technologies. Therefore, the independent variable is the green total factor productivity of agriculture in the next period, $AGTFP_{t+1}$ and then the regression is carried out, and the results are shown in column (1) of Table 6. The results show that digital technology innovation still has a significant positive effect on $AGTFP_{t+1}$ and passes the 10% significance level test. The result also reflects that digital technology innovation not only has a positive effect on agricultural green total factor productivity in the current period, and the result is robust.

5.2.2 Instrumental variable method

The improvement of agricultural green total factor productivity is closely linked to the development of digital technology innovation, and there may be a reverse causality between the two. On the one hand, digital technology innovation is a driver of AGTFP; on the other hand, an increase in AGTFP also increases the demand for digital innovation, which in turn promotes the further development of digital technology innovation. At the same time, the endogeneity issue is particularly prominent considering that the results may also be potentially affected by some unobservable factors. Therefore, the instrumental variable approach is utilised and the 2SLS model is applied for in-depth estimation.

$$AGTFP_{it} = \alpha_0 + \alpha_1 DTI_{it} + \alpha_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (7)$$

$$AGTFP_{it} = \alpha_0 + \alpha_1 IV_{it} + \alpha_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (8)$$

Equation 7 is the same as Equation 1, and in Equation 8, IV represents the instrumental variable. The article regards digital technological innovation as an endogenous variable and refers to the study of He Ying et al. The article chooses the mean value of digital technological innovation of other provinces in the same year as an instrumental variable (He et al., 2024). On the one hand, there may be similar trends and patterns in the accumulation and use of digital technological innovation among provinces, and this instrumental variable meets the requirement of correlation. On the other hand, the digital technology innovation of other provinces is not directly related to the AGTFP of this province, so it satisfies the exogeneity requirement of the instrumental variable.

Column (2) of Table 6 demonstrates the results of the first stage. The coefficient of IV reaches the 1% level of significance with an F-statistic of 47.85, which is much higher than the rule of thumb

TABLE 3 Multicollinearity test.

Variables	VIF	1/VIF
DTI	8.950	0.112
PGDP	8.130	0.123
Indstru	7.170	0.139
Open	4.710	0.212
Tel	4.390	0.228
Popden	4.180	0.239
Trl	4.000	0.250
Tax	3.290	0.304
Incomegap	3.260	0.307
HUM	3.050	0.328
Rd	2.730	0.367
Indlevel	2.130	0.469
Consume	1.360	0.736
Infor	1.170	0.857
Mean VIF		4.180

TABLE 4 F-test, Hausman test, and heteroscedasticity test.

Variables	F-test		Hausman test		Heteroscedasticity test	
	F statistic	p value	χ^2	p value	$\chi^2(1)$	p value
AGTFP	4.11	0.000	26.69	0.0211	429.60	0.000

TABLE 5 Benchmark regression results.

Variables	(1) <i>AGTFP</i>	(2) <i>AGTFP</i>	(3) Rate of technological progress
<i>DTI</i>	0.0398*** (4.5461)	0.0500*** (2.9745)	0.0557*** (4.0801)
Control variables	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes
Area fixed effects	No	Yes	Yes
Observations	420	420	420
R-squared	0.218	0.436	0.452

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent, and 10 per cent, respectively. Parentheses in the table contain *t*-values.

TABLE 6 Endogeneity test results.

Variables	Explained variable lagged 1 period	Instrumental variable method		PSM-DID
	(1) <i>AGTFP</i>	First stage	Second stage	(4) <i>AGTFP</i>
		(2) <i>DTI</i>	(3) <i>AGTFP</i>	
<i>DTI</i>	0.0637* (1.8932)		0.0885*** (4.0854)	
<i>IV</i>		0.6687*** (6.8612)		
<i>Treat*Post</i>				0.0129* (1.7665)
Control variables	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	390	420	420	220
R-squared	0.454		0.068	0.189
F-test		47.85***		
Kleibergen-Paap rk LM statistic		3.85**		
Cragg-Donald Wald F statistic		47.85*** [16.38]		

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

suggestion of 10, suggesting that there is a strong correlation between endogenous and instrumental variables and there is no weak instrumental variable problem. Also, the Cragg-Donald Wald F-statistic exceeds the broad value of 16.38 for the Stock-Yogo weak instrumental variable test, further rejecting the original hypothesis of weak instrumental variables. Also, the Kleibergen-Paap rk LM statistic rejects the under-identification of instrumental variables, suggesting that instrumental variables are justified. Column (3) presents the results of the second stage in which the *DTI* coefficient remains significantly positive and passes the 1% significance level. It indicates that after considering the endogeneity problem, digital technological innovation in provinces still has a significant contribution to its *AGTFP* growth, and the regression results are reliable.

5.2.3 PSM-DID

To mitigate possible sample selection bias and reverse causality issues, endogeneity tests using the PSM-DID method were also

conducted to explore the impact of digital technology innovations on *AGTFP*. In 2016, in order to accelerate the implementation of the big data strategy with the acceleration of the digital transformation process, the State Ministry of Industry and Information Technology (MIIT) released the “Big Data Industry Development Plan (2016–2020)”. Referring to He et al. study, this is selected as an exogenous shock event (Dippel et al., 2020). The *Treat* variable is constructed first. The digital technology innovation level of the province where the province is located in 2016 is less than the median of all provinces as the experimental group, and *Treat* takes the value of 1, and vice versa is 0. The time variable *Post* is constructed. 2016 and later is 1, and vice versa is 0.

(1) PSM Matching

Propensity score matching was performed on the data prior to the treatment behaviour. Logit regression is used for the *Treat* variable, along

with 1:2 nearest-neighbour matching, and the selected covariates are the level of tax burden (*Tax*), the level of economic development (*PGDP*), the level of social consumption (*Consume*), the high level of industrial structure (*Indstru*), the urban–rural residents' income gap (*Incomegap*), the population density (*Popden*), the level of transport infrastructure level (*Trl*), technology market development level (*Tel*), informatisation level (*Infor*), R&D intensity (*Rd*), openness to the outside world level (*Open*), industrialisation level (*Indlevel*) and human capital level (*HUM*). The results of the balance test show that the difference between the covariates of the control group and the treatment group after matching is small, which satisfies the balance test of the PSM [the results of the balance test of the PSM are not shown due to space reasons, and they can be obtained from the corresponding authors if needed].

(2) DID regression

The model is designed in the following form:

$$AGTFP_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + \sigma_j X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (9)$$

The PSM-matched samples are regressed again according to Equation 9 and the results are shown in column (4) of Table 6, where the *Treat*Post* coefficient is still significantly positive, which again validates the robustness of the results.

(3) Parallel trend test

Articles were subjected to parallel trend tests and placebo tests. Figure 2 illustrates the results of the parallel trend test. As can be seen from the figure, before the policy was implemented, there was no significant difference between the treatment and control groups, with the

data points fluctuating around the zero line. At the time of the intervention, although the data points rose slightly, they then fell back around the zero line. After the intervention, the data points showed some fluctuation, but overall there was no sustained upward or downward trend. This suggests that the results support the parallel trend hypothesis, i.e., in the absence of the intervention, the trends in the treatment and control groups were similar. Furthermore, while the intervention may have had some impact in the short term, the long-term effect of this impact was not significant.

(4) Placebo testing

A placebo test is conducted to avoid that the effect of policy on green total factor productivity in provincial agriculture is affected by unobservable omitted variables. The basic logic lies in finding an erroneous policy variable that does not have a shock to capacity utilisation and is stochastic in nature, thus generating an incorrectly estimated coefficient, and repeating the above regression process 1,000 times and finally calculating a kernel density distribution of 1,000 coefficients β . As shown in Figure 3, the mean of the regression coefficients is close to zero and exhibits the characteristics of a normal distribution. The vast majority of the regression coefficients are not significant, which indirectly indicates that the unobservable omitted variables did not have an impact on the reliability of the conclusions, in line with the requirements of the placebo test.

5.3 Robustness tests

5.3.1 Replacement of core explanatory variables

In order to verify the robustness of the results, the following three variables are selected as alternative indicators. The following three

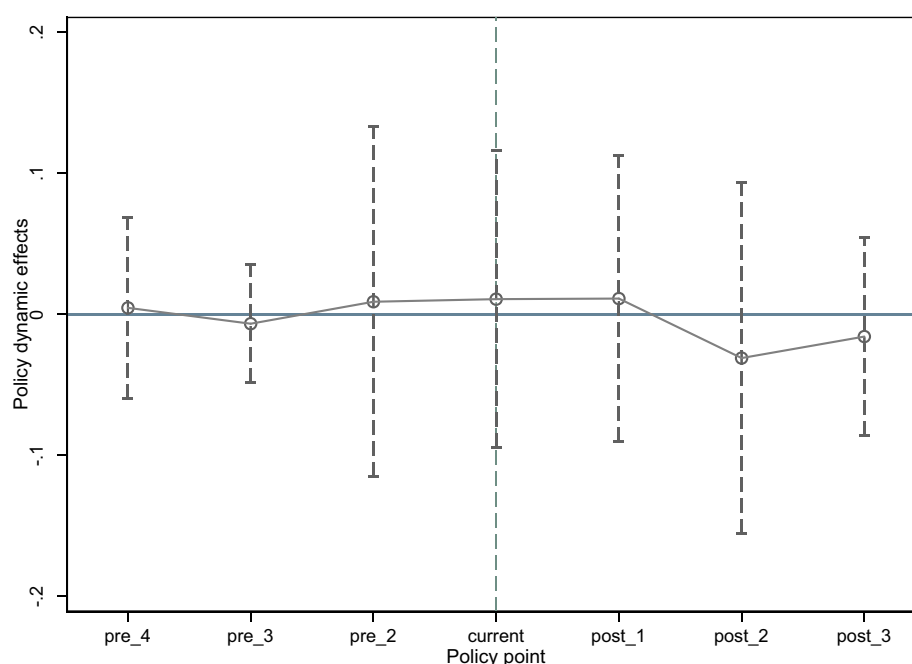


FIGURE 2
Parallel trend test chart.

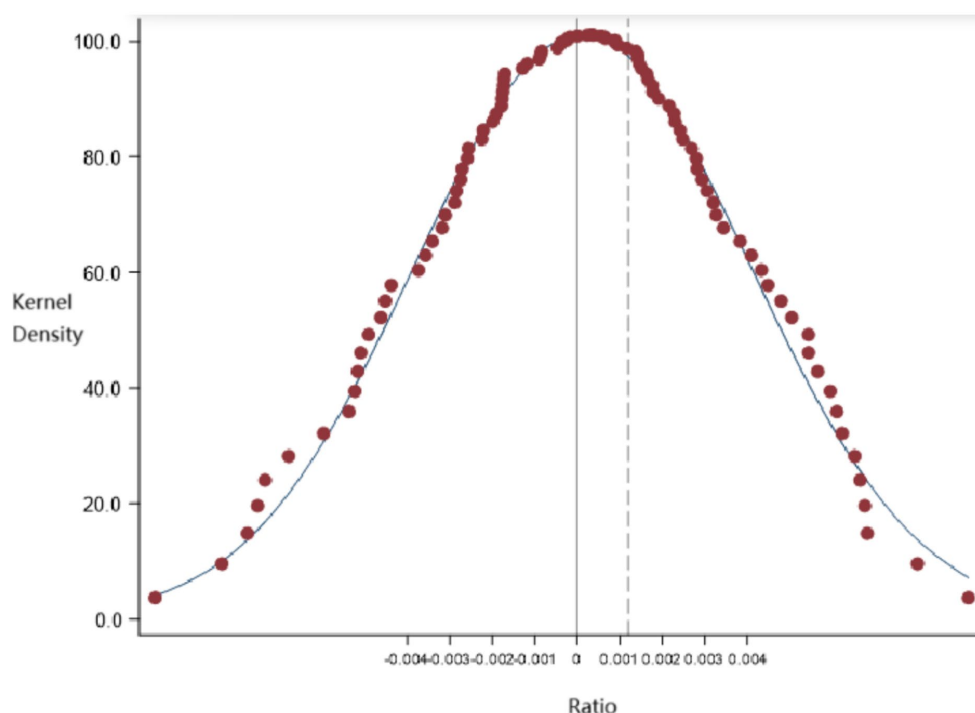


FIGURE 3
Placebo chart.

variables are used as proxy indicators: “the number of inventions related to the digital economy filed in the same year” (*DTI2*), “the number of utility models related to the digital economy filed in the same year” (*DTI3*), and “the number of utility models related to the digital economy authorised in the same year” (*DTI4*), respectively. Number of digital economy-related utility models” (*DTI4*) as alternative indicators, and re-run the regression, and the results are shown in columns (1)–(3) of [Table 7](#). The results show that digital technology innovation still has a significant positive impact on AGTFP, which indicates that the conclusions of this paper are robust and reliable.

5.3.2 Adjusting the time horizon

Considering that the outbreak of COVID-19 in late 2019 had a great impact on global economic and social activities, as well as a significant impact on agricultural production, supply chain and market demand. In order to ensure the accuracy and robustness of the research results, and to avoid the potential interference and bias of the epidemic as an exogenous event on the research results, the article excludes the data of the year 2019. The regression results are shown in column (4) of [Table 7](#). After excluding the year 2019, digital technological innovation still enhances AGTFP, and this result reflects robustness.

5.3.3 Excluding the municipalities sample

Beijing, Shanghai, Tianjin and Chongqing have a relatively higher degree of economic development compared to other cities, and the promotion effect of digital technology innovation on AGTFP may be amplified in the full sample. Therefore, after removing the municipalities, the regression is re-run and the results are presented

in column (5) of [Table 7](#). The data show that the estimated coefficient of *DTI* is still significantly positive, which indicates the robustness of the findings.

5.4 Analysis of the mechanism of action

The article will continue to conduct an in-depth test of the mechanism of capital allocation effect of digital technology innovation on the growth of green total factor productivity in agriculture. Due to data availability constraints, the mechanism analysis sample is reduced to 400 observations (compared to the baseline 420), primarily because RAE measurement requires additional financial and agricultural investment data that are not fully available for all provinces in every year. The results are reported to [Table 8](#). It can be seen that the estimated coefficient of *DTI* is 0.3569 and reaches the significance level of 10%. This statistical result implies that there is a relatively obvious correlation between the improvement of the level of digital technology innovation and the improvement of the capital allocation efficiency of the province, i.e., the improvement of the level of digital technology innovation can promote the improvement of the capital allocation efficiency of the province to a certain extent. On the one hand, digital technology (e.g., big data analysis, cloud computing platform) significantly reduces human capital mismatch in agricultural research by accurately matching R&D personnel's professional skills and innovation needs. For example, intelligent algorithms can analyse the patent output and research field matching of researchers, and allocate highly skilled personnel more effectively to key green technology research links (e.g., biopesticide research and development, intelligent irrigation system optimisation). The significant positive coefficients of *DTI* in [Table 8](#) indicate that this optimal allocation of R&D human capital directly

TABLE 7 Robustness test results.

Variables	Replacement of core explanatory variables			Adjust time interval	Exclude municipality samples
	(1) <i>AGTFP</i>	(2) <i>AGTFP</i>	(3) <i>AGTFP</i>	(4) <i>AGTFP</i>	(5) <i>AGTFP</i>
<i>DTI2</i>	0.0597**				
	(2.6954)				
<i>DTI3</i>		0.0617***			
		(3.0389)			
<i>DTI4</i>			0.0523**		
			(2.0583)		
<i>DTI</i>				0.0434***	
				(2.8747)	
Control variables	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Area fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	390	364
R-squared	0.443	0.444	0.440	0.399	0.457

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

TABLE 8 Results of the test of the mechanism of action.

Variables	(1) <i>RAE</i>
<i>DTI</i>	0.3569*
	(1.7913)
Control variables	Yes
Province fixed effects	Yes
Time fixed effects	Yes
Observations	400
R-squared	0.132

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

enhances the output efficiency of the agricultural innovation system. On the other hand, digital technology platforms (e.g., agricultural research collaboration cloud, open-source databases) break down the information barriers of traditional agricultural R&D, enabling green technology innovations (e.g., soil remediation technologies, low-carbon planting models) to spread more quickly across different regions and institutions. This knowledge spillover effect reduces the duplication of R&D inputs and increases the marginal output of innovation resources. The significance of *DTI* in the empirical results confirms that digital technology indirectly improves the overall utilisation efficiency of R&D capital by building an open innovation network.

Improvements in capital allocation efficiency contribute to provincial *AGTFP* growth in a number of ways. Efficient allocation of R&D manpower and capital accelerates innovative breakthroughs in precision agriculture technologies (e.g., variable fertiliser application, plant protection by drones) and sustainable solutions (e.g., agricultural waste resourcing), which directly enhances the environmental friendliness of agricultural production. On the other hand, reducing R&D mismatch can reduce ineffective research expenditures, so that more funds flow to high-potential green projects (e.g., drought-tolerant crop breeding, agricultural carbon sink research), forming a virtuous cycle of innovation resources, which is ultimately reflected in the sustained growth of *AGTFP*.

TABLE 9 Results of causal effect test.

Variable	Capital Allocation Efficiency
	(1) <i>RAE</i>
Indirect effect	0.0838* (0.0620)
Direct effect	0.0621*** (0.0000)
Total effect	0.1460*** (0.0000)
Total explanatory power	57.43%

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

Referring to the causal effect model based on instrumental variable approach proposed by Dippel et al. (2020), the results of Table 8 are further analysed as shown in Table 9. The results show that digital technological innovations have an indirect effect of 0.0838 on *AGTFP* by promoting capital allocation efficiency (significant at the 10% level), with an explanatory power of 57.43% for the total effect. It can be seen that the results of Table 8 are re-validated and have good robustness.

5.5 Moderating effect analysis

Considering that there is a potential interaction between digital technological innovation and environmental regulation, this relationship is particularly significant in agriculture. As can be seen in column (3) of Table 10, digital technological innovation still has a significant positive effect on *AGTFP* after adding *DTI*ER1*. Under the moderation of environmental regulation, every 1 per cent increase in *DTI* raises *AGTFP* by 0.0280 per cent. This suggests that environmental regulation reinforces the positive effect of digital technology innovation on agricultural green total factor productivity. To ensure robustness, we reintroduced the more robust environmental regulation variable *ER2*. After adding *DTI*ER2*, digital technology innovation still had a significant positive effect on *AGTFP*. In other words, environmental regulation plays a positive moderating role and hypothesis H3 is tested.

TABLE 10 Results of regulation effects.

Variables	(1) <i>AGTFP</i>	(2) <i>ER1</i>	(3) <i>AGTFP</i>	(4) <i>ER2</i>	(5) <i>AGTFP</i>
<i>DTI</i>	0.0500*** (2.9745)	−0.1474 (−0.9608)	0.0281** (2.1754)	1.1326** (2.6501)	0.0327* (2.0161)
<i>ER1</i>			−0.1226** (−2.5687)		
<i>DTI*ER1</i>			0.1209** (2.4287)		
<i>ER2</i>					−0.1491*** (−2.7828)
<i>DTI*ER2</i>					0.1442*** (2.8047)
Control variables	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	420	420
R-squared	0.436	0.621	0.451	0.647	0.446

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

Based on the Porter's hypothesis of the compensating effect of innovation, regions facing additional cost pressures from environmental regulation often resort to technological innovation to achieve cost reductions and efficiency improvements. Environmental regulation exerts strong external pressure on agribusinesses or farmers by setting strict environmental standards and constructing enforcement and monitoring mechanisms, and successfully internalises this pressure into innovation momentum, which is a powerful impetus for the reorientation of changes in agricultural production. At the institutional level, institutional regulation becomes a key factor driving agribusinesses or farmers to explore more environmentally friendly and efficient production strategies. Resource-based theory emphasises that a firm's competitive advantage derives from the effective control and use of its unique resources. As environmental regulations continue to tighten, traditional models of resource consumption are being severely restricted. If agribusinesses want to maintain their competitiveness in the new environmental regulatory landscape, they must re-examine and optimise the way they use resources. At this point, the advantages of digital technology come to the fore, it can accurately monitor the soil, climate and other key elements, according to the actual situation to achieve the supply of resources on demand, greatly improving the efficiency of resource use, effectively reducing the cost of production and environmental costs. The innovative atmosphere and orientation created by environmental regulation can also encourage farmers to actively adopt more environmentally friendly agricultural technologies. The adoption of environmentally friendly technologies by farmers can help reduce resource wastage and environmental pollution, and promote the overall development of agricultural production in the direction of green and sustainable development, which in turn can better enhance *AGTFP*.

5.6 Heterogeneity analysis

- (1) Financial development level heterogeneity. To test the effect of digital technological innovation (*DTI*) on the heterogeneity of

the level of financial development of agricultural green total factor productivity (*AGTFP*), the Equation 10, is constructed:

$$AGTFP_{it} = \beta_0 + \beta_1 DTI_{it} + \beta_2 FINA + \beta_3 (DTI * FINA) + \beta_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (10)$$

where *FINA* is the regional level of financial development (e.g., deposit and loan balances/GDP). As shown in column (1) of Table 11, the interaction term coefficient *DTI*FINA* is significantly positive (0.0121*), indicating that the level of financial development strengthens the contribution of *DTI* to *AGTFP*. In order to verify the structural differences between groups, the sample is divided into higher and lower financial development level groups according to the median financial development level, and further group regression is conducted, and columns (2) and (3) of Table 11 show that the higher financial development level is more significant in the region. This may be due to the fact that in regions with higher levels of financial development, agribusinesses and farmers are more likely to obtain credit support (e.g., digital equipment financial leasing, special loans for green technology), which eases the financial constraints of digital technology application and allows the full release of the green efficiency potential of *DTI*.

- (2) Inland coastal heterogeneity. To test the heterogeneous impact of digital technology innovation (*DTI*) on agricultural green total factor productivity (*AGTFP*) in inland and coastal regions, the Equation 11 is constructed:

$$AGTFP_{it} = \beta_0 + \beta_1 DTI_{it} + \beta_2 COASTAL + \beta_3 (DTI * COASTAL) + \beta_k X_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \quad (11)$$

where *COASTAL* is a dummy variable for coastal provinces (coastal = 1, inland = 0). As shown in column (1) of Table 12, the

TABLE 11 Results of the analysis of heterogeneity in levels of financial development.

Variable	Full sample	High level of financial development	Low level of financial development
	(1) <i>AGTFP</i>	(2) <i>AGTFP</i>	(3) <i>AGTFP</i>
<i>DTI</i>	0.0286* (1.7593)	0.0520*** (3.2447)	0.0149 (0.6371)
<i>FINA</i>	0.0312* (1.7364)		
<i>DTI*FINA</i>	0.0121* (1.9904)		
Control variables	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	410	242	175
R-squared	0.440	0.436	0.731

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

TABLE 12 Results of heterogeneity analysis.

Variable	Full sample	Coastal	Inland
	(1) <i>AGTFP</i>	(2) <i>AGTFP</i>	(3) <i>AGTFP</i>
<i>DTI</i>	0.0242* (1.7188)	0.0777*** (2.8812)	−0.0037 (−0.2651)
<i>COASTAL</i>	0.0497* (1.7393)		
<i>DTI*COASTAL</i>	0.0167** (2.1524)		
Control variables	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	400	154	263
R-squared	0.518	0.479	0.283

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

interaction term coefficient *DTI*COASTAL* is significantly positive (0.0167**), suggesting that the green efficiency gains of *DTI* are stronger in coastal areas. In order to verify the structural differences between groups, the sample is divided into groups with higher and lower levels of financial development according to the median level of financial development, and further group regressions are conducted, which are shown in columns (2) and (3) of Table 12, indicating that it is more significant for regions with higher levels of financial development. This may be due to the fact that for coastal provinces, with the rapid development of the digital economy, they have stronger digital technology systems and better infrastructure, so the effect of digital technology innovation on *AGTFP* is more significant.

5.7 Further analyses

The article further explores the economic consequences of the impact of digital technological innovations on green total factor productivity in agriculture, including its impact on the high quality

development of provincial economies and the reduction of wastewater discharges, with a view to comprehensively understanding the multidimensional impact of digital technological innovations on agricultural performance and environmental protection.

Referring to the practice of Sun Ho et al., the entropy method is used to construct the variable of high quality economic development (*GERE*) (Sun et al., 2020). Specific indicators are shown in Table 13. High-quality economic development is a form of development where innovation serves as the primary driving force, coordination is an inherent characteristic, green development is the norm, openness is an inevitable path, and shared benefits are the fundamental objective. It abandons the model of pursuing economic growth speed alone, placing greater emphasis on the quality, efficiency, and sustainability of economic development. It stresses the coordinated advancement of multiple aspects, including economic structural optimisation, enhanced innovation capabilities, ecological and environmental protection, and social fairness and justice. The aim is to achieve comprehensive, coordinated, and sustainable development of the economy, society,

TABLE 13 Indicator system of high quality economic development (*GERE*).

Variables	Second-level indicators	Third-level indicators	Indicator measurement
High quality economic development (<i>GERE</i>)	Innovative development	GDP growth rate	Regional GDP growth rate
		R&D intensity	R&D expenditure of large-scale industrial
		Investment efficiency	Incremental capital output ratio (ICOR) = Investment rate/Regional GDP growth rate
		Technology transaction activity	Technology transaction volume/Regional GDP
	Coordinated development	Demand structure	Total retail sales of consumer goods/regional GDP
		Urban–rural structure	Urbanisation rate
		Industrial structure	Increase in the proportion of the tertiary industry in regional GDP
		Government debt burden	Government debt balance/regional GDP
	Green development	Energy consumption elasticity coefficient	Energy consumption growth rate/regional GDP growth rate
		Wastewater per unit of output	Total wastewater discharge/regional GDP
		Air emissions per unit of output	Sulphur oxide emissions/regional GDP
	Open development	Foreign trade dependency	Total imports and exports/regional GDP
		Foreign investment ratio	Actual utilisation of foreign investment/regional GDP
		Marketization level	Regional marketization index
	Shared development	Share of labour compensation	Labour compensation/regional GDP
		Resident income growth elasticity	Growth rate of per capita disposable income of residents/ growth rate of regional GDP
		Urban–rural consumption gap	Per capita consumption expenditure of urban residents/ per capita consumption expenditure of rural residents
		Share of fiscal expenditure on livelihood	Share of local fiscal expenditure on education, medical care, housing security, social security, and employment in local fiscal budget expenditure

TABLE 14 Economic outcome test.

Variables	(1) <i>GERE</i>	(2) <i>Water</i>
<i>DTI</i>	0.0429**	−0.2857*
	(2.4351)	(−2.0316)
Control variables	Yes	Yes
Province fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	420	410
R-squared	0.954	0.971

***, ** and * indicate that the test was passed at a significance level of 1 per cent, 5 per cent and 10 per cent, respectively. Parentheses in the table are *t*-values.

and environment, thereby meeting the people's growing needs for a better life. The data in column (1) of Table 14 show that the estimated coefficient of digital technology innovation on the high-quality development of the economy is 0.0429 and passes the significance level of 5%. This indicates that digital technological innovation has a facilitating effect on the improvement of China's AGTFP, which in turn promotes the high-quality development of China's economy. At the level of scientific and technological empowerment, the use of digital technological innovation can achieve real-time monitoring and optimisation of the agricultural production process and improve the efficiency of resource allocation. In addition, from the perspective of sustainable development, digital technological innovation through the empowerment of agricultural enterprises or farmers to implement precision agriculture and intelligent management, effectively reducing the amount of chemical fertilisers and pesticides, is conducive to the protection of the ecological environment. From the perspective of improving economic efficiency, digital technology innovation can improve the quality and value of agricultural products by optimising the agricultural industry chain, thus enhancing the efficiency of the agricultural economy, and thus strongly promoting the high-quality development of the economy. Therefore, the production mode of digital technology innovation not only improves the green total factor productivity of agriculture, but also responds to the demand for sustainability in high-quality economic development.

In addition, the effect of digital technological innovation on wastewater discharge by enhancing agricultural green total factor productivity (AGTFP) was tested and the results are presented in column (2) of Table 14. It can be seen that the estimated coefficient of digital technology innovation on wastewater discharge (Water) is −0.2857 and passes the 10% significance level, which indicates that digital technology innovation can reduce wastewater discharge by enhancing AGTFP. The application of digital technology in precision agriculture, such as precise monitoring and management of water, nutrient and pesticide application on farmland, can reduce excessive irrigation and chemical application, which directly reduces agricultural wastewater production and improves the efficiency of water and agricultural inputs by optimising the agricultural production process. In addition, digital technological innovation provides the government with efficient means of data analysis and monitoring, which helps the government to formulate and implement more stringent environmental protection policies, and encourage agriculture to

shift to a greener and more sustainable model, thereby reducing wastewater discharge.

6 Conclusions and policy recommendations

6.1 Main conclusions

Taking China's 30 provincial panel data (except Hong Kong, Macao, Taiwan, and Tibet) from 2009 to 2022 as samples, the article finds that: (1) There is a significant positive association between digital technology innovation and green total factor productivity in agriculture, and this conclusion still holds after a series of robustness and endogeneity tests. (2) There is a correlation between digital technological innovation and optimal resource allocation, and optimal resource allocation is associated with the improvement of green total factor productivity in agriculture, so it is hypothesised that digital technological innovation can contribute to the improvement of green total factor productivity in agriculture through the optimisation of resource allocation; environmental regulation can strengthen the enhancement of agricultural green total factor productivity by digital technological innovation; heterogeneity analysis shows that the enhancement of agricultural green total factor productivity by digital technological innovation is more obvious in the areas with higher level of financial development and the coastal areas. (3) Digital technology innovation can promote the high-quality development of regional economy while improving agricultural green total factor productivity, and it can also effectively reduce the amount of agricultural wastewater discharge.

6.2 Policies recommendations

- (1) Enhance investment in digital technology innovation and comprehensively improve innovation capacity.

The government should substantially increase its financial support, focusing on cutting-edge basic research and high-end key technology R&D in agricultural digital technology, such as the application of artificial intelligence in the accurate prediction of agricultural pests and diseases, in areas with a high level of financial development and coastal areas to consolidate its leading edge; for areas with a low level of financial development and inland areas, focusing on the construction of demonstration projects for digital technology and the promotion of mature and applicable digital technologies, such as simple intelligent irrigation systems, and lowering the threshold of technology application. At the same time, optimise tax policies and implement nationwide tax relief measures to encourage enterprises to increase investment in digital technology R&D, especially guiding them to carry out targeted R&D in different regions based on local agricultural characteristics, such as developing water-saving digital agricultural technologies in arid regions in the north. In addition, the deployment of 5G networks and the construction of big data centres should be accelerated in regions with low levels of financial development and inland areas, so as to provide hardware support for the digitisation of agriculture in these regions. On the part of enterprises, they should actively invest resources in the development of high-end green agricultural digital technologies, such as

big-data-based precision fertiliser application systems, in regions with high levels of financial development and coastal areas, and practical green agricultural digital technologies, such as solar-powered simple agricultural monitoring equipment, in inland areas.

- (2) Strengthen economic interaction across regions to create a digital synergy green economic development circle.

For lower levels of financial development and inland regions, the first priority is to increase funding for digital infrastructure and deploy key 5G networks, IoT technologies and cloud computing platforms to narrow the digital infrastructure gap with regions with higher levels of financial development and coastal regions. The government needs to formulate a customised digital economy development strategy that takes into account the characteristics of local agricultural resources, such as the rich speciality agricultural resources in inland areas, and promotes the digital transformation of these regions through incentives such as tax incentives and financial subsidies. The government should actively promote cross-regional digital technology transfer and cooperation, organise cooperation between enterprises and scientific research institutions in regions with higher levels of financial development and coastal regions and inland regions, jointly set up research and development institutes and technology trading platforms, and accelerate the circulation and application transformation of digital technology achievements suitable for inland regions, such as introducing advanced agricultural e-commerce models in coastal regions to inland regions. Promote cross-regional cooperation in green finance, jointly establish green investment funds and issue green bonds, with a focus on supporting the implementation of synergistic green economic strategies in regions with poor financial development and inland regions, such as supporting the development of eco-agriculture tourism and other green industries in inland regions. Promote cross-regional talent mobility and exchanges, establish talent incentive mechanisms, and guide the transfer of talents from coastal regions to inland regions, especially composite talents in the fields of digital technology and agriculture, so as to provide sufficient human resources support for digital technology innovation in inland regions.

- (3) Optimise resource allocation to promote the synergistic development of digital and green.

Across the country, IoT equipment, satellite remote sensing and drone technology are being used to comprehensively collect information on soil moisture, temperature and crop growth on farmland, so as to achieve precise agricultural management. In regions with higher levels of financial development and coastal areas, a more advanced and comprehensive agricultural big data platform can be established to integrate multi-channel data such as meteorological data, market trends, crop growth conditions, and dynamics of the international agricultural market for in-depth analyses and forecasts, providing precise decision-making support for agribusinesses and large-scale farms and realising efficient allocation of resources. For lower levels of financial development and inland areas, a comprehensive agricultural big data platform suitable for local scale and needs should be established, integrating basic data such as local meteorology, soil, and market to provide practical decision-making advice and help farmers rationally arrange planting plans and use of resources. Strengthen education, training and knowledge dissemination, and formulate differentiated training programmes

according to the level of agricultural development and farmers' acceptance in different regions, so as to improve the digital skills and awareness of green agriculture among farmers and agricultural practitioners, and enable them to make effective use of digital technology to optimise resource allocation, for example, in the inland areas, through simple and easy-to-understand training courses and on-site demonstrations, so as to enable farmers to master the use of smart irrigation systems

- (4) Reasonable environmental regulation to promote digital green co-development.

In regions with a high level of financial development and coastal areas, higher pollutant emission ceilings and resource efficiency indicators can be set to promote the greening of agriculture in these regions towards the high-end, for example, by requiring large-scale agribusinesses in coastal areas to achieve zero sewage discharge. For lower levels of financial development and inland areas, set environmental standards that are in line with local realities, and gradually guide the green transformation of agricultural activities, for example, by first requiring small farms in inland areas to reduce the amount of chemical fertiliser used. Establish a synergistic mechanism between environmental regulation and digital innovation, and encourage enterprises in different regions to use digital technological innovation to achieve environmental regulation goals, such as supporting enterprises in areas with high levels of financial development to research and develop agricultural waste recycling systems based on digital technology. Implement differentiated environmental regulatory strategies for agribusinesses in different regions and sizes, avoiding a one-size-fits-all approach. For small-scale agricultural enterprises in regions with a low level of financial development and inland areas, a certain transition period and technical support should be given to help them gradually meet environmental standards; for large-scale agricultural enterprises in regions with a high level of financial development and coastal areas, they should be strictly required to meet high standards immediately, so as to ensure the fairness and effectiveness of regulation and to promote synergistic development of digital technology and green development of agriculture on a nationwide scale.

6.3 Comparison of findings with evidence to the contrary

Based on the panel data of 30 provinces in China from 2009 to 2022, this study finds that digital technology innovation is positively associated with agricultural green total factor productivity. However, there is evidence to the contrary, such as the fact that digital technology innovation does not significantly enhance agricultural green development in some less economically developed regions due to weak digital infrastructure; there are also arguments that it may bring negative effects such as resource mismatch and increased environmental pressure, and that the effect of regional differences is uncertain. Comparison reveals that the small sample range, research methodology, and short time span are the main reasons for the different conclusions. Despite the contrary voices, the conclusions of this study are robust and should be followed up by strengthening

digital infrastructure, scientific planning of regulatory projects, developing differentiated strategies, and strengthening policy guidance in order to promote the synergy between digital technological innovation and green agricultural development.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

QG: Writing – original draft, Funding acquisition, Visualization, Software, Resources, Formal analysis, Validation, Supervision, Project administration, Conceptualization, Methodology, Writing – review & editing, Investigation, Data curation. WT: Writing – review & editing, Investigation, Project administration, Formal analysis, Methodology.

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